aml-group-8-assignment-2

March 31, 2024

[ ]:
```
from google.colab import files
files.upload()

!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
!kaggle competitions download -c dogs-vs-cats
!unzip -qq dogs-vs-cats.zip
!unzip -qq train.zip
```

```
<IPython.core.display.HTML object>
```

```
Saving kaggle.json to kaggle.json
Downloading dogs-vs-cats.zip to /content
99% 805M/812M [00:04<00:00, 187MB/s]
100% 812M/812M [00:04<00:00, 194MB/s]
```

[ ]:
```
import os, shutil, pathlib

old_dir = pathlib.Path("train")
new_dir = pathlib.Path("cats_vs_dogs_small")

def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_dir / subset_name / category
        os.makedirs(dir)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            shutil.copyfile(src=old_dir/ fname,
                            dst=dir / fname)

make_subset("test", start_index=0, end_index=500)
make_subset("validation", start_index=500, end_index=1000)
make_subset("train", start_index=1000, end_index=2000)
```

[ ]:
```
from tensorflow import keras
from tensorflow.keras import layers
```

```
inputs = keras.Input(shape=(180, 180, 3))
x = layers.Rescaling(1./255)(inputs)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)
```

[ ]:
```
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 180, 180, 3)]	0
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 256)	295168
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 256)	0
conv2d_4 (Conv2D)	(None, 7, 7, 256)	590080

```
 flatten (Flatten)            (None, 12544)          0

 dense (Dense)                (None, 1)              12545

=================================================================
Total params: 991041 (3.78 MB)
Trainable params: 991041 (3.78 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```
model.compile(optimizer = "rmsprop", loss = "binary_crossentropy", metrics =␣
↪["accuracy"])
```

[ ]:
```
#image_dataset_from_directory is to setup a data pipeline that can␣
↪automatically turn images to preprocessed tensors.
from tensorflow.keras.utils import image_dataset_from_directory

#this below directory it will do the subdirectories of directory and assume␣
↪each one contains images from one of our classes.
#it will create and return tf.data.Dataset that inturns read, shuffle, and␣
↪decode them.
train_datset = image_dataset_from_directory(
    new_dir / "train",
    image_size=(180, 180),
    batch_size=32)
validation_datset = image_dataset_from_directory(
    new_dir / "validation",
    image_size=(180, 180),
    batch_size=32)
test_datset = image_dataset_from_directory(
    new_dir / "test",
    image_size=(180, 180),
    batch_size=32)
```

```
Found 2000 files belonging to 2 classes.
Found 1000 files belonging to 2 classes.
Found 1000 files belonging to 2 classes.
```

[ ]:
```
for data_batch, labels_batch in train_datset:
    print("data_batch_shape:", data_batch.shape)
    print("labels_batch_shape:", labels_batch.shape)
    break
```

```
data_batch_shape: (32, 180, 180, 3)
labels_batch_shape: (32,)
```

[ ]:
```python
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="conv_from_scratch1.keras",

        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_datset,
    epochs=20,
    validation_data=validation_datset,
    callbacks=callbacks)
```

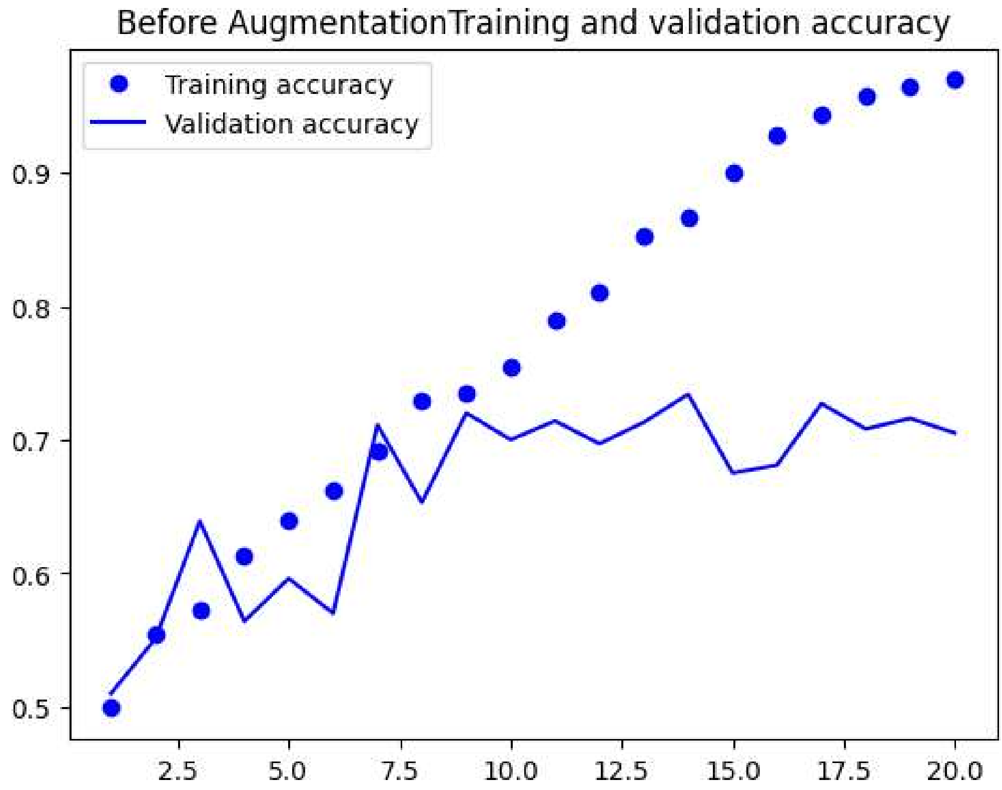
```
Epoch 1/20
63/63 [==============================] - 207s 3s/step - loss: 0.7035 - accuracy:
0.4990 - val_loss: 0.6922 - val_accuracy: 0.5100
Epoch 2/20
63/63 [==============================] - 207s 3s/step - loss: 0.6959 - accuracy:
0.5540 - val_loss: 0.6852 - val_accuracy: 0.5510
Epoch 3/20
63/63 [==============================] - 204s 3s/step - loss: 0.6779 - accuracy:
0.5730 - val_loss: 0.6550 - val_accuracy: 0.6390
Epoch 4/20
63/63 [==============================] - 205s 3s/step - loss: 0.6604 - accuracy:
0.6125 - val_loss: 0.7214 - val_accuracy: 0.5640
Epoch 5/20
63/63 [==============================] - 191s 3s/step - loss: 0.6426 - accuracy:
0.6395 - val_loss: 0.6729 - val_accuracy: 0.5960
Epoch 6/20
63/63 [==============================] - 242s 4s/step - loss: 0.6230 - accuracy:
0.6615 - val_loss: 0.6678 - val_accuracy: 0.5700
Epoch 7/20
63/63 [==============================] - 206s 3s/step - loss: 0.5911 - accuracy:
0.6915 - val_loss: 0.5860 - val_accuracy: 0.7110
Epoch 8/20
63/63 [==============================] - 201s 3s/step - loss: 0.5649 - accuracy:
0.7290 - val_loss: 0.6276 - val_accuracy: 0.6530
Epoch 9/20
63/63 [==============================] - 196s 3s/step - loss: 0.5377 - accuracy:
0.7345 - val_loss: 0.5605 - val_accuracy: 0.7200
Epoch 10/20
63/63 [==============================] - 210s 3s/step - loss: 0.5048 - accuracy:
0.7550 - val_loss: 0.5985 - val_accuracy: 0.7000
Epoch 11/20
63/63 [==============================] - 217s 3s/step - loss: 0.4524 - accuracy:
0.7895 - val_loss: 0.6128 - val_accuracy: 0.7140
Epoch 12/20
```

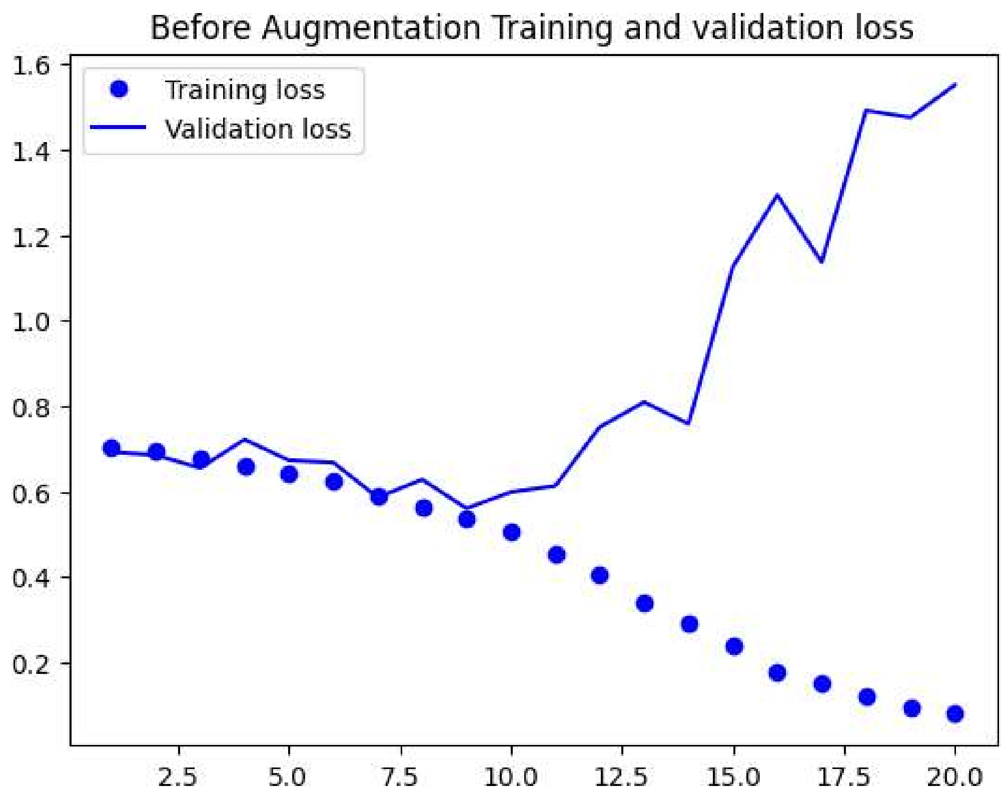
```
63/63 [==============================] - 220s 4s/step - loss: 0.4054 - accuracy:
0.8110 - val_loss: 0.7505 - val_accuracy: 0.6970
Epoch 13/20
63/63 [==============================] - 218s 3s/step - loss: 0.3419 - accuracy:
0.8530 - val_loss: 0.8088 - val_accuracy: 0.7130
Epoch 14/20
63/63 [==============================] - 220s 4s/step - loss: 0.2903 - accuracy:
0.8660 - val_loss: 0.7583 - val_accuracy: 0.7340
Epoch 15/20
63/63 [==============================] - 210s 3s/step - loss: 0.2375 - accuracy:
0.8995 - val_loss: 1.1255 - val_accuracy: 0.6750
Epoch 16/20
63/63 [==============================] - 220s 3s/step - loss: 0.1763 - accuracy:
0.9275 - val_loss: 1.2931 - val_accuracy: 0.6810
Epoch 17/20
63/63 [==============================] - 229s 4s/step - loss: 0.1536 - accuracy:
0.9435 - val_loss: 1.1366 - val_accuracy: 0.7270
Epoch 18/20
63/63 [==============================] - 209s 3s/step - loss: 0.1202 - accuracy:
0.9580 - val_loss: 1.4912 - val_accuracy: 0.7080
Epoch 19/20
63/63 [==============================] - 201s 3s/step - loss: 0.0944 - accuracy:
0.9640 - val_loss: 1.4747 - val_accuracy: 0.7160
Epoch 20/20
63/63 [==============================] - 211s 3s/step - loss: 0.0797 - accuracy:
0.9695 - val_loss: 1.5506 - val_accuracy: 0.7050
```

Displaying curves of loss and accuracy during training

let's plot the loss and accuracy of the model within the training and validation data during training.

[ ]:
```
import matplotlib.pyplot as plt
accuracy1 = history.history["accuracy"]
val_accuracy1 = history.history["val_accuracy"]
loss1 = history.history["loss"]
val_loss1 = history.history["val_loss"]
epochs = range(1, len(accuracy1) + 1)
plt.plot(epochs, accuracy1, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy1, "b", label="Validation accuracy")
plt.title("Before AugmentationTraining and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss1, "bo", label="Training loss")
plt.plot(epochs, val_loss1, "b", label="Validation loss")
plt.title("Before Augmentation Training and validation loss")
plt.legend()
plt.show()
```


Before AugmentationTraining and validation accuracy
Training accuracy
Validation accuracy
0.9
0.8
0.7
0.6
0.5
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0



The overfitting qualities may be seen in the preceding plots, where validation accuracy is barely at 75% and training accuracy rises linearly over time to almost 100%. Additionally, after increasing rapidly for up to ten epochs, the validation loss stalls, whereas the training loss continues to decrease linearly as training goes on.

Evaluating the model on test set

Let's check test accuracy

[ ]:
```
test_model1 = keras.models.load_model("conv_from_scratch1.keras")
test_loss, test_acc = test_model1.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 2s 33ms/step - loss: 0.5411 - accuracy:
0.7330
Test accuracy: 0.733
```

we got a test accuracy of 70% because of less training data that leads to overfitting etc,. so that we need to work with specific one to computer vision when processing images with Deep learning models called Data Augmentation

Data Augmentation

To add an image model, define a data augmentation stage

[ ]:
```python
#we are doing random flip, random rotation, random zoom
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
```

Displaying randomly Augmented training images

It's just like dropout where it overcome overfitting they're inactive during inference, it will behave as same model like when we not include data augmentation and dropout.

Defining a convnet that includes image augmentation and dropout

[ ]:
```python
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

