EE6770_F24_HW5

October 28, 2024

#

EE6770 Fall 2024 Homework 5: Cats and Dogs Classifier

1. **Write comments** in the code to explain your thoughts.
2. **Important: Execute the codes and show the results**.
3. **Do your own work.**

0.0.1 Submission:

- **Submit this notebook file and the pdf version** - remember to add your name in the filename.
- Deadline: 11:59 pm, 10/28 (Monday)

0.1 Assignment Objectives:

0.1.1 In this assignment, you will develop a CNN model for the cat-and-dog classifer.

You will create `at least two models`, applying the various techniques we discussed for improving the performance.

1. Deeper Conv layers and/or FC layers
2. Image augmentation
3. Transfer learning
4. Regularization: L1/L2, Batch Normalization, Dropout, Max Norm
5. Increasing image size
6. Increasing size of the train/validation/test dataset

- You will compare the performance of your models with the baseline VGG-5 model that we discussed in class.
- Image size is limited to 128-by-128 or smaller
- Performance requirement: the accuracy on the test data needs to be better than 87.5% for at least one of your models

0.1.2 Cats & Dogs Dataset

-
-
-

0.1.3 Load tool modules

[1]:
```python
import tensorflow as tf
from tensorflow import keras
from keras import layers, models

print(tf.config.list_physical_devices())
```

```
2024-10-28 11:16:43.189394: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-10-28 11:16:43.301756: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:485] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-10-28 11:16:43.326821: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:8454] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-10-28 11:16:43.333645: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1452] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
2024-10-28 11:16:43.445783: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: SSE4.1 SSE4.2 AVX AVX2 AVX512F AVX512_VNNI
AVX512_BF16 FMA, in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

```
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU'),
PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

```
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1730128606.523224    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128606.762438    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128606.762492    1056 cuda_executor.cc:1001] could not open file
```

```
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
```

0.1.4 Load CNN models

[2]:
```python
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dropout
```

0.1.5 Load the image processing tools

[3]:
```python
from keras.preprocessing.image import load_img, img_to_array
from keras.utils import image_dataset_from_directory
```

0.1.6 Load and Process the dataset

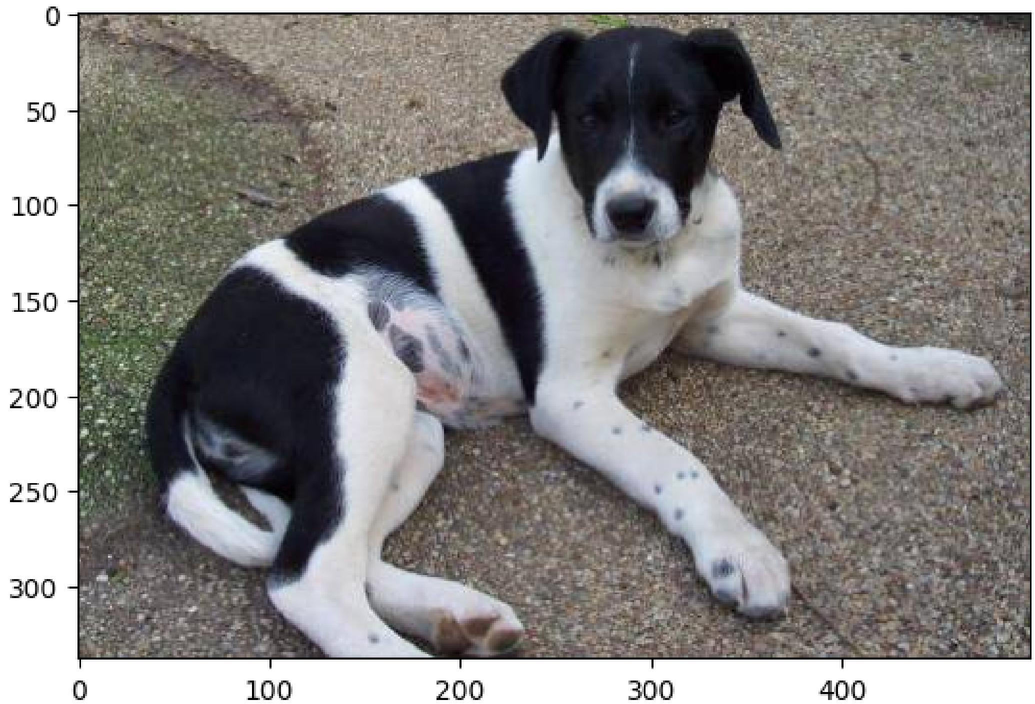
Create the subdirectory structures per the requirement.

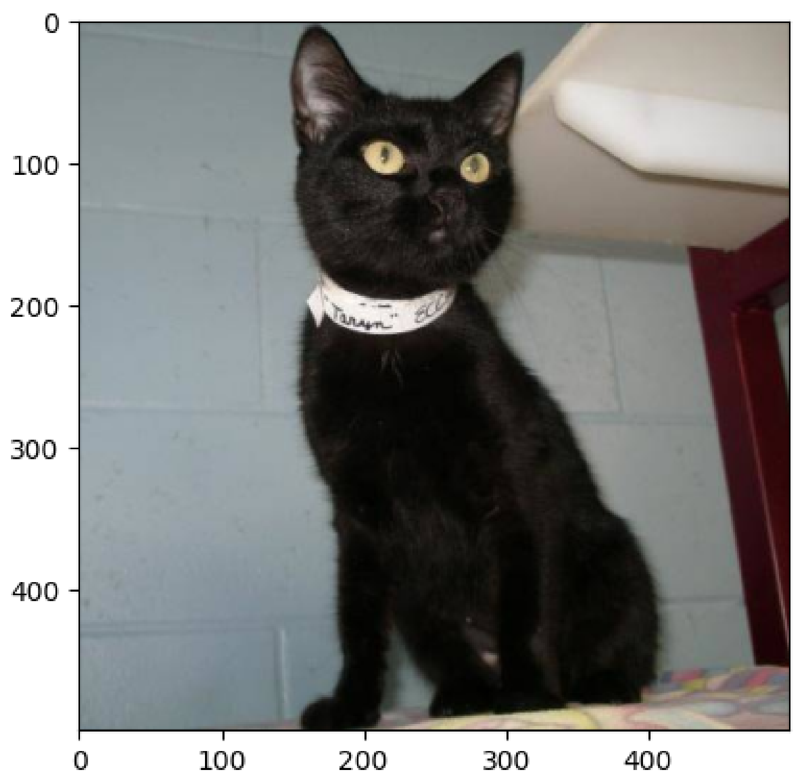
[4]:
```python
import os
import shutil

#--------------------------------------#
# Select the number of files to train  #
N = 25000                              #
#--------------------------------------#

source_dir = "./train"
train_dir = "./cats_dogs"

os.makedirs(train_dir, exist_ok=True)

def organize_images(name, start, stop):
    for pet in ("cat", "dog"):
        dir = train_dir + "/" + name + "/" + pet
        os.makedirs(dir, exist_ok=True)

        images = [f"{pet}.{i}.jpg" for i in range(start, stop)]
        for file in images:
            shutil.copy(src=source_dir + '/' + file, dst=dir + '/ '+ file)
```

```
N_split = int(25000 / 2)
train_perc = int(N_split * 0.6)
val_percent = train_perc + int(N_split * 0.15)
test_percent = val_percent + int(N_split * 0.25)

organize_images("train", start=0, stop=train_perc)
organize_images("validation", start=train_perc, stop=val_percent)
organize_images("test", start=val_percent, stop=test_percent)
```

