

```
In [1]: ▶ import pandas as pd
import numpy as np
import os
import cv2
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import tensorflow as tf
```

```
In [2]: ▶ from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(rescale=1./255)
batch_size = 20

# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    # This is the target directory
    'C:/Users/Xhensil/Downloads/archive(2)/chest_xray/train',
    batch_size=batch_size,
    # Since we use binary_crossentropy loss, we need binary labels
    class_mode='binary')

validation_generator = test_datagen.flow_from_directory(
    'C:/Users/Xhensil/Downloads/archive(2)/chest_xray/val',
    batch_size=batch_size,
    class_mode='binary')

test_generator = test_datagen.flow_from_directory(
    'C:/Users/Xhensil/Downloads/archive(2)/chest_xray/chest_xray/tes

Found 4192 images belonging to 2 classes.
Found 1040 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

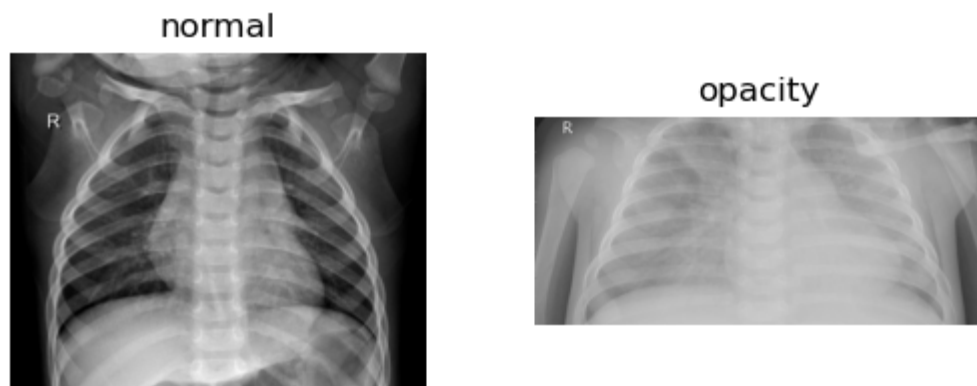
```
In [51]: ▶ xx_test=np.concatenate([test.next()[0] for i in range(test.__len__())])
xx_test.shape
yy_test=np.concatenate([test.next()[1] for i in range(test.__len__())])
```

```
Out[51]: (array([0., 1.], dtype=float32), array([234, 390]))
```

```
In [3]: ► img = cv2.imread("C:/Users/Xhensil/Downloads/archive(2)/chest_xray/train
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plt.subplot(2, 2, 1)
plt.title('normal')
plt.imshow(img)
plt.axis("off")

img = cv2.imread("C:/Users/Xhensil/Downloads/archive(2)/chest_xray/train
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plt.subplot(2, 2, 2)
plt.title('opacity')
plt.imshow(img)
```

Out[3]: (-0.5, 1127.5, 519.5, -0.5)



## Convolutional Neural Network

### Baseline Model

```
In [4]: ► model_CNN = models.Sequential()
model_CNN.add(layers.Conv2D(32, (3, 3), activation='relu',
                           input_shape=(256, 256, 3)))
model_CNN.add(layers.MaxPooling2D((2, 2)))
model_CNN.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_CNN.add(layers.MaxPooling2D((2, 2)))
model_CNN.add(layers.Conv2D(128, (3, 3), activation='relu'))
model_CNN.add(layers.MaxPooling2D((2, 2)))
model_CNN.add(layers.Conv2D(128, (3, 3), activation='relu'))
model_CNN.add(layers.MaxPooling2D((2, 2)))
model_CNN.add(layers.Flatten())
model_CNN.add(layers.Dropout(0.35))
model_CNN.add(layers.Dense(512, activation='relu'))
model_CNN.add(layers.Dropout(0.25))
```

In [5]:

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dropout (Dropout)	(None, 25088)	0
dense (Dense)	(None, 512)	12845568
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

=====  
Total params: 13,086,913  
Trainable params: 13,086,913  
Non-trainable params: 0  
=====

In [6]:

```
from tensorflow.keras import optimizers

model_CNN.compile(loss='binary_crossentropy',
                  optimizer=optimizers.Adam(learning_rate=1e-4),
```

In [7]:

```
Epoch 1/15
210/210 [=====] - 118s 519ms/step - loss: 0.2
852 - acc: 0.8752 - val_loss: 0.1318 - val_acc: 0.9510
Epoch 2/15
210/210 [=====] - 69s 329ms/step - loss: 0.11
51 - acc: 0.9561 - val_loss: 0.1080 - val_acc: 0.9529
Epoch 3/15
210/210 [=====] - 69s 328ms/step - loss: 0.08
72 - acc: 0.9680 - val_loss: 0.0853 - val_acc: 0.9683
Epoch 4/15
210/210 [=====] - 71s 336ms/step - loss: 0.07
41 - acc: 0.9728 - val_loss: 0.0781 - val_acc: 0.9731
Epoch 5/15
210/210 [=====] - 69s 331ms/step - loss: 0.07
17 - acc: 0.9723 - val_loss: 0.0663 - val_acc: 0.9731
Epoch 6/15
210/210 [=====] - 71s 338ms/step - loss: 0.06
84 - acc: 0.9716 - val_loss: 0.0606 - val_acc: 0.9769
Epoch 7/15
210/210 [=====] - 72s 340ms/step - loss: 0.06
29 - acc: 0.9757 - val_loss: 0.0736 - val_acc: 0.9731
Epoch 8/15
210/210 [=====] - 71s 339ms/step - loss: 0.05
23 - acc: 0.9783 - val_loss: 0.0763 - val_acc: 0.9712
Epoch 9/15
210/210 [=====] - 71s 335ms/step - loss: 0.05
00 - acc: 0.9838 - val_loss: 0.0523 - val_acc: 0.9798
Epoch 10/15
210/210 [=====] - 69s 329ms/step - loss: 0.04
39 - acc: 0.9833 - val_loss: 0.0474 - val_acc: 0.9827
Epoch 11/15
210/210 [=====] - 76s 364ms/step - loss: 0.03
50 - acc: 0.9874 - val_loss: 0.0579 - val_acc: 0.9760
Epoch 12/15
210/210 [=====] - 77s 365ms/step - loss: 0.03
49 - acc: 0.9869 - val_loss: 0.0555 - val_acc: 0.9817
Epoch 13/15
210/210 [=====] - 69s 328ms/step - loss: 0.03
38 - acc: 0.9876 - val_loss: 0.0500 - val_acc: 0.9827
Epoch 14/15
210/210 [=====] - 68s 326ms/step - loss: 0.02
74 - acc: 0.9902 - val_loss: 0.0501 - val_acc: 0.9808
Epoch 15/15
210/210 [=====] - 69s 328ms/step - loss: 0.03
50 - acc: 0.9876 - val_loss: 0.0656 - val_acc: 0.9731
```

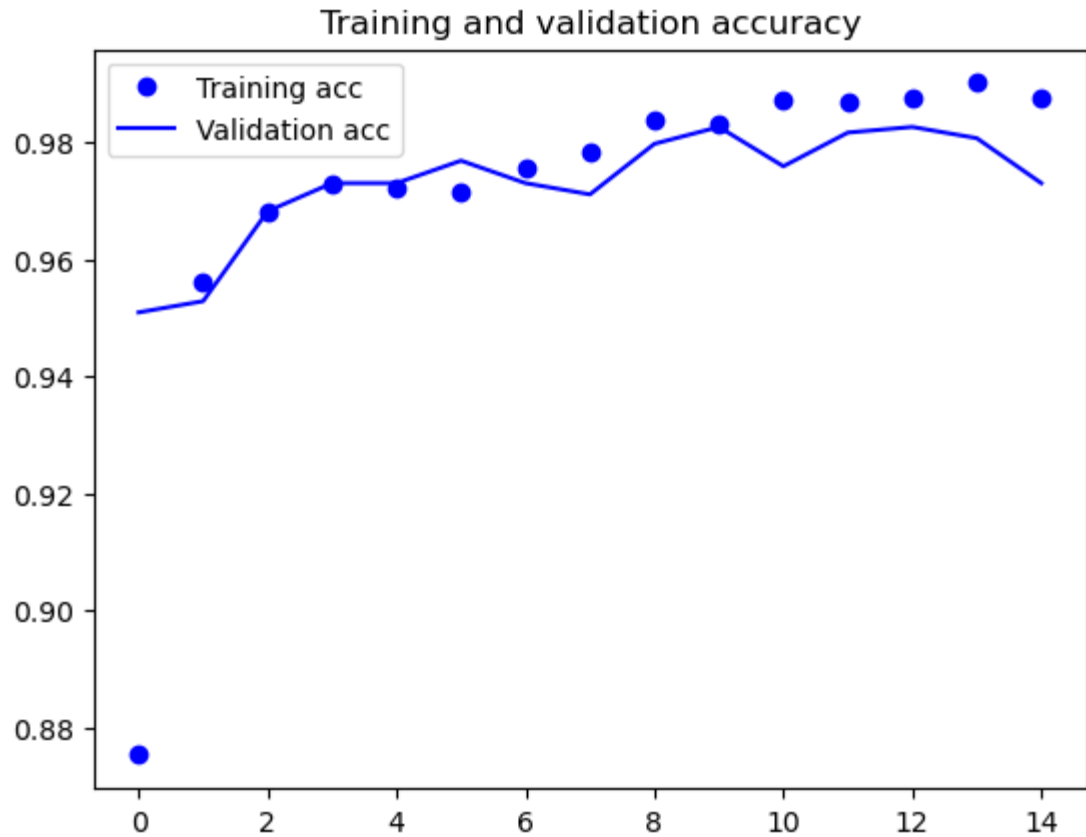
```
In [8]: import matplotlib.pyplot as plt