Training the regularized convnet

we train the model using data augmentation and dropout to overcome overfitting we will train as many number of times—-100

[ ]:
```python
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="conv_from_scratch_with_augmentation.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_datset,
```

```
    epochs=20,
    validation_data=validation_datset,
    callbacks=callbacks)
```

```
Epoch 1/20
63/63 [==============================] - 8s 83ms/step - loss: 0.7123 - accuracy:
0.5000 - val_loss: 0.6921 - val_accuracy: 0.5000
Epoch 2/20
63/63 [==============================] - 4s 59ms/step - loss: 0.6882 - accuracy:
0.5565 - val_loss: 0.6748 - val_accuracy: 0.5940
Epoch 3/20
63/63 [==============================] - 4s 60ms/step - loss: 0.6779 - accuracy:
0.5980 - val_loss: 0.6638 - val_accuracy: 0.6420
Epoch 4/20
63/63 [==============================] - 7s 106ms/step - loss: 0.6644 -
accuracy: 0.6210 - val_loss: 0.6529 - val_accuracy: 0.6430
Epoch 5/20
63/63 [==============================] - 4s 58ms/step - loss: 0.6586 - accuracy:
0.6160 - val_loss: 0.8199 - val_accuracy: 0.5080
Epoch 6/20
63/63 [==============================] - 6s 84ms/step - loss: 0.6383 - accuracy:
0.6520 - val_loss: 0.6372 - val_accuracy: 0.6550
Epoch 7/20
63/63 [==============================] - 4s 58ms/step - loss: 0.6209 - accuracy:
0.6625 - val_loss: 0.5997 - val_accuracy: 0.6910
Epoch 8/20
63/63 [==============================] - 4s 63ms/step - loss: 0.5939 - accuracy:
0.6890 - val_loss: 0.6702 - val_accuracy: 0.6400
Epoch 9/20
63/63 [==============================] - 7s 108ms/step - loss: 0.5932 -
accuracy: 0.6955 - val_loss: 0.6321 - val_accuracy: 0.6540
Epoch 10/20
63/63 [==============================] - 4s 58ms/step - loss: 0.5735 - accuracy:
0.7065 - val_loss: 0.7696 - val_accuracy: 0.5620
Epoch 11/20
63/63 [==============================] - 4s 62ms/step - loss: 0.5695 - accuracy:
0.6970 - val_loss: 0.5502 - val_accuracy: 0.7350
Epoch 12/20
63/63 [==============================] - 6s 94ms/step - loss: 0.5578 - accuracy:
0.7080 - val_loss: 0.5627 - val_accuracy: 0.7350
Epoch 13/20
63/63 [==============================] - 4s 60ms/step - loss: 0.5453 - accuracy:
0.7330 - val_loss: 0.5130 - val_accuracy: 0.7550
Epoch 14/20
63/63 [==============================] - 6s 86ms/step - loss: 0.5432 - accuracy:
0.7295 - val_loss: 0.6262 - val_accuracy: 0.6770
Epoch 15/20
```

```
63/63 [==============================] - 4s 59ms/step - loss: 0.5219 - accuracy:
0.7385 - val_loss: 0.5040 - val_accuracy: 0.7590
Epoch 16/20
63/63 [==============================] - 5s 74ms/step - loss: 0.5004 - accuracy:
0.7550 - val_loss: 0.5202 - val_accuracy: 0.7630
Epoch 17/20
63/63 [==============================] - 6s 86ms/step - loss: 0.5075 - accuracy:
0.7515 - val_loss: 0.5105 - val_accuracy: 0.7640
Epoch 18/20
63/63 [==============================] - 4s 63ms/step - loss: 0.4981 - accuracy:
0.7545 - val_loss: 0.4977 - val_accuracy: 0.7660
Epoch 19/20
63/63 [==============================] - 4s 58ms/step - loss: 0.4847 - accuracy:
0.7755 - val_loss: 0.5324 - val_accuracy: 0.7570
Epoch 20/20
63/63 [==============================] - 7s 102ms/step - loss: 0.4787 -
accuracy: 0.7715 - val_loss: 0.5174 - val_accuracy: 0.7680
```

Re-evaluating the model on the test dataset

[ ]:
```
test_model2 = keras.models.load_model(
    "conv_from_scratch_with_augmentation.keras")
test_loss, test_acc = test_model2.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 2s 29ms/step - loss: 0.4765 - accuracy:
0.7810
Test accuracy: 0.781
```

[ ]:
```
inputs = keras.Input(shape=(180, 180, 3))
x = layers.Rescaling(1./255)(inputs)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

Training the regularized convnet

[ ]:
```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="conv_from_scratch_with_dropout.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_datset,
    epochs=20,
    validation_data=validation_datset,
    callbacks=callbacks)
```