0.1.7 Display 2 input images: one for dog, and one for cat

[5]:
```
import matplotlib.pyplot as plt
import random


dog_dir = os.listdir(train_dir+'/test'+'/dog')
cat_dir = os.listdir(train_dir+'/test'+'/cat')
dog_sample = random.choice(dog_dir)
cat_sample = random.choice(cat_dir)


dog_img = load_img(os.path.join(train_dir+'/test'+'/dog', dog_sample))
cat_img = load_img(os.path.join(train_dir+'/test'+'/cat', cat_sample))

plt.imshow(dog_img)
plt.show()

plt.imshow(cat_img)
plt.show()
```


0
50
100
150
200
250
300
0
100
200
300
400


0
100
200
300
400
0
100
200
300
400

1 Baseline CNN Model: VGG-5

[6]:

```
# create data generator

# ----------- Target Picture Size ------------ #
target_pic_size = (64, 64)                       #
target_pic_shape = target_pic_size + (3,)        #
# -------------------------------------------- #



train_data = image_dataset_from_directory(train_dir + '/train',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)

val_data = image_dataset_from_directory(train_dir + '/validation',
           color_mode='rgb', batch_size=64, image_size=target_pic_size)

test_data = image_dataset_from_directory(train_dir + '/test',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)




model = Sequential()

# Layer 1
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=target_pic_shape))
model.add(MaxPooling2D((2, 2)))

# Layer 2
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

# Layer 3
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))

model.add(Flatten())

# FC Layers
model.add(Dense(128, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

```python
model.summary()
```

```
Found 15000 files belonging to 2 classes.
```

```
I0000 00:00:1730128623.915966    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128623.916072    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128623.916097    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128624.143644    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
I0000 00:00:1730128624.143758    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2024-10-28 11:17:04.143778: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:2112] Could not identify NUMA
node of platform GPU id 0, defaulting to 0.  Your kernel may not have been built
with NUMA support.
I0000 00:00:1730128624.143835    1056 cuda_executor.cc:1001] could not open file
to read NUMA node: /sys/bus/pci/devices/0000:01:00.0/numa_node
Your kernel may have been built without NUMA support.
2024-10-28 11:17:04.143862: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:2021] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 3539 MB memory:  -> device: 0,
name: NVIDIA GeForce RTX 4050 Laptop GPU, pci bus id: 0000:01:00.0, compute
capability: 8.9
```

```
Found 3750 files belonging to 2 classes.
Found 6250 files belonging to 2 classes.
```

```
/home/rbrin/miniconda3/envs/tf-gpu2/lib/python3.12/site-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 128)	589,952
dense_1 (Dense)	(None, 1)	129

Total params: 683,329 (2.61 MB)

Trainable params: 683,329 (2.61 MB)

Non-trainable params: 0 (0.00 B)

[7]:
```python
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

history = model.fit(train_data, epochs=10, batch_size=64, validation_data=val_data, verbose=1)
```