acc = history_CNN.history['acc']
val_acc = history_CNN.history['val_acc']

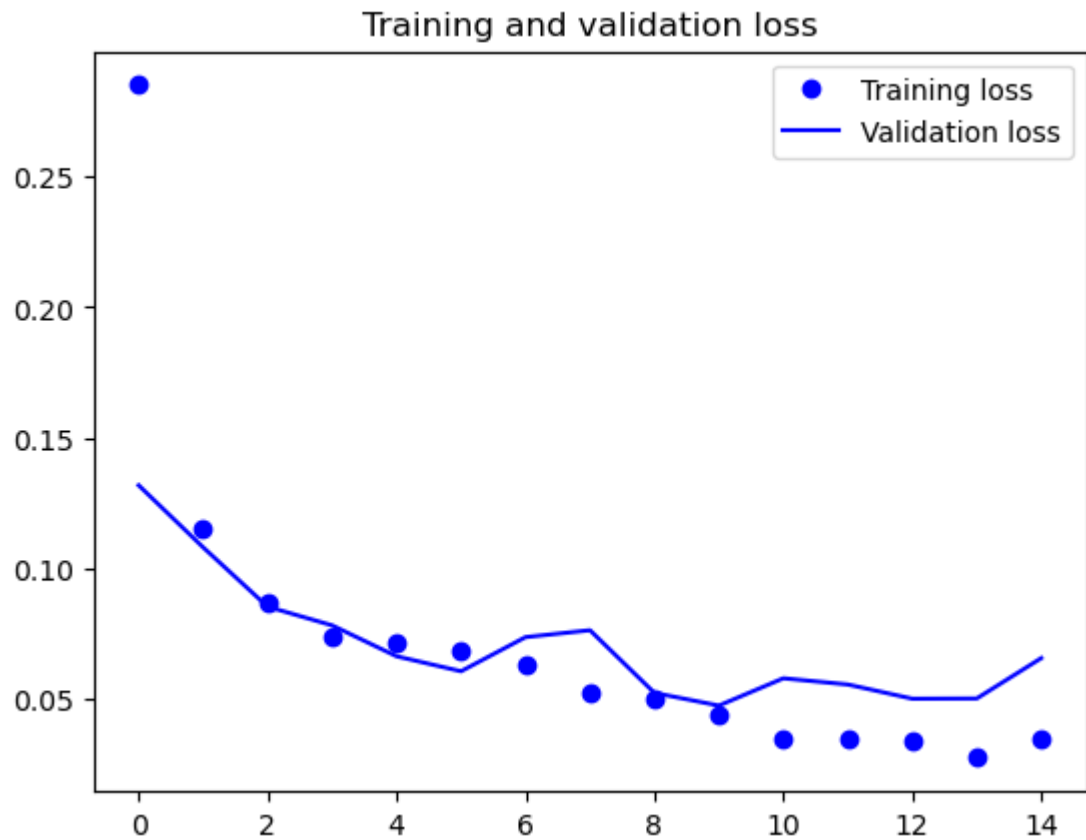
epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
```

Out[8]: <matplotlib.legend.Legend at 0x7f55e561d8d0>