```
Epoch 1/20
63/63 [==============================] - 6s 60ms/step - loss: 0.7177 - accuracy:
0.4905 - val_loss: 0.6926 - val_accuracy: 0.5000
Epoch 2/20
63/63 [==============================] - 5s 83ms/step - loss: 0.6972 - accuracy:
0.5185 - val_loss: 0.7041 - val_accuracy: 0.5000
Epoch 3/20
63/63 [==============================] - 4s 58ms/step - loss: 0.6962 - accuracy:
0.5380 - val_loss: 0.6879 - val_accuracy: 0.5640
Epoch 4/20
63/63 [==============================] - 6s 85ms/step - loss: 0.6759 - accuracy:
0.5670 - val_loss: 0.6629 - val_accuracy: 0.5850
Epoch 5/20
63/63 [==============================] - 5s 80ms/step - loss: 0.6722 - accuracy:
0.5955 - val_loss: 0.6787 - val_accuracy: 0.5760
Epoch 6/20
63/63 [==============================] - 4s 57ms/step - loss: 0.6502 - accuracy:
0.6200 - val_loss: 0.6512 - val_accuracy: 0.5910
Epoch 7/20
63/63 [==============================] - 4s 56ms/step - loss: 0.6349 - accuracy:
0.6320 - val_loss: 0.6709 - val_accuracy: 0.5840
Epoch 8/20
63/63 [==============================] - 6s 96ms/step - loss: 0.6090 - accuracy:
0.6690 - val_loss: 0.6200 - val_accuracy: 0.6570
Epoch 9/20
63/63 [==============================] - 5s 67ms/step - loss: 0.5830 - accuracy:
0.6885 - val_loss: 0.5859 - val_accuracy: 0.6980
Epoch 10/20
63/63 [==============================] - 4s 57ms/step - loss: 0.5563 - accuracy:
0.7180 - val_loss: 0.7046 - val_accuracy: 0.6620
Epoch 11/20
63/63 [==============================] - 4s 64ms/step - loss: 0.5215 - accuracy:
0.7355 - val_loss: 0.5486 - val_accuracy: 0.7160
Epoch 12/20
```

```
63/63 [==============================] - 6s 96ms/step - loss: 0.4872 - accuracy:
0.7625 - val_loss: 0.6544 - val_accuracy: 0.6960
Epoch 13/20
63/63 [==============================] - 4s 57ms/step - loss: 0.4651 - accuracy:
0.7910 - val_loss: 0.8187 - val_accuracy: 0.6060
Epoch 14/20
63/63 [==============================] - 4s 57ms/step - loss: 0.4347 - accuracy:
0.8105 - val_loss: 0.5246 - val_accuracy: 0.7380
Epoch 15/20
63/63 [==============================] - 5s 83ms/step - loss: 0.3883 - accuracy:
0.8245 - val_loss: 0.6111 - val_accuracy: 0.7220
Epoch 16/20
63/63 [==============================] - 4s 59ms/step - loss: 0.3552 - accuracy:
0.8435 - val_loss: 0.5590 - val_accuracy: 0.7350
Epoch 17/20
63/63 [==============================] - 5s 83ms/step - loss: 0.3028 - accuracy:
0.8770 - val_loss: 0.7316 - val_accuracy: 0.7410
Epoch 18/20
63/63 [==============================] - 6s 82ms/step - loss: 0.2647 - accuracy:
0.8925 - val_loss: 0.6243 - val_accuracy: 0.7350
Epoch 19/20
63/63 [==============================] - 4s 57ms/step - loss: 0.2329 - accuracy:
0.9065 - val_loss: 0.6565 - val_accuracy: 0.7430
Epoch 20/20
63/63 [==============================] - 7s 102ms/step - loss: 0.1893 -
accuracy: 0.9240 - val_loss: 0.8561 - val_accuracy: 0.7530
```

[ ]:
```
test_model2 = keras.models.load_model(
    "conv_from_scratch_with_dropout.keras")
test_loss, test_acc = test_model2.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 1s 29ms/step - loss: 0.5081 - accuracy:
0.7570
Test accuracy: 0.757
```

Using Image Augmentation and Dropout method

[ ]:
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
```

Here a new convnet that includes both image augmentation and dropout

```
[ ]: inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

Training the regularized convnet

```
[ ]: callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="conv_from_scratch_with_augmentation_dropout.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_datset,
    epochs=20,
    validation_data=validation_datset,
    callbacks=callbacks)
```

```
Epoch 1/20
63/63 [==============================] - 6s 67ms/step - loss: 0.6952 - accuracy:
0.5070 - val_loss: 0.6934 - val_accuracy: 0.5000
Epoch 2/20
63/63 [==============================] - 6s 86ms/step - loss: 0.7000 - accuracy:
0.5250 - val_loss: 0.6895 - val_accuracy: 0.6000
Epoch 3/20
63/63 [==============================] - 6s 82ms/step - loss: 0.7043 - accuracy:
0.5610 - val_loss: 0.6792 - val_accuracy: 0.5790
Epoch 4/20
63/63 [==============================] - 4s 58ms/step - loss: 0.6857 - accuracy:
0.5790 - val_loss: 0.6813 - val_accuracy: 0.5540
Epoch 5/20
```

```
63/63 [==============================] - 4s 59ms/step - loss: 0.6743 - accuracy: 0.5995 - val_loss: 0.6409 - val_accuracy: 0.6250
Epoch 6/20
63/63 [==============================] - 7s 95ms/step - loss: 0.6681 - accuracy: 0.6295 - val_loss: 0.6607 - val_accuracy: 0.5970
Epoch 7/20
63/63 [==============================] - 4s 60ms/step - loss: 0.6352 - accuracy: 0.6405 - val_loss: 0.6290 - val_accuracy: 0.6440
Epoch 8/20
63/63 [==============================] - 4s 59ms/step - loss: 0.6335 - accuracy: 0.6465 - val_loss: 0.6054 - val_accuracy: 0.6760
Epoch 9/20
63/63 [==============================] - 7s 105ms/step - loss: 0.6341 - accuracy: 0.6655 - val_loss: 0.6263 - val_accuracy: 0.6580
Epoch 10/20
63/63 [==============================] - 4s 64ms/step - loss: 0.5924 - accuracy: 0.6810 - val_loss: 0.5807 - val_accuracy: 0.6930
Epoch 11/20
63/63 [==============================] - 4s 59ms/step - loss: 0.5930 - accuracy: 0.6915 - val_loss: 0.6790 - val_accuracy: 0.6430
Epoch 12/20
63/63 [==============================] - 6s 86ms/step - loss: 0.5920 - accuracy: 0.6995 - val_loss: 0.7611 - val_accuracy: 0.5970
Epoch 13/20
63/63 [==============================] - 4s 59ms/step - loss: 0.5745 - accuracy: 0.6905 - val_loss: 0.5513 - val_accuracy: 0.7220
Epoch 14/20
63/63 [==============================] - 4s 62ms/step - loss: 0.5892 - accuracy: 0.6995 - val_loss: 0.5943 - val_accuracy: 0.6770
Epoch 15/20
63/63 [==============================] - 10s 154ms/step - loss: 0.5601 - accuracy: 0.7230 - val_loss: 0.5842 - val_accuracy: 0.7100
Epoch 16/20
63/63 [==============================] - 4s 60ms/step - loss: 0.5547 - accuracy: 0.7145 - val_loss: 0.5345 - val_accuracy: 0.7350
Epoch 17/20
63/63 [==============================] - 5s 83ms/step - loss: 0.5324 - accuracy: 0.7285 - val_loss: 0.5537 - val_accuracy: 0.7400
Epoch 18/20
63/63 [==============================] - 6s 86ms/step - loss: 0.5325 - accuracy: 0.7375 - val_loss: 0.5490 - val_accuracy: 0.7170
Epoch 19/20
63/63 [==============================] - 4s 63ms/step - loss: 0.5134 - accuracy: 0.7465 - val_loss: 0.4904 - val_accuracy: 0.7680
Epoch 20/20
63/63 [==============================] - 7s 100ms/step - loss: 0.5188 - accuracy: 0.7500 - val_loss: 0.5499 - val_accuracy: 0.7460
```

Evaluating the model on the test set

```
[ ]: test_model2 = keras.models.load_model(
         "conv_from_scratch_with_augmentation_dropout.keras")
     test_loss, test_acc = test_model2.evaluate(test_datset)
     print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 1s 29ms/step - loss: 0.4599 - accuracy:
0.7840
Test accuracy: 0.784
```

2. Increase your training sample size. You may pick any amount. Keep the validation and test samples the same as above. Optimize your network (again training from scratch). What performance did you achieve?

Here i am increasing the samples to 5000 and the model performance needs to be evaluated.

The technique here i am using data augmentation and dropout due to the performance was high based on the previous models by using this.