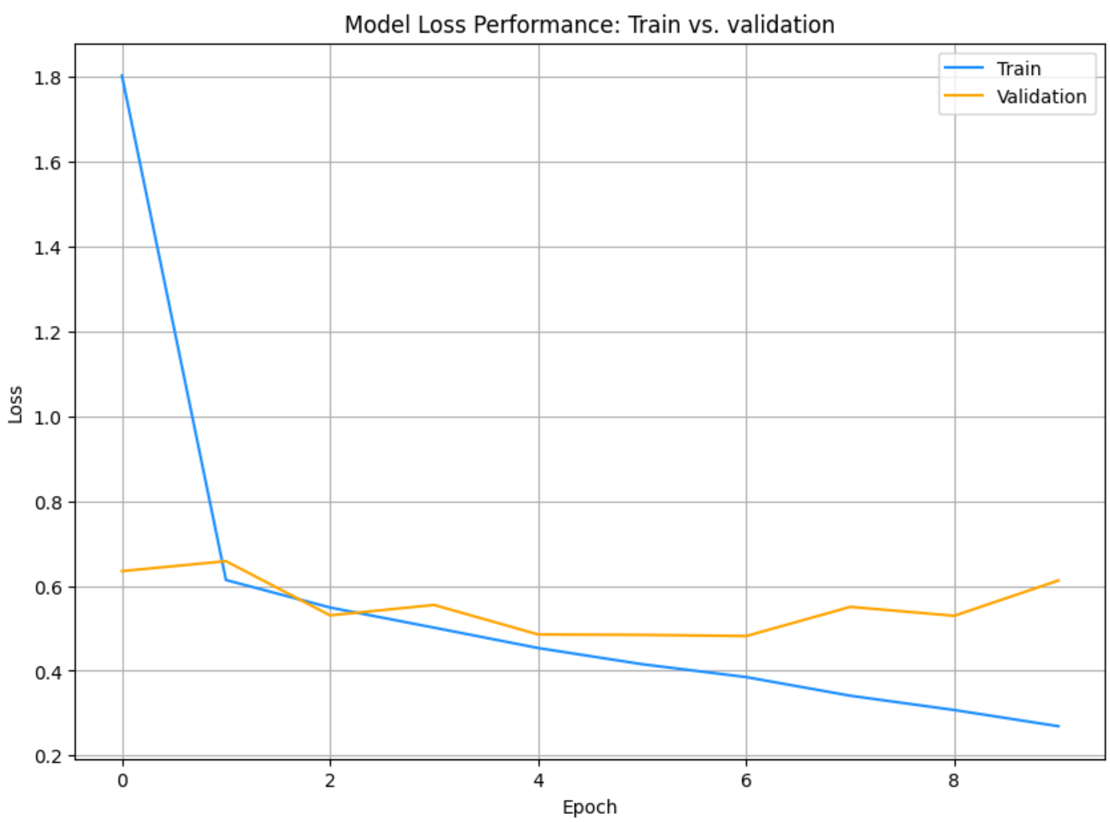
```
Epoch 1/10
```

```
I0000 00:00:1730128626.613970   12987 service.cc:146] XLA service 0x7fb53c0168e0
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1730128626.614003   12987 service.cc:154]   StreamExecutor device
(0): NVIDIA GeForce RTX 4050 Laptop GPU, Compute Capability 8.9
2024-10-28 11:17:06.671619: I
tensorflow/compiler/mlir/tensorflow/utils/dump_mlir_util.cc:268] disabling MLIR
crash reproducer, set env var `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
2024-10-28 11:17:06.833960: I
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:531] Loaded cuDNN
version 90101


 18/235            2s 10ms/step -
accuracy: 0.5101 - loss: 34.9637


I0000 00:00:1730128629.020013   12987 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.


235/235            9s 24ms/step -
accuracy: 0.5486 - loss: 6.1784 - val_accuracy: 0.6325 - val_loss: 0.6350
Epoch 2/10
235/235            3s 12ms/step -
accuracy: 0.6495 - loss: 0.6250 - val_accuracy: 0.6440 - val_loss: 0.6584
Epoch 3/10
235/235            3s 12ms/step -
accuracy: 0.6955 - loss: 0.5733 - val_accuracy: 0.7315 - val_loss: 0.5307
Epoch 4/10
235/235            3s 12ms/step -
accuracy: 0.7503 - loss: 0.5125 - val_accuracy: 0.7125 - val_loss: 0.5552
Epoch 5/10
235/235            3s 12ms/step -
accuracy: 0.7766 - loss: 0.4743 - val_accuracy: 0.7661 - val_loss: 0.4856
Epoch 6/10
235/235            3s 12ms/step -
accuracy: 0.8020 - loss: 0.4260 - val_accuracy: 0.7781 - val_loss: 0.4846
Epoch 7/10
235/235            3s 12ms/step -
accuracy: 0.8191 - loss: 0.4025 - val_accuracy: 0.7856 - val_loss: 0.4819
Epoch 8/10
235/235            3s 12ms/step -
accuracy: 0.8483 - loss: 0.3451 - val_accuracy: 0.7824 - val_loss: 0.5507
Epoch 9/10
235/235            5s 12ms/step -
```

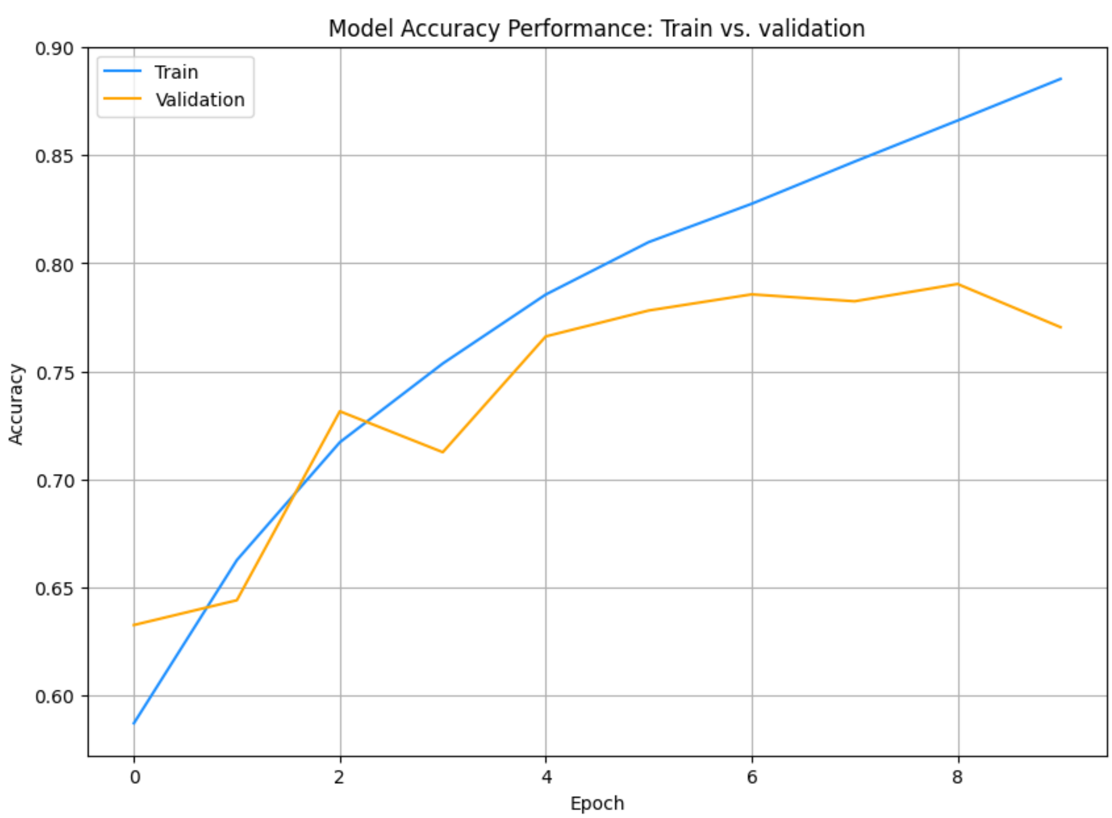
```
accuracy: 0.8639 - loss: 0.3123 - val_accuracy: 0.7904 - val_loss: 0.5297
Epoch 10/10
235/235            3s 12ms/step -
accuracy: 0.8857 - loss: 0.2731 - val_accuracy: 0.7704 - val_loss: 0.6129
```