```
[ ]: make_subset("train__2", start_index=1000, end_index=8000)

     train_dataset_2 = image_dataset_from_directory(
         new_dir / "train_2",
         image_size=(180, 180),
         batch_size=32)
```

```
Found 14000 files belonging to 2 classes.
```

New convnet that includes both image augmentation and dropout

```
[ ]: inputs = keras.Input(shape=(180, 180, 3))
     x = data_augmentation(inputs)
     x = layers.Rescaling(1./255)(inputs)
     x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.Flatten()(x)
     x = layers.Dropout(0.5)(x)
     outputs = layers.Dense(1, activation="sigmoid")(x)
     model = keras.Model(inputs=inputs, outputs=outputs)

     model.compile(loss="binary_crossentropy",
                   optimizer="rmsprop",
```

```
             metrics=["accuracy"])
```

Training a reglularized convnet

```
[ ]: callbacks = [
         keras.callbacks.ModelCheckpoint(
             filepath="conv_from_scratch1.keras",
             save_best_only=True,
             monitor="val_loss")
     ]
     history = model.fit(
         train_dataset_2,
         epochs=20,
         validation_data=validation_datset,
         callbacks=callbacks)
```

```
Epoch 1/20
438/438 [==============================] - 129s 292ms/step - loss: 0.1675 -
accuracy: 0.9354 - val_loss: 0.0674 - val_accuracy: 0.9800
Epoch 2/20
438/438 [==============================] - 134s 304ms/step - loss: 0.1503 -
accuracy: 0.9417 - val_loss: 0.0588 - val_accuracy: 0.9800
Epoch 3/20
438/438 [==============================] - 133s 302ms/step - loss: 0.1334 -
accuracy: 0.9493 - val_loss: 0.0569 - val_accuracy: 0.9770
Epoch 4/20
438/438 [==============================] - 131s 299ms/step - loss: 0.1255 -
accuracy: 0.9515 - val_loss: 0.0590 - val_accuracy: 0.9790
Epoch 5/20
438/438 [==============================] - 132s 300ms/step - loss: 0.1201 -
accuracy: 0.9561 - val_loss: 0.3475 - val_accuracy: 0.9320
Epoch 6/20
438/438 [==============================] - 131s 300ms/step - loss: 0.1147 -
accuracy: 0.9569 - val_loss: 0.0686 - val_accuracy: 0.9830
Epoch 7/20
438/438 [==============================] - 132s 301ms/step - loss: 0.1196 -
accuracy: 0.9564 - val_loss: 0.0552 - val_accuracy: 0.9820
Epoch 8/20
438/438 [==============================] - 131s 298ms/step - loss: 0.1021 -
accuracy: 0.9614 - val_loss: 0.0977 - val_accuracy: 0.9740
Epoch 9/20
438/438 [==============================] - 131s 299ms/step - loss: 0.1086 -
accuracy: 0.9618 - val_loss: 0.0675 - val_accuracy: 0.9770
Epoch 10/20
438/438 [==============================] - 132s 300ms/step - loss: 0.1129 -
accuracy: 0.9605 - val_loss: 0.0555 - val_accuracy: 0.9780
Epoch 11/20
438/438 [==============================] - 132s 300ms/step - loss: 0.0967 -
```

```
accuracy: 0.9645 - val_loss: 0.1096 - val_accuracy: 0.9730
Epoch 12/20
438/438 [==============================] - 133s 304ms/step - loss: 0.0967 -
accuracy: 0.9659 - val_loss: 0.0773 - val_accuracy: 0.9800
Epoch 13/20
438/438 [==============================] - 131s 298ms/step - loss: 0.1057 -
accuracy: 0.9623 - val_loss: 0.0588 - val_accuracy: 0.9760
Epoch 14/20
438/438 [==============================] - 132s 300ms/step - loss: 0.0912 -
accuracy: 0.9686 - val_loss: 0.0702 - val_accuracy: 0.9730
Epoch 15/20
438/438 [==============================] - 133s 302ms/step - loss: 0.1007 -
accuracy: 0.9678 - val_loss: 0.0809 - val_accuracy: 0.9780
Epoch 16/20
438/438 [==============================] - 132s 301ms/step - loss: 0.0931 -
accuracy: 0.9685 - val_loss: 0.0599 - val_accuracy: 0.9780
Epoch 17/20
438/438 [==============================] - 132s 302ms/step - loss: 0.1056 -
accuracy: 0.9651 - val_loss: 0.0645 - val_accuracy: 0.9810
Epoch 18/20
438/438 [==============================] - 134s 306ms/step - loss: 0.0959 -
accuracy: 0.9679 - val_loss: 0.0691 - val_accuracy: 0.9710
Epoch 19/20
438/438 [==============================] - 133s 303ms/step - loss: 0.0976 -
accuracy: 0.9666 - val_loss: 0.0550 - val_accuracy: 0.9820
Epoch 20/20
438/438 [==============================] - 134s 306ms/step - loss: 0.0965 -
accuracy: 0.9681 - val_loss: 0.0586 - val_accuracy: 0.9850
```

[ ]:
```
test_model= keras.models.load_model(
    "convent_from_scrath3.keras")
test_loss,  test_acc=test_model.evaluate(test_dataset)
printf(f"Test Accuracy: {test_acc:.3f}")
```

3. Now change your training sample so that you achieve better performance than those from Steps 1 and 2. This sample size may be larger, or smaller than those in the previous steps. The objective is to find the ideal training sample size to get best prediction results

Increased the samples from 8000 to 10000 in order to check the efficiency of the model

[ ]:
```
make_subset("train_3", start_index=1000, end_index=10000)

train_dataset2 = image_dataset_from_directory(
    new_dir / "train_3",
    image_size=(180, 180),
    batch_size=32)
```

Model Building with both Image augmentation and dropout new convnet that includes both image augmentation and dropout

```
[ ]: from tensorflow import keras
     from tensorflow.keras import layers

     inputs = keras.Input(shape=(180, 180, 3))
     x = layers.Rescaling(1./255)(inputs)
     x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.Flatten()(x)
     outputs = layers.Dense(1, activation="sigmoid")(x)
     model = keras.Model(inputs=inputs, outputs=outputs)

     model.compile(loss="binary_crossentropy",
                   optimizer="rmsprop",
                   metrics=["accuracy"])
```

Training the regularized convnet

```
[ ]: callbacks = [
         keras.callbacks.ModelCheckpoint(
             filepath="conv_from_scratch_test1.keras",
             save_best_only=True,
             monitor="val_loss")
     ]

     history = model.fit(
         train_dataset_2,
         epochs=20,
         validation_data=validation_datset,
         callbacks=callbacks)
```

```
Epoch 1/20
438/438 [==============================] - 25s 54ms/step - loss: 0.6584 -
accuracy: 0.5966 - val_loss: 0.5972 - val_accuracy: 0.7100
Epoch 2/20
438/438 [==============================] - 22s 50ms/step - loss: 0.5350 -
accuracy: 0.7309 - val_loss: 0.5364 - val_accuracy: 0.7410
Epoch 3/20
438/438 [==============================] - 22s 50ms/step - loss: 0.4547 -
accuracy: 0.7919 - val_loss: 0.5353 - val_accuracy: 0.7330
```

```
Epoch 4/20
438/438 [==============================] - 27s 61ms/step - loss: 0.3883 -
accuracy: 0.8268 - val_loss: 0.3925 - val_accuracy: 0.8390
Epoch 5/20
438/438 [==============================] - 22s 50ms/step - loss: 0.3225 -
accuracy: 0.8598 - val_loss: 0.3900 - val_accuracy: 0.8320
Epoch 6/20
438/438 [==============================] - 22s 49ms/step - loss: 0.2668 -
accuracy: 0.8901 - val_loss: 0.4118 - val_accuracy: 0.8450
Epoch 7/20
438/438 [==============================] - 22s 50ms/step - loss: 0.2155 -
accuracy: 0.9109 - val_loss: 0.3531 - val_accuracy: 0.8780
Epoch 8/20
438/438 [==============================] - 24s 54ms/step - loss: 0.1632 -
accuracy: 0.9358 - val_loss: 0.4064 - val_accuracy: 0.8630
Epoch 9/20
438/438 [==============================] - 25s 56ms/step - loss: 0.1296 -
accuracy: 0.9486 - val_loss: 0.4851 - val_accuracy: 0.8550
Epoch 10/20
438/438 [==============================] - 24s 54ms/step - loss: 0.1018 -
accuracy: 0.9634 - val_loss: 0.6415 - val_accuracy: 0.8350
Epoch 11/20
438/438 [==============================] - 28s 64ms/step - loss: 0.0834 -
accuracy: 0.9684 - val_loss: 0.5291 - val_accuracy: 0.8690
Epoch 12/20
438/438 [==============================] - 25s 58ms/step - loss: 0.0765 -
accuracy: 0.9736 - val_loss: 0.6307 - val_accuracy: 0.8590
Epoch 13/20
438/438 [==============================] - 28s 63ms/step - loss: 0.0705 -
accuracy: 0.9759 - val_loss: 0.5666 - val_accuracy: 0.8670
Epoch 14/20
438/438 [==============================] - 22s 50ms/step - loss: 0.0616 -
accuracy: 0.9799 - val_loss: 0.7903 - val_accuracy: 0.8480
Epoch 15/20
438/438 [==============================] - 28s 63ms/step - loss: 0.0597 -
accuracy: 0.9805 - val_loss: 0.6777 - val_accuracy: 0.8720
Epoch 16/20
438/438 [==============================] - 25s 57ms/step - loss: 0.0628 -
accuracy: 0.9806 - val_loss: 0.7201 - val_accuracy: 0.8850
Epoch 17/20
438/438 [==============================] - 24s 55ms/step - loss: 0.0625 -
accuracy: 0.9805 - val_loss: 0.8220 - val_accuracy: 0.8900
Epoch 18/20
438/438 [==============================] - 23s 52ms/step - loss: 0.0619 -
accuracy: 0.9808 - val_loss: 0.7733 - val_accuracy: 0.8840
Epoch 19/20
438/438 [==============================] - 22s 51ms/step - loss: 0.0532 -
accuracy: 0.9850 - val_loss: 0.9373 - val_accuracy: 0.8770
```

```
Epoch 20/20
438/438 [==============================] - 23s 51ms/step - loss: 0.0585 -
accuracy: 0.9840 - val_loss: 1.1149 - val_accuracy: 0.8640
```

Evaluating the model with test set