[8]:

```
J = history.history['loss']  # Loss data for Training
J_val = history.history['val_loss']

plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



[9]:
```
accu = history.history['accuracy']  # Loss data for Training
accu_val = history.history['val_accuracy']

plt.figure(figsize=(10,7))

plt.title('Model Accuracy Performance: Train vs. validation')
plt.plot(accu, color='DodgerBlue', label='Train')
plt.plot(accu_val, color='orange', label='Validation')

plt.ylabel('Accuracy')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()

loss, accuracy = model.evaluate(test_data, verbose=1)

y_pred = model.predict(test_data)
```



```
98/98              2s 16ms/step -
accuracy: 0.7796 - loss: 0.5987
98/98              1s 10ms/step
```

[10]:
```
print("Accuracy = ", accuracy *100, "%")
print("Loss = ", loss, "%")
```

```
Accuracy =  76.46399736404419 %
Loss =  0.6199353337287903 %
```

2 Build CNN Model One

2.1 Define the CNN model

Use CONV, POOL and FC layers to construct your CNN model. You can also load pre-trained model, if transfer learning is used. You will train and test the model after this step.

[28]:
```
# ----------- Target Picture Size ------------ #
target_pic_size = (128, 128)                    #
target_pic_shape = target_pic_size + (3,)      #
# -------------------------------------------- #

train_data = image_dataset_from_directory(train_dir + '/train',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)

val_data = image_dataset_from_directory(train_dir + '/validation',
           color_mode='rgb', batch_size=64, image_size=target_pic_size)

test_data = image_dataset_from_directory(train_dir + '/test',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)



cnn1 = Sequential()


# Input layer
cnn1.add(keras.Input(shape=target_pic_shape))

# Layer 1
cnn1.add(Conv2D(32, (3, 3), activation='relu', kernel_regularizer='l2'))
cnn1.add(MaxPooling2D((2, 2)))
```

```
# Layer 2
cnn1.add(Conv2D(64, (3, 3), activation='relu', kernel_regularizer='l2'))
cnn1.add(MaxPooling2D((2, 2)))

# Layer 3
cnn1.add(Conv2D(128, (3, 3), activation='relu', kernel_regularizer='l2'))
cnn1.add(MaxPooling2D((2, 2)))

# Layer 4
cnn1.add(Conv2D(256, (3, 3), activation='relu', kernel_regularizer='l2'))
cnn1.add(MaxPooling2D((2, 2)))

# Layer 5
cnn1.add(Conv2D(512, (3, 3), activation='relu', kernel_regularizer='l2'))
cnn1.add(MaxPooling2D((2, 2)))

cnn1.add(Flatten())
cnn1.add(Dropout(rate=0.25))

# FC Layers
cnn1.add(Dense(128, activation=keras.activations.gelu))
cnn1.add(Dense(128, activation=keras.activations.gelu))
cnn1.add(Dense(1, activation=keras.activations.sigmoid))
```

```
Found 15000 files belonging to 2 classes.
Found 3750 files belonging to 2 classes.
Found 6250 files belonging to 2 classes.
```

2.1.1 Print the model summary that shows the output shape and # of parameters for each layer.

[29]:
```
cnn1.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv2d_13 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_13 (MaxPooling2D)	(None, 63, 63, 32)	0

```
conv2d_14 (Conv2D)                   (None, 61, 61, 64)           18,496

max_pooling2d_14 (MaxPooling2D)      (None, 30, 30, 64)                0

conv2d_15 (Conv2D)                   (None, 28, 28, 128)          73,856

max_pooling2d_15 (MaxPooling2D)      (None, 14, 14, 128)               0

conv2d_16 (Conv2D)                   (None, 12, 12, 256)         295,168

max_pooling2d_16 (MaxPooling2D)      (None, 6, 6, 256)                 0

conv2d_17 (Conv2D)                   (None, 4, 4, 512)         1,180,160

max_pooling2d_17 (MaxPooling2D)      (None, 2, 2, 512)                 0

flatten_3 (Flatten)                  (None, 2048)                      0

dropout_1 (Dropout)                  (None, 2048)                      0

dense_7 (Dense)                      (None, 128)                 262,272

dense_8 (Dense)                      (None, 128)                  16,512

dense_9 (Dense)                      (None, 1)                       129


Total params: 1,847,489 (7.05 MB)


Trainable params: 1,847,489 (7.05 MB)


Non-trainable params: 0 (0.00 B)
```

2.1.2 Question: What are the total number of parameters for the model?

Answer: This model has 1,844,641 parameters and takes up 7.04 MB

2.2 Train the CNN Model

Note: Display the history when running model.fit( )

[30]:
```
cnn1.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
↪['accuracy'])

history = cnn1.fit(train_data, epochs=20, batch_size=64,␣
↪validation_data=val_data, verbose=1)
```

```
Epoch 1/20
235/235              16s 55ms/step -
accuracy: 0.5181 - loss: 5.9819 - val_accuracy: 0.5763 - val_loss: 2.4099
Epoch 2/20
235/235              9s 40ms/step -
accuracy: 0.5934 - loss: 2.1706 - val_accuracy: 0.7003 - val_loss: 1.5884
Epoch 3/20
235/235              9s 40ms/step -
accuracy: 0.6715 - loss: 1.4946 - val_accuracy: 0.7197 - val_loss: 1.1957
Epoch 4/20
235/235              9s 40ms/step -
accuracy: 0.7433 - loss: 1.1135 - val_accuracy: 0.7544 - val_loss: 0.9589
Epoch 5/20
235/235              9s 40ms/step -
accuracy: 0.7683 - loss: 0.9085 - val_accuracy: 0.7755 - val_loss: 0.8121
Epoch 6/20
235/235              9s 40ms/step -
accuracy: 0.7940 - loss: 0.7690 - val_accuracy: 0.7456 - val_loss: 0.8056
Epoch 7/20
235/235              9s 39ms/step -
accuracy: 0.8075 - loss: 0.6783 - val_accuracy: 0.7853 - val_loss: 0.6881
Epoch 8/20
235/235              9s 40ms/step -
accuracy: 0.8072 - loss: 0.6462 - val_accuracy: 0.8408 - val_loss: 0.5589
Epoch 9/20
235/235              9s 40ms/step -
accuracy: 0.8347 - loss: 0.5750 - val_accuracy: 0.8363 - val_loss: 0.5517
Epoch 10/20
235/235              9s 40ms/step -
accuracy: 0.8454 - loss: 0.5283 - val_accuracy: 0.8459 - val_loss: 0.5231
Epoch 11/20
235/235              9s 40ms/step -
accuracy: 0.8590 - loss: 0.5038 - val_accuracy: 0.8363 - val_loss: 0.5295
Epoch 12/20
235/235              9s 40ms/step -
accuracy: 0.8646 - loss: 0.4865 - val_accuracy: 0.8699 - val_loss: 0.4656
Epoch 13/20
```

```
235/235 9s 40ms/step -
accuracy: 0.8679 - loss: 0.4671 - val_accuracy: 0.8339 - val_loss: 0.5330
Epoch 14/20
235/235 10s 41ms/step -
accuracy: 0.8717 - loss: 0.4584 - val_accuracy: 0.8331 - val_loss: 0.5527
Epoch 15/20
235/235 9s 40ms/step -
accuracy: 0.8710 - loss: 0.4622 - val_accuracy: 0.8805 - val_loss: 0.4455
Epoch 16/20
235/235 9s 40ms/step -
accuracy: 0.8847 - loss: 0.4295 - val_accuracy: 0.8355 - val_loss: 0.5260
Epoch 17/20
235/235 9s 40ms/step -
accuracy: 0.8902 - loss: 0.4153 - val_accuracy: 0.8528 - val_loss: 0.5027
Epoch 18/20
235/235 9s 40ms/step -
accuracy: 0.8914 - loss: 0.4137 - val_accuracy: 0.8811 - val_loss: 0.4379
Epoch 19/20
235/235 9s 40ms/step -
accuracy: 0.8957 - loss: 0.4003 - val_accuracy: 0.8829 - val_loss: 0.4318
Epoch 20/20
235/235 9s 40ms/step -
accuracy: 0.9050 - loss: 0.3796 - val_accuracy: 0.8789 - val_loss: 0.4458
```

2.2.1 Question: What is the estimated total model training time?

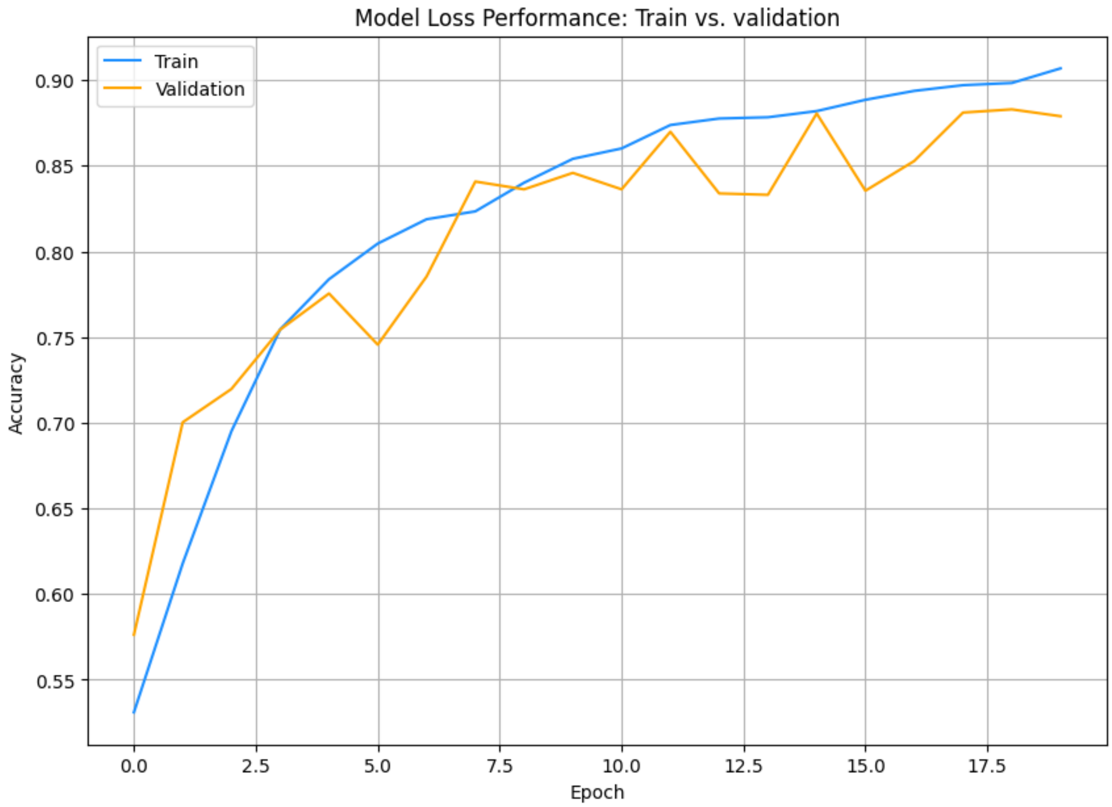
Answer: With the CPU/GPU combination I have it takes about 4 minutes to run