```
[ ]: test_model4 = keras.models.load_model(
         "conv_from_scratch_test1.keras")
     test_loss, test_acc = test_model4.evaluate(test_datset)
     print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 3s 66ms/step - loss: 0.3261 - accuracy:
0.8740
Test accuracy: 0.874
```

with dropout

```
[ ]: inputs = keras.Input(shape=(180, 180, 3))
     x = data_augmentation(inputs)
     x = layers.Rescaling(1./255)(inputs)
     x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.Flatten()(x)
     x = layers.Dropout(0.5)(x)
     outputs = layers.Dense(1, activation="sigmoid")(x)
     model = keras.Model(inputs=inputs, outputs=outputs)

     model.compile(loss="binary_crossentropy",
                   optimizer="rmsprop",
                   metrics=["accuracy"])
```

Training the regularized convnet

```
[ ]: callbacks = [
         keras.callbacks.ModelCheckpoint(
             filepath="conv_from_scratch2.keras",
             save_best_only=True,
             monitor="val_loss")
     ]

     history = model.fit(
         train_dataset_2,
```

```
    epochs=20,
    validation_data=validation_datset,
    callbacks=callbacks)
```

```
Epoch 1/20
438/438 [==============================] - 25s 54ms/step - loss: 0.6954 - accuracy: 0.5421 - val_loss: 0.7436 - val_accuracy: 0.5240
Epoch 2/20
438/438 [==============================] - 26s 59ms/step - loss: 0.5879 - accuracy: 0.6922 - val_loss: 0.5297 - val_accuracy: 0.7560
Epoch 3/20
438/438 [==============================] - 29s 67ms/step - loss: 0.4926 - accuracy: 0.7676 - val_loss: 0.4792 - val_accuracy: 0.7700
Epoch 4/20
438/438 [==============================] - 23s 52ms/step - loss: 0.4227 - accuracy: 0.8101 - val_loss: 0.4400 - val_accuracy: 0.7940
Epoch 5/20
438/438 [==============================] - 25s 56ms/step - loss: 0.3610 - accuracy: 0.8407 - val_loss: 0.4546 - val_accuracy: 0.8020
Epoch 6/20
438/438 [==============================] - 23s 51ms/step - loss: 0.3122 - accuracy: 0.8685 - val_loss: 0.2915 - val_accuracy: 0.8770
Epoch 7/20
438/438 [==============================] - 22s 51ms/step - loss: 0.2650 - accuracy: 0.8896 - val_loss: 0.4001 - val_accuracy: 0.8230
Epoch 8/20
438/438 [==============================] - 23s 52ms/step - loss: 0.2243 - accuracy: 0.9072 - val_loss: 0.3046 - val_accuracy: 0.8870
Epoch 9/20
438/438 [==============================] - 25s 58ms/step - loss: 0.1903 - accuracy: 0.9237 - val_loss: 0.4764 - val_accuracy: 0.8230
Epoch 10/20
438/438 [==============================] - 22s 51ms/step - loss: 0.1612 - accuracy: 0.9372 - val_loss: 0.3615 - val_accuracy: 0.8810
Epoch 11/20
438/438 [==============================] - 25s 56ms/step - loss: 0.1389 - accuracy: 0.9459 - val_loss: 0.4245 - val_accuracy: 0.8590
Epoch 12/20
438/438 [==============================] - 22s 50ms/step - loss: 0.1236 - accuracy: 0.9518 - val_loss: 0.3406 - val_accuracy: 0.8860
Epoch 13/20
438/438 [==============================] - 23s 52ms/step - loss: 0.1112 - accuracy: 0.9588 - val_loss: 0.3176 - val_accuracy: 0.8870
Epoch 14/20
438/438 [==============================] - 22s 50ms/step - loss: 0.1047 - accuracy: 0.9612 - val_loss: 0.4277 - val_accuracy: 0.8930
Epoch 15/20
```

```
438/438 [==============================] - 22s 50ms/step - loss: 0.0978 -
accuracy: 0.9650 - val_loss: 0.5801 - val_accuracy: 0.8860
Epoch 16/20
438/438 [==============================] - 24s 54ms/step - loss: 0.1002 -
accuracy: 0.9666 - val_loss: 0.3523 - val_accuracy: 0.8980
Epoch 17/20
438/438 [==============================] - 22s 50ms/step - loss: 0.0946 -
accuracy: 0.9684 - val_loss: 0.5883 - val_accuracy: 0.8890
Epoch 18/20
438/438 [==============================] - 24s 55ms/step - loss: 0.0925 -
accuracy: 0.9698 - val_loss: 0.5656 - val_accuracy: 0.8840
Epoch 19/20
438/438 [==============================] - 22s 49ms/step - loss: 0.0928 -
accuracy: 0.9702 - val_loss: 0.6549 - val_accuracy: 0.8770
Epoch 20/20
438/438 [==============================] - 22s 49ms/step - loss: 0.0899 -
accuracy: 0.9718 - val_loss: 0.6822 - val_accuracy: 0.8880
```

evaluating the model with test set

[ ]:
```
test_model = keras.models.load_model(
    "conv_from_scratch2.keras")
test_loss, test_acc = test_model.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 1s 31ms/step - loss: 0.2916 - accuracy:
0.8730
Test accuracy: 0.873
```

4. Repeat Steps 1-3, but now using a pretrained network. The sample sizes you use in Steps 2 and 3 for the pretrained network may be the same or different from those using the network where you trained from scratch. Again, use any and all optimization techniques to get best performance

Pre-training model–1000 training samples

Here install and freezing the VGG16 convolution base

[ ]:
```
conv_base = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 [==============================] - 0s 0us/step
```

Let's get the summary of the convbase

[ ]:
```
conv_base.summary()
```

```
Model: "vgg16"
```

```
Layer (type)                Output Shape              Param #
=================================================================
input_8 (InputLayer)        [(None, 180, 180, 3)]     0

block1_conv1 (Conv2D)       (None, 180, 180, 64)      1792

block1_conv2 (Conv2D)       (None, 180, 180, 64)      36928

block1_pool (MaxPooling2D)  (None, 90, 90, 64)        0

block2_conv1 (Conv2D)       (None, 90, 90, 128)       73856

block2_conv2 (Conv2D)       (None, 90, 90, 128)       147584

block2_pool (MaxPooling2D)  (None, 45, 45, 128)       0

block3_conv1 (Conv2D)       (None, 45, 45, 256)       295168

block3_conv2 (Conv2D)       (None, 45, 45, 256)       590080

block3_conv3 (Conv2D)       (None, 45, 45, 256)       590080

block3_pool (MaxPooling2D)  (None, 22, 22, 256)       0

block4_conv1 (Conv2D)       (None, 22, 22, 512)       1180160

block4_conv2 (Conv2D)       (None, 22, 22, 512)       2359808

block4_conv3 (Conv2D)       (None, 22, 22, 512)       2359808

block4_pool (MaxPooling2D)  (None, 11, 11, 512)       0

block5_conv1 (Conv2D)       (None, 11, 11, 512)       2359808

block5_conv2 (Conv2D)       (None, 11, 11, 512)       2359808

block5_conv3 (Conv2D)       (None, 11, 11, 512)       2359808

block5_pool (MaxPooling2D)  (None, 5, 5, 512)         0

=================================================================
Total params: 14714688 (56.13 MB)
Trainable params: 14714688 (56.13 MB)
Non-trainable params: 0 (0.00 Byte)
```

Fine-tuning a pretrained model

```
[ ]: conv_base  = keras.applications.vgg16.VGG16(
         weights="imagenet",
         include_top=False)
```

Freezing all layers except the last

Adding a data augmentation and a classifier to the convnet base.

```
[ ]: data_augmentation = keras.Sequential(
         [
             layers.RandomFlip("horizontal"),
             layers.RandomRotation(0.3),
             layers.RandomZoom(0.5),
         ]
     )

     inputs = keras.Input(shape=(180, 180, 3))
     x = data_augmentation(inputs)
     x = layers.Rescaling(1./255)(x)
     x  = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x  = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x  = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x  = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x = layers.MaxPooling2D(pool_size=2)(x)
     x  = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
     x  = layers.Flatten()(x)
     x = layers.Dropout(0.5)(x)
     outputs = layers.Dense(1, activation="sigmoid")(x)
     model = keras.Model(inputs=inputs, outputs=outputs)

     model.
      compile(loss="binary_crossentropy",optimizer="rmsprop",metrics=["accuracy"])
```

Training the regularized convnet

```
[ ]: callbacks = [
         keras.callbacks.ModelCheckpoint(
             filepath="convnet_from_scratch_augmentation.keras",
             save_best_only=True,
             monitor="val_loss")
     ]
     history = model.fit(
        train_datset,
        epochs=50,
        validation_data=validation_datset,
```