2.2.2 Compare Loss and Accuracy Performance for train and validation data

Plot the loss data, for both train and validation data

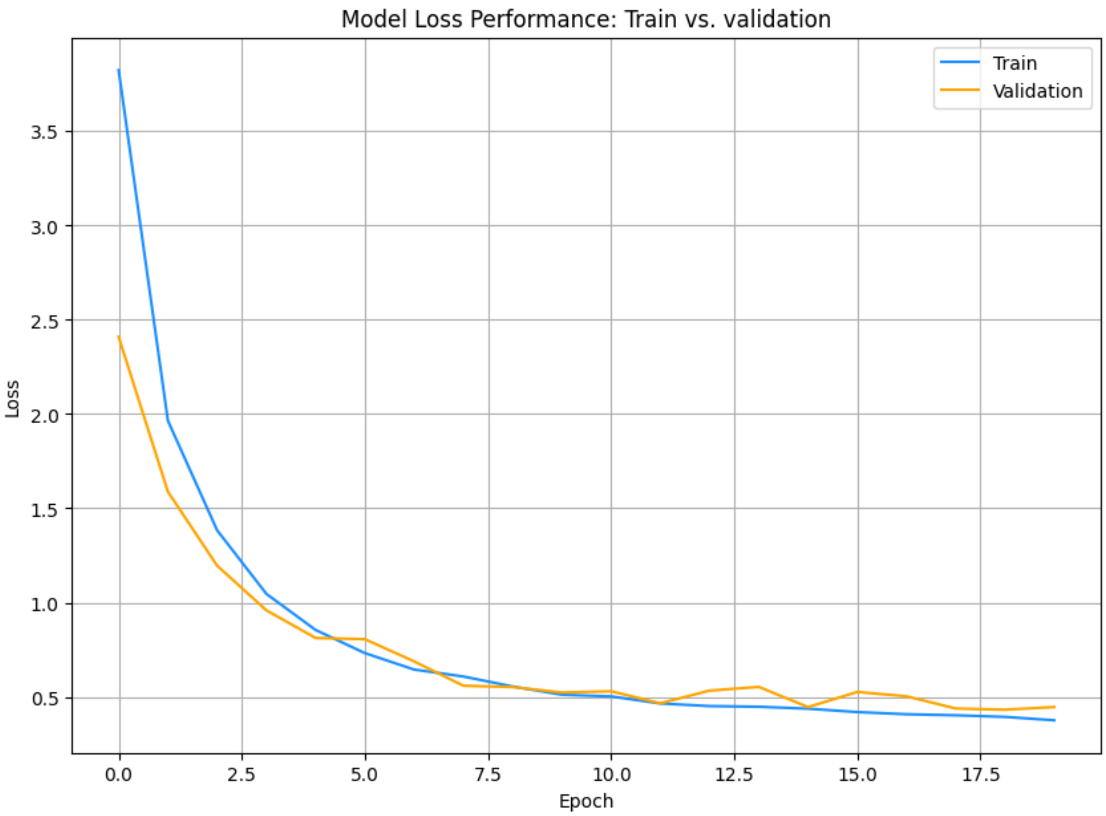
[31]:
```python
J = history.history['accuracy']  # Loss data for Training
J_val = history.history['val_accuracy']

plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Accuracy')
plt.xlabel('Epoch')

plt.legend()
```

```
plt.grid()
plt.show()
```



Plot the accuracy data, for both train and validation data

[32]:
```
J = history.history['loss']  # Loss data for Training
J_val = history.history['val_loss']

plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



2.3 Test the CNN Model

Note: Display the history when running model.evaluate( )

2.3.1 Question: What is the estimated inference (testing) time on test dataset?

Answer: It took 14 seconds to run the inference

2.3.2 Print the final loss and accuracy of the test data

[33]:
```
loss, accuracy = cnn1.evaluate(test_data, verbose=1)

y_pred = cnn1.predict(test_data)

print("Accuracy: ", round(accuracy * 100, 2), "%")
print("Loss: ", round(loss, 2))
```

```
98/98              1s 13ms/step -
accuracy: 0.8704 - loss: 0.4730
98/98              1s 11ms/step
Accuracy:  87.57 %
Loss:  0.46
```

2.3.3 Save the CNN model parameters

[34]:
```
cnn1.save('./cnn1.keras')
```

3 Build CNN Model Two

For your second and subsequent models, follow the same set of instructions provided for Model One

[35]:
```
# ----------- Target Picture Size ------------ #
target_pic_size = (128, 128)                     #
target_pic_shape = target_pic_size + (3,)      #
# -------------------------------------------- #

train_data = image_dataset_from_directory(train_dir + '/train',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)

val_data = image_dataset_from_directory(train_dir + '/validation',
           color_mode='rgb', batch_size=64, image_size=target_pic_size)

test_data = image_dataset_from_directory(train_dir + '/test',
            color_mode='rgb', batch_size=64, image_size=target_pic_size)



cnn2 = Sequential()

cnn2.add(keras.Input(shape=target_pic_shape))

cnn2.add(Conv2D(16, (3,3), activation= 'relu'))
cnn2.add(MaxPooling2D((2,2)))

cnn2.add(Conv2D(32, (3,3), activation= 'relu'))
cnn2.add(MaxPooling2D((2,2)))

cnn2.add(Conv2D(64, (3,3), activation= 'relu'))
cnn2.add(MaxPooling2D((2,2)))

cnn2.add(Conv2D(128, (3,3), activation= 'relu'))
cnn2.add(MaxPooling2D((2,2)))

cnn2.add(Conv2D(256, (3,3), activation= 'relu'))
cnn2.add(MaxPooling2D((2,2)))

cnn2.add(Flatten())

cnn2.add(Dense(128, activation='relu'))
```

```python
cnn2.add(Dense(1, activation='sigmoid'))
```

```
Found 15000 files belonging to 2 classes.
Found 3750 files belonging to 2 classes.
Found 6250 files belonging to 2 classes.
```

[36]:
```python
cnn2.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 126, 126, 16)	448
max_pooling2d_18 (MaxPooling2D)	(None, 63, 63, 16)	0
conv2d_19 (Conv2D)	(None, 61, 61, 32)	4,640
max_pooling2d_19 (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_20 (Conv2D)	(None, 28, 28, 64)	18,496
max_pooling2d_20 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_21 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_21 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_22 (Conv2D)	(None, 4, 4, 256)	295,168
max_pooling2d_22 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten_4 (Flatten)	(None, 1024)	0
dense_10 (Dense)	(None, 128)	131,200
dense_11 (Dense)	(None, 1)	129

Total params: 523,937 (2.00 MB)

Trainable params: 523,937 (2.00 MB)

Non-trainable params: 0 (0.00 B)

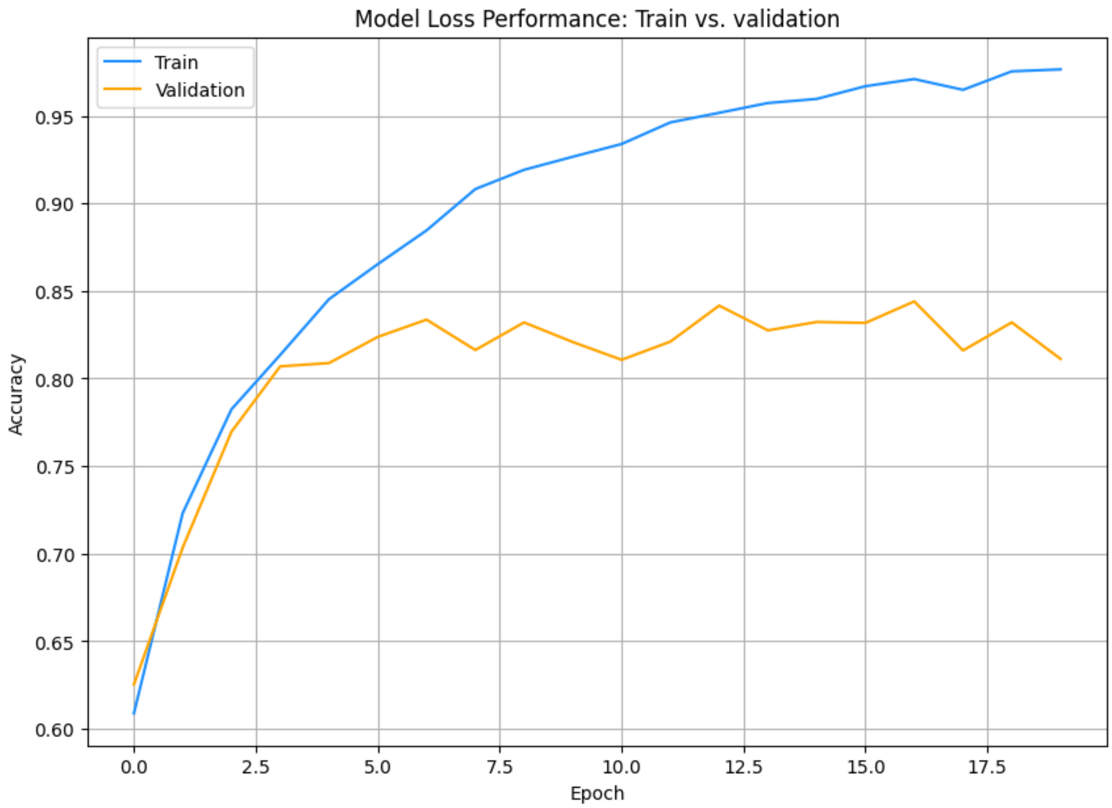
[37]:
```
cnn2.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =
    ['accuracy'])

history = cnn2.fit(train_data, epochs=20, batch_size=64,
    validation_data=val_data, verbose=1)
```

```
Epoch 1/20
235/235                12s 44ms/step -
accuracy: 0.5648 - loss: 2.2576 - val_accuracy: 0.6253 - val_loss: 0.6676
Epoch 2/20
235/235                5s 22ms/step -
accuracy: 0.7011 - loss: 0.5731 - val_accuracy: 0.7035 - val_loss: 0.5782
Epoch 3/20
235/235                5s 22ms/step -
accuracy: 0.7674 - loss: 0.4849 - val_accuracy: 0.7696 - val_loss: 0.5096
Epoch 4/20
235/235                5s 21ms/step -
accuracy: 0.7928 - loss: 0.4408 - val_accuracy: 0.8069 - val_loss: 0.4135
Epoch 5/20
235/235                5s 22ms/step -
accuracy: 0.8353 - loss: 0.3714 - val_accuracy: 0.8088 - val_loss: 0.4292
Epoch 6/20
235/235                5s 22ms/step -
accuracy: 0.8532 - loss: 0.3311 - val_accuracy: 0.8237 - val_loss: 0.3977
Epoch 7/20
235/235                5s 22ms/step -
accuracy: 0.8803 - loss: 0.2802 - val_accuracy: 0.8336 - val_loss: 0.4099
Epoch 8/20
235/235                5s 22ms/step -
accuracy: 0.9052 - loss: 0.2305 - val_accuracy: 0.8163 - val_loss: 0.4976
Epoch 9/20
235/235                5s 22ms/step -
accuracy: 0.9201 - loss: 0.1951 - val_accuracy: 0.8320 - val_loss: 0.4414
Epoch 10/20
235/235                5s 22ms/step -
accuracy: 0.9215 - loss: 0.1846 - val_accuracy: 0.8208 - val_loss: 0.4951
Epoch 11/20
235/235                5s 22ms/step -
accuracy: 0.9318 - loss: 0.1618 - val_accuracy: 0.8107 - val_loss: 0.4857
Epoch 12/20
235/235                5s 22ms/step -
accuracy: 0.9439 - loss: 0.1409 - val_accuracy: 0.8211 - val_loss: 0.5359
Epoch 13/20
235/235                5s 22ms/step -
accuracy: 0.9468 - loss: 0.1301 - val_accuracy: 0.8416 - val_loss: 0.5659
Epoch 14/20
235/235                5s 21ms/step -
accuracy: 0.9571 - loss: 0.1121 - val_accuracy: 0.8275 - val_loss: 0.5741
```