```
    callbacks=callbacks)
```

```
Epoch 1/50
63/63 [==============================] - 7s 68ms/step - loss: 0.7011 - accuracy:
0.4860 - val_loss: 0.6929 - val_accuracy: 0.5000
Epoch 2/50
63/63 [==============================] - 4s 60ms/step - loss: 0.6943 - accuracy:
0.5005 - val_loss: 0.6928 - val_accuracy: 0.5030
Epoch 3/50
63/63 [==============================] - 6s 94ms/step - loss: 0.6948 - accuracy:
0.5160 - val_loss: 0.6916 - val_accuracy: 0.5080
Epoch 4/50
63/63 [==============================] - 5s 70ms/step - loss: 0.6957 - accuracy:
0.5230 - val_loss: 0.6867 - val_accuracy: 0.5450
Epoch 5/50
63/63 [==============================] - 4s 61ms/step - loss: 0.6846 - accuracy:
0.5845 - val_loss: 0.7106 - val_accuracy: 0.5040
Epoch 6/50
63/63 [==============================] - 4s 62ms/step - loss: 0.6762 - accuracy:
0.5845 - val_loss: 0.7215 - val_accuracy: 0.5690
Epoch 7/50
63/63 [==============================] - 7s 98ms/step - loss: 0.6655 - accuracy:
0.6050 - val_loss: 0.6518 - val_accuracy: 0.6520
Epoch 8/50
63/63 [==============================] - 4s 60ms/step - loss: 0.6900 - accuracy:
0.6235 - val_loss: 0.6275 - val_accuracy: 0.6480
Epoch 9/50
63/63 [==============================] - 4s 60ms/step - loss: 0.6287 - accuracy:
0.6285 - val_loss: 0.6347 - val_accuracy: 0.6720
Epoch 10/50
63/63 [==============================] - 5s 78ms/step - loss: 0.6394 - accuracy:
0.6360 - val_loss: 0.6503 - val_accuracy: 0.6250
Epoch 11/50
63/63 [==============================] - 6s 81ms/step - loss: 0.6430 - accuracy:
0.6245 - val_loss: 0.6832 - val_accuracy: 0.5170
Epoch 12/50
63/63 [==============================] - 4s 58ms/step - loss: 0.6462 - accuracy:
0.6315 - val_loss: 0.6115 - val_accuracy: 0.6770
Epoch 13/50
63/63 [==============================] - 4s 60ms/step - loss: 0.6252 - accuracy:
0.6485 - val_loss: 0.6279 - val_accuracy: 0.6470
Epoch 14/50
63/63 [==============================] - 6s 91ms/step - loss: 0.6312 - accuracy:
0.6390 - val_loss: 0.6399 - val_accuracy: 0.6200
Epoch 15/50
63/63 [==============================] - 4s 58ms/step - loss: 0.6255 - accuracy:
0.6380 - val_loss: 0.6081 - val_accuracy: 0.6890
```

```
Epoch 16/50
63/63 [==============================] - 4s 59ms/step - loss: 0.6264 - accuracy:
0.6530 - val_loss: 0.6029 - val_accuracy: 0.6750
Epoch 17/50
63/63 [==============================] - 7s 111ms/step - loss: 0.6205 -
accuracy: 0.6625 - val_loss: 0.6385 - val_accuracy: 0.6250
Epoch 18/50
63/63 [==============================] - 4s 57ms/step - loss: 0.6126 - accuracy:
0.6530 - val_loss: 0.5956 - val_accuracy: 0.6920
Epoch 19/50
63/63 [==============================] - 4s 57ms/step - loss: 0.6082 - accuracy:
0.6580 - val_loss: 0.5826 - val_accuracy: 0.7080
Epoch 20/50
63/63 [==============================] - 5s 71ms/step - loss: 0.6088 - accuracy:
0.6705 - val_loss: 0.5957 - val_accuracy: 0.7040
Epoch 21/50
63/63 [==============================] - 5s 80ms/step - loss: 0.6039 - accuracy:
0.6800 - val_loss: 0.6090 - val_accuracy: 0.6780
Epoch 22/50
63/63 [==============================] - 4s 61ms/step - loss: 0.6080 - accuracy:
0.6680 - val_loss: 0.5910 - val_accuracy: 0.6810
Epoch 23/50
63/63 [==============================] - 6s 89ms/step - loss: 0.5986 - accuracy:
0.6815 - val_loss: 0.5770 - val_accuracy: 0.7080
Epoch 24/50
63/63 [==============================] - 4s 56ms/step - loss: 0.6026 - accuracy:
0.6720 - val_loss: 0.5993 - val_accuracy: 0.6730
Epoch 25/50
63/63 [==============================] - 4s 57ms/step - loss: 0.5843 - accuracy:
0.6810 - val_loss: 0.6718 - val_accuracy: 0.6190
Epoch 26/50
63/63 [==============================] - 6s 87ms/step - loss: 0.5859 - accuracy:
0.6845 - val_loss: 0.5662 - val_accuracy: 0.7320
Epoch 27/50
63/63 [==============================] - 5s 74ms/step - loss: 0.5837 - accuracy:
0.6845 - val_loss: 0.6239 - val_accuracy: 0.6640
Epoch 28/50
63/63 [==============================] - 4s 57ms/step - loss: 0.5861 - accuracy:
0.6880 - val_loss: 0.6243 - val_accuracy: 0.6530
Epoch 29/50
63/63 [==============================] - 4s 60ms/step - loss: 0.5863 - accuracy:
0.6940 - val_loss: 0.6229 - val_accuracy: 0.6820
Epoch 30/50
63/63 [==============================] - 7s 107ms/step - loss: 0.5868 -
accuracy: 0.6845 - val_loss: 0.5698 - val_accuracy: 0.7180
Epoch 31/50
63/63 [==============================] - 4s 60ms/step - loss: 0.5829 - accuracy:
0.6960 - val_loss: 0.5786 - val_accuracy: 0.6950
```

Epoch 32/50
63/63 [==============================] - 4s 58ms/step - loss: 0.5772 - accuracy: 0.6915 - val_loss: 0.6261 - val_accuracy: 0.6550
Epoch 33/50
63/63 [==============================] - 6s 94ms/step - loss: 0.5705 - accuracy: 0.6985 - val_loss: 0.5872 - val_accuracy: 0.6970
Epoch 34/50
63/63 [==============================] - 5s 67ms/step - loss: 0.5861 - accuracy: 0.6870 - val_loss: 0.5748 - val_accuracy: 0.7040
Epoch 35/50
63/63 [==============================] - 4s 61ms/step - loss: 0.5724 - accuracy: 0.6985 - val_loss: 0.5538 - val_accuracy: 0.7290
Epoch 36/50
63/63 [==============================] - 5s 84ms/step - loss: 0.5685 - accuracy: 0.7025 - val_loss: 0.5744 - val_accuracy: 0.7030
Epoch 37/50
63/63 [==============================] - 6s 82ms/step - loss: 0.5698 - accuracy: 0.7110 - val_loss: 0.5814 - val_accuracy: 0.6860
Epoch 38/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5787 - accuracy: 0.6960 - val_loss: 0.5577 - val_accuracy: 0.7160
Epoch 39/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5640 - accuracy: 0.7115 - val_loss: 0.5778 - val_accuracy: 0.7060
Epoch 40/50
63/63 [==============================] - 7s 101ms/step - loss: 0.5578 - accuracy: 0.7165 - val_loss: 0.5721 - val_accuracy: 0.7040
Epoch 41/50
63/63 [==============================] - 4s 61ms/step - loss: 0.5525 - accuracy: 0.7145 - val_loss: 0.5483 - val_accuracy: 0.7050
Epoch 42/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5574 - accuracy: 0.7215 - val_loss: 0.5526 - val_accuracy: 0.7330
Epoch 43/50
63/63 [==============================] - 5s 71ms/step - loss: 0.5681 - accuracy: 0.7035 - val_loss: 0.5617 - val_accuracy: 0.7310
Epoch 44/50
63/63 [==============================] - 6s 85ms/step - loss: 0.5486 - accuracy: 0.7190 - val_loss: 0.6529 - val_accuracy: 0.6880
Epoch 45/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5600 - accuracy: 0.7165 - val_loss: 0.5997 - val_accuracy: 0.7150
Epoch 46/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5536 - accuracy: 0.7155 - val_loss: 0.5378 - val_accuracy: 0.7420
Epoch 47/50
63/63 [==============================] - 7s 111ms/step - loss: 0.5464 - accuracy: 0.7240 - val_loss: 0.5575 - val_accuracy: 0.7010

```
Epoch 48/50
63/63 [==============================] - 4s 59ms/step - loss: 0.5602 - accuracy:
0.7125 - val_loss: 0.6616 - val_accuracy: 0.6670
Epoch 49/50
63/63 [==============================] - 4s 58ms/step - loss: 0.5606 - accuracy:
0.7010 - val_loss: 0.5458 - val_accuracy: 0.7250
Epoch 50/50
63/63 [==============================] - 6s 89ms/step - loss: 0.5349 - accuracy:
0.7275 - val_loss: 0.5900 - val_accuracy: 0.6790
```

Plotting the curves for loss and accuracy during training

[ ]:
```
import matplotlib.pyplot as plt
accuracy = history.history["accuracy"]
val_accuracy = history.history["val_accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(accuracy) + 1)
plt.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy with Data Augmentation")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss with Data Augmentation")
plt.legend()
plt.show()
```

Evaluating the model on the test set

[ ]:
```
test_model5 = keras.models.load_model("convnet_from_scratch_augmentation.keras")
test_loss, test_acc = test_model5.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

Leveraging a Pretrained model

[ ]:
```
conv_base = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
conv_base.summary()
```

Extracting the VGG16 features and corresponding labels by calling predict() method of the convolution base without Data Augmentation

[ ]:
```
import numpy as np
def get_features_and_labels(dataset):
    all_features = []
```

```
    all_labels = []
    for images, labels in dataset:
        preprocessed_images = keras.applications.vgg16.preprocess_input(images)
        features = conv_base.predict(preprocessed_images)
        all_features.append(features)
        all_labels.append(labels)
    return np.concatenate(all_features), np.concatenate(all_labels)

train_features, train_labels = get_features_and_labels(train_datset)
val_features, val_labels = get_features_and_labels(validation_datset)
test_features, test_labels = get_features_and_labels(test_datset)
```

Defining and training the densely connected classifier

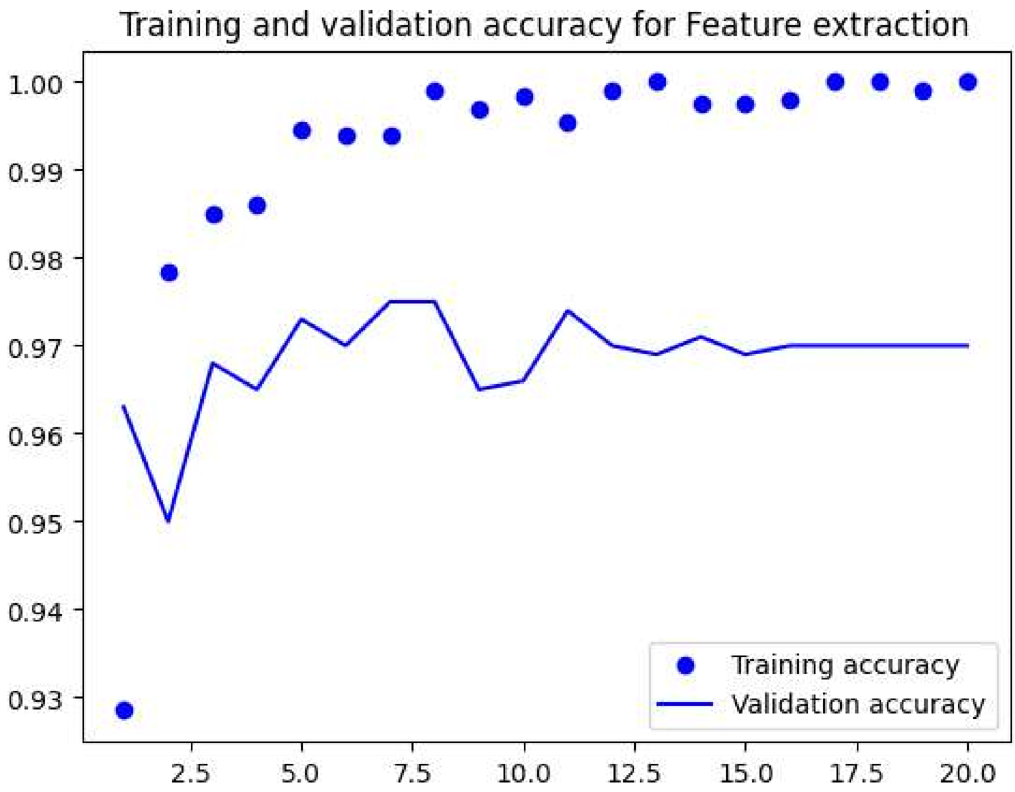
[ ]:
```
inputs = keras.Input(shape=(5, 5, 512))
x = layers.Flatten()(inputs)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)

model.compile(loss="binary_crossentropy", optimizer="rmsprop",␣
 ↪metrics=["accuracy"])
```

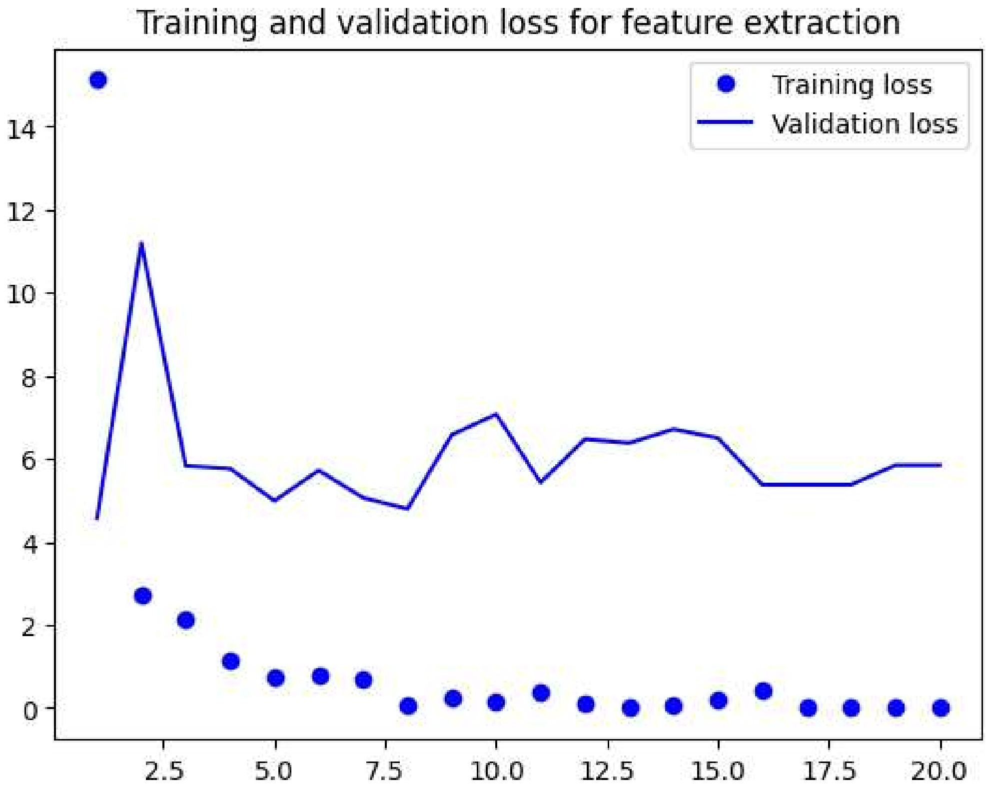
[ ]:
```
callbacks = [
 keras.callbacks.ModelCheckpoint(
 filepath="feature_extraction.keras",
 save_best_only=True,
 monitor="val_loss")
]
history = model.fit(
 train_features, train_labels,
 epochs=20,
 validation_data=(val_features, val_labels),
 callbacks=callbacks)
```

Plotting the results

[ ]:
```
import matplotlib.pyplot as plt
acc = history.history["accuracy"]
val_acc = history.history["val_accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(acc) + 1)
plt.plot(epochs, acc, "bo", label="Training accuracy")
plt.plot(epochs, val_acc, "b", label="Validation accuracy")
plt.title("Training and validation accuracy for Feature extraction")
plt.legend()
```

```
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss for feature extraction")
plt.legend()
plt.show()
```





Feature extraction with data augmentation

```
[ ]: conv_base = keras.applications.vgg16.VGG16(weights="imagenet",include_top=False)
     conv_base.trainable = False
```

```
[ ]: conv_base.summary()
```

Freezing all layers

```
[ ]: conv_base.trainable = True
     for layer in conv_base.layers[:-4]:
      layer.trainable = False
```

Fine tuning a model

```
[ ]: data_augmentation = keras.Sequential(
         [
             layers.RandomFlip("horizontal"),
             layers.RandomRotation(0.3),
             layers.RandomZoom(0.5),
         ]
     )
```

```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = keras.layers.Lambda(lambda x: keras.applications.vgg16.
↪preprocess_input(x))(x)
conv_base = keras.applications.VGG16(weights="imagenet", include_top=False,␣
↪input_shape=(180, 180, 3))
x = conv_base(x)
x  =  layers.Flatten()(x)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])
```

Training the regularized network

[ ]:
```
callbacks = [
 keras.callbacks.ModelCheckpoint(
 filepath="fine_tuning.keras",
 save_best_only=True,
 monitor="val_loss")
]
history = model.fit(
 train_datset,
 epochs=20,
 validation_data=validation_datset,
 callbacks=callbacks)
```

```
Epoch 1/20
63/63 [==============================] - 41s 453ms/step - loss: 2.3936 -
accuracy: 0.5970 - val_loss: 0.5101 - val_accuracy: 0.7740
Epoch 2/20
63/63 [==============================] - 23s 357ms/step - loss: 0.6690 -
accuracy: 0.6635 - val_loss: 0.2966 - val_accuracy: 0.8620
Epoch 3/20
63/63 [==============================] - 23s 358ms/step - loss: 0.5144 -
accuracy: 0.7465 - val_loss: 0.2505 - val_accuracy: 0.8890
Epoch 4/20
63/63 [==============================] - 23s 361ms/step - loss: 0.4001 -
accuracy: 0.8105 - val_loss: 0.1462 - val_accuracy: 0.9430
Epoch 5/20
63/63 [==============================] - 22s 345ms/step - loss: 0.3500 -
accuracy: 0.8350 - val_loss: 0.2113 - val_accuracy: 0.9370
Epoch 6/20
```

```
63/63 [==============================] - 23s 367ms/step - loss: 0.2978 -
accuracy: 0.8595 - val_loss: 0.1065 - val_accuracy: 0.9580
Epoch 7/20
63/63 [==============================] - 23s 357ms/step - loss: 0.2683 -
accuracy: 0.8730 - val_loss: 0.1021 - val_accuracy: 0.9640
Epoch 8/20
63/63 [==============================] - 22s 349ms/step - loss: 0.2318 -
accuracy: 0.8975 - val_loss: 0.1425 - val_accuracy: 0.9570
Epoch 9/20
63/63 [==============================] - 23s 364ms/step - loss: 0.2081 -
accuracy: 0.9090 - val_loss: 0.0993 - val_accuracy: 0.9640
Epoch 10/20
63/63 [==============================] - 23s 355ms/step - loss: 0.2194 -
accuracy: 0.9165 - val_loss: 0.0929 - val_accuracy: 0.9670
Epoch 11/20
63/63 [==============================] - 23s 360ms/step - loss: 0.1810 -
accuracy: 0.9270 - val_loss: 0.0837 - val_accuracy: 0.9800
Epoch 12/20
63/63 [==============================] - 22s 349ms/step - loss: 0.1828 -
accuracy: 0.9280 - val_loss: 0.0839 - val_accuracy: 0.9680
Epoch 13/20
63/63 [==============================] - 24s 382ms/step - loss: 0.1602 -
accuracy: 0.9350 - val_loss: 0.0896 - val_accuracy: 0.9700
Epoch 14/20
63/63 [==============================] - 22s 342ms/step - loss: 0.1623 -
accuracy: 0.9350 - val_loss: 0.1312 - val_accuracy: 0.9600
Epoch 15/20
63/63 [==============================] - 23s 356ms/step - loss: 0.1431 -
accuracy: 0.9470 - val_loss: 0.0668 - val_accuracy: 0.9700
Epoch 16/20
63/63 [==============================] - 21s 337ms/step - loss: 0.1562 -
accuracy: 0.9335 - val_loss: 0.0723 - val_accuracy: 0.9770
Epoch 17/20
63/63 [==============================] - 24s 373ms/step - loss: 0.1458 -
accuracy: 0.9395 - val_loss: 0.2243 - val_accuracy: 0.9460
Epoch 18/20
63/63 [==============================] - 21s 334ms/step - loss: 0.1056 -
accuracy: 0.9530 - val_loss: 0.0687 - val_accuracy: 0.9780
Epoch 19/20
63/63 [==============================] - 21s 335ms/step - loss: 0.1084 -
accuracy: 0.9575 - val_loss: 0.1144 - val_accuracy: 0.9700
Epoch 20/20
63/63 [==============================] - 22s 340ms/step - loss: 0.1124 -
accuracy: 0.9595 - val_loss: 0.1622 - val_accuracy: 0.9680
```