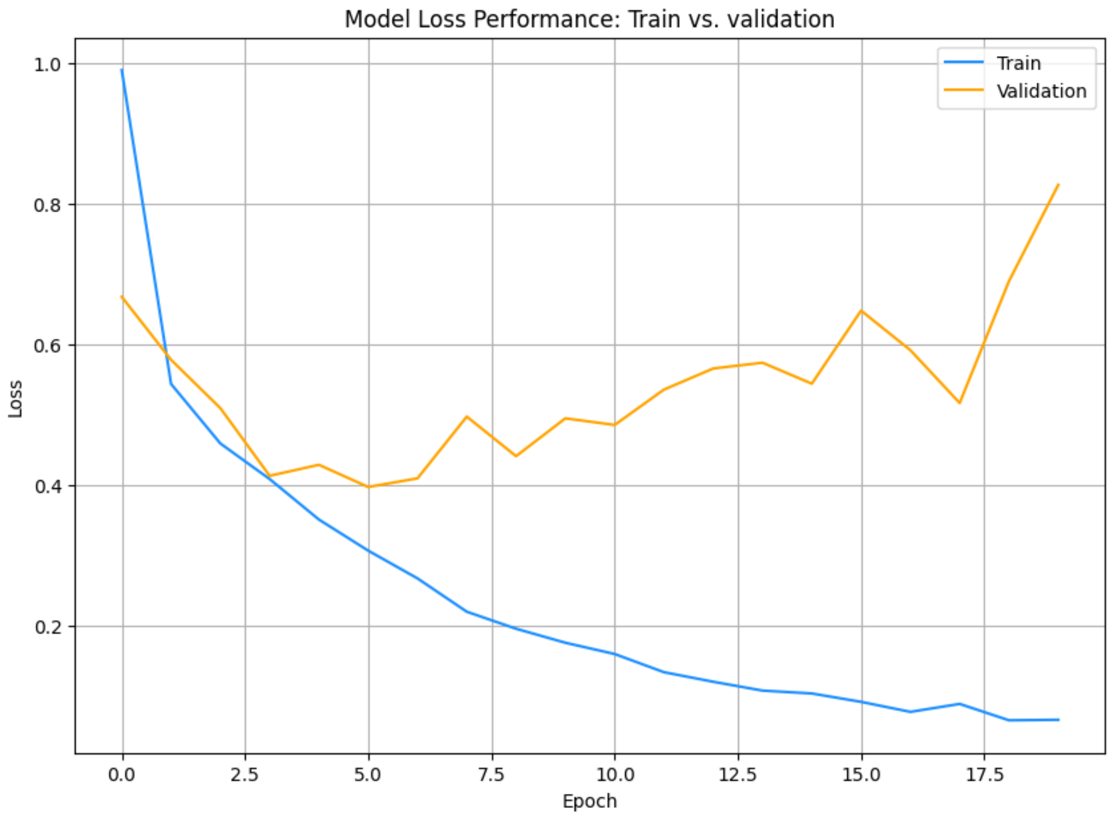
```
Epoch 15/20
235/235              5s 21ms/step -
accuracy: 0.9566 - loss: 0.1091 - val_accuracy: 0.8323 - val_loss: 0.5443
Epoch 16/20
235/235              5s 22ms/step -
accuracy: 0.9692 - loss: 0.0857 - val_accuracy: 0.8317 - val_loss: 0.6481
Epoch 17/20
235/235              5s 22ms/step -
accuracy: 0.9713 - loss: 0.0799 - val_accuracy: 0.8440 - val_loss: 0.5919
Epoch 18/20
235/235              5s 22ms/step -
accuracy: 0.9725 - loss: 0.0710 - val_accuracy: 0.8160 - val_loss: 0.5169
Epoch 19/20
235/235              5s 23ms/step -
accuracy: 0.9727 - loss: 0.0737 - val_accuracy: 0.8320 - val_loss: 0.6898
Epoch 20/20
235/235              5s 23ms/step -
accuracy: 0.9774 - loss: 0.0626 - val_accuracy: 0.8112 - val_loss: 0.8266
```

[38]:

```
J = history.history['accuracy']  # Loss data for Training
J_val = history.history['val_accuracy']

plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Accuracy')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



[39]:
```
J = history.history['loss']  # Loss data for Training
J_val = history.history['val_loss']

plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



[40]:
```
loss, accuracy = cnn2.evaluate(test_data, verbose=1)

y_pred = cnn2.predict(test_data)

print("Accuracy: ", round(accuracy * 100, 2), "%")
print("Loss: ", round(loss, 2))
```

```
98/98              1s 12ms/step -
accuracy: 0.8229 - loss: 0.7701
98/98              1s 11ms/step
Accuracy:  81.22 %
Loss:  0.83
```

[41]:
```
cnn2.save('./cnn2.keras')
```

3.1 Conclusion

3.1.1 You will fill out information in this table:

Model	Accuracy	Number of Parameters	Training Time	Inference Speed
Baseline VGG-5	74.04%	683,329	0:30	02.3
CNN1	88.34%	1,847,489	3:15	0:2.4

Model	Accuracy	Number of Parameters	Training Time	Inference Speed
CNN2	80.45%	523,937	1:41	0:2.2

Please add comments on what you tried and observed while working on the assignment.

The first thing I realized is that CNNs of any note are computationally demanding. The first couple of architectures I put together pinned my CPU at 100% and took around 1 minute per epoch. I set out then to get Tensorflow to recognize my GPU. This created a lot of headach. After days of struggling, I realized that the core of the issue is that the version of CUDA and cuDNN I am on are newer then the Tensorflow version I originally was using had. After chaning to the latest version of Tensorflow, my GPU was automatically detected. I then ran into the issue that certain features used in the provided codes were depricated. I had to code these features out and replace them with up-to-date equivalents.

I was then able to focus on iterating my architectures in earnest. At first I tried to replicate VGG-16. This was not possible because we are limeted to using a 128x128 picture size and a 3x3 filter would decrease the matrix size too fast. So I then went on to capture the spirit of VGG-16 and started out with a small number of filters, and gradually increased the number until the final CNN layer before flattening. This did a good job but I was getting low to mid 80% on my testinging accuracy. I also tried making fewer layers, but multiple filters, but that provided no advantage. I added a second hidden layer but that only increased my success marginally. The true key was adding a dropout layer after flattening.

The dropout layer that I added was extrememly successful and allowed for my training and validation accuracy to increase in tandom together for longer numbers of epochs. Preventing over training was one of the hardest things about creating a good CNN architecture. A lot of the architectures I created would see divergence between the training and validation accuracy fairly quickly, around the 10 epoch mark. But the dropout allowed for the delay of the divergence for longer in a lot of my testing. It appears that the dropout layer allows the neural network to generalize the features a lot more and really helps prevent over training.

##

Remember to turn in both the notebook and the pdf version.