Plotting the curves of loss and accuracy during training for fine-tuning model

```
[ ]: import matplotlib.pyplot as plt
accuracy = history.history["accuracy"]
val_accuracy = history.history["val_accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(accuracy) + 1)
plt.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```

Evaluating the test set for fine-tuning

```
[ ]: model = keras.models.load_model("fine_tuning.keras")
test_loss, test_acc = model.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

Pre-trianed model-5000 Training samples

same as we did above by installing and freezing the VGG16 conv base.

```
[ ]: conv_base = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
```

Fine tuning the pretrained model by freezing the layers

```
[ ]: conv_base = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False)

conv_base.trainable = True
for layer in conv_base.layers[:-4]:
    layer.trainable = False
```

By adding of augmentation and classifier to conv base

```
[ ]: data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
```

```
    ]
)

inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = keras.applications.vgg16.preprocess_input(x)
x = conv_base(x)
x = layers.Flatten()(x)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="fine_tuning2.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset_2,
    epochs=10,
    validation_data=validation_datset,
    callbacks=callbacks)
```

evaluating the model with test set

```
[ ]: model = keras.models.load_model("fine_tuning2.keras")
     test_loss, test_acc = model.evaluate(test_datset)
     print(f"Test accuracy: {test_acc:.3f}")
```

Pre-trained model with 10000 samples by install and freezing the VGG16 comv base

```
[ ]: conv_base = keras.applications.vgg16.VGG16(
         weights="imagenet",
         include_top=False,
         input_shape=(180, 180, 3))
```

Fine tuning the pretrained model and freezing the layers except last one

```
[ ]: conv_base = keras.applications.vgg16.VGG16(
         weights="imagenet",
         include_top=False)

     conv_base.trainable = True
```

```
for layer in conv_base.layers[:-4]:
    layer.trainable = False
```

By adding augmentation and classifier to the conv base

```
[ ]: data_augmentation = keras.Sequential(
         [
             layers.RandomFlip("horizontal"),
             layers.RandomRotation(0.1),
             layers.RandomZoom(0.2),
         ]
     )

     inputs = keras.Input(shape=(180, 180, 3))
     x = data_augmentation(inputs)
     x = keras.applications.vgg16.preprocess_input(x)
     x = conv_base(x)
     x = layers.Flatten()(x)
     x = layers.Dense(256)(x)
     x = layers.Dropout(0.5)(x)
     outputs = layers.Dense(1, activation="sigmoid")(x)
     model = keras.Model(inputs, outputs)
     model.compile(loss="binary_crossentropy",
                   optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
                   metrics=["accuracy"])

     callbacks = [
         keras.callbacks.ModelCheckpoint(
             filepath="fine_tuning3.keras",
             save_best_only=True,
             monitor="val_loss")
     ]
     history = model.fit(
         train_dataset2,
         epochs=30,
         validation_data=validation_datset,
         callbacks=callbacks)
```

Plotting the curves for loss and accuracy during training for fine tuning with 10000 samples

```
[ ]: import matplotlib.pyplot as plt
     accuracy = history.history["accuracy"]
     val_accuracy = history.history["val_accuracy"]
     loss = history.history["loss"]
     val_loss = history.history["val_loss"]
     epochs = range(1, len(accuracy) + 1)
     plt.plot(epochs, accuracy, "bo", label="Training accuracy")
     plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
```

```
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```

Evaluating the model with test set

[ ]:
```
model = keras.models.load_model("fine_tuning3.keras")
test_loss, test_acc = model.evaluate(test_datset)
print(f"Test accuracy: {test_acc:.3f}")
```

Summary:

1. Consider the Cats & Dogs example. Start initially with a training sample of 1000, a validation sample of 500, and a test sample of 500 (like in the text). Use any technique to reduce overfitting and improve performance in developing a network that you train from scratch. What performance did you achieve?

Observations:

• The graphs shown above are examples of overfitting. Whereas validation accuracy only reaches 70–72%, training accuracy rises linearly over time to almost 100%. • Our primary problem will be overfitting because there aren't many training data. A number of strategies, including dropout, regularization, and data augmentation, can be used to lessen overfitting.

I have used three techniques to improve the performance of the model and evaluated all those three on test dataset on 100 epochs.

a) Drop out Method

b) Data Augmentation

c) Data Augmentation and drop out method.

MODEL	TEST ACCURACY	VALID ACCURACY
Unregularized Model	0.733	0.7331
Model with Data Augmentation	0.781	0.76
Model with Dropout	0.757	0.753
Model with Data Augmentation and Dropout	0.784	0.746

Observations:

• Based on the performance metrics of the models that combine the unregularized model with three performance improvement strategies, we can infer from the values in the above table that the model that incorporates both the dropout technique and data augmentation performs well. • To regularize the model, I utilized the best-performing method—data augmentation and dropout—for the remaining training samples.

2. Increase your training sample size. You may pick any amount. Keep the validation and test samples the same as above. Optimize your network (again training from scratch). What performance did you achieve?**

- For this model I have increased the training sample size to 5000.

MODEL	TEST LOSS	TEST ACCURACY	VALID ACCURACY
Regularized model with 5000 training samples	0.096	0.968	0.985

Observations:

•For regularized model it is observed that the loss: 0.3669 - accuracy: 0.848.

- In contrast to the unregularized model regularized model seems to have a bit higher accuracy.
- In comparison to the previous model the accuracy seems to be improved while the loss is slightly reduced.

3. Now change your training sample so that you achieve better performance than those from Steps1 and 2. This sample size may be larger, or smaller than those in the previous steps. The objective is to find the ideal training sample size to get best prediction results?

- For this model,I have increased sample size to

MODEL	TEST LOSS	TEST ACCURACY	VALID ACCURACY
Regularized model with 5000 training samples	0.3261	0.8740	0.864

Observations:

From the above table,

- For regularized model it is observed that the loss: 0.22 - accuracy: 0.912
- In comparison with the unregularized model, this model is better.

Below is the chart that describes the comparison of test and validation accuracies for the different training samples size.

MODEL	TEST LOSS	TEST ACCURACY	VALID ACCURACY
Regularized model with 1000 training samples	0.4599	0.7840	0.7460
Regularized model with 5000 training samples	0.096	0.968	0.985
Regularized model with 10000 training samples	0.2916	0.873	0.888

Observations:

- There is a correlation between test loss and training sample size, which shows that test loss decreases over time and the test accuracy increases from 86% to 92.2%, which shows a better improvement over time.

- Therefore, we can say that the performance of the model increases as the number of training samples increases.

4. **Repeat Steps 1-3, but now using a pretrained network. The sample sizes you use in Steps 2 and 3,for the pretrained network may be the same or different from those using the network where you trained from scratch. Again, use any and all optimization techniques to get best performance.**

MODEL	TEST LOSS	TEST ACCURACY	VALID ACCURACY
Regularized model with 1000 training samples	0.534	0.727	0.679
Regularized model with 5000 training samples	0.492	0.739	0.680
Regularized model with 10000 training samples	0.435	0.739	0.680

Observations:

We can observe from the data in the above table that when the training sample size rises, both the testing and validation accuracy tend to get better. As sample size grows, we observe a stronger improvement when test loss is taken into account.

Recommendations:

- Convolutional network-based machine learning models are the most successful in computer vision applications.

- When starting from scratch and training from a relatively little dataset, the outcomes can still be respectable.

- Overfitting is the fundamental issue with short datasets. Preventing overfitting in picture data can be effectively achieved by data augmentation techniques.

- Model performance rises as the amount of the training sample grows.

- We can improve the model's performance even further by fine-tuning the previously trained model.