```
In [9]: ▶ loss = history_CNN.history['loss']  
        val_loss = history_CNN.history['val_loss']  
  
        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()
```



```
In [10]: ▶ 32/32 [=====] - 11s 335ms/step - loss: 1.4924  
          - acc: 0.7564
```

## Data Augmentation

```
In [11]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.imagenet_utils import preprocess_input

batch_size = 32
datagen = ImageDataGenerator(rescale = 1/255,
                             rotation_range=15,
                             width_shift_range=0.1,
                             height_shift_range=0.1,
                             shear_range=0.05,
                             zoom_range=0.2,
                             horizontal_flip=True,
                             fill_mode='nearest')

train = datagen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(
val_gen = ImageDataGenerator(rescale = 1/255)
val = val_gen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(2)
test_gen = ImageDataGenerator(rescale = 1/255)
test = test_gen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(

Found 4192 images belonging to 2 classes.
Found 1040 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

```
In [12]: xx_test=np.concatenate([test.next()[0] for i in range(test.__len__())])
xx_test.shape
yy_test=np.concatenate([test.next()[1] for i in range(test.__len__())])
yy_test.shape
```

Out[12]: (624, 256, 256, 3)

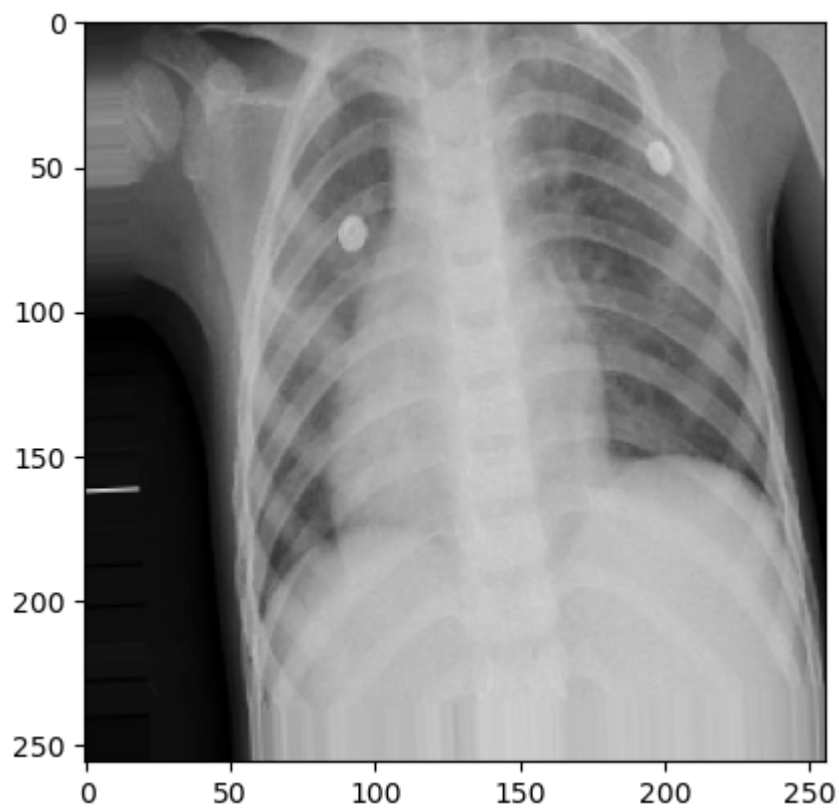
```
In [13]: from tensorflow.keras.preprocessing import image

img = xx_test[0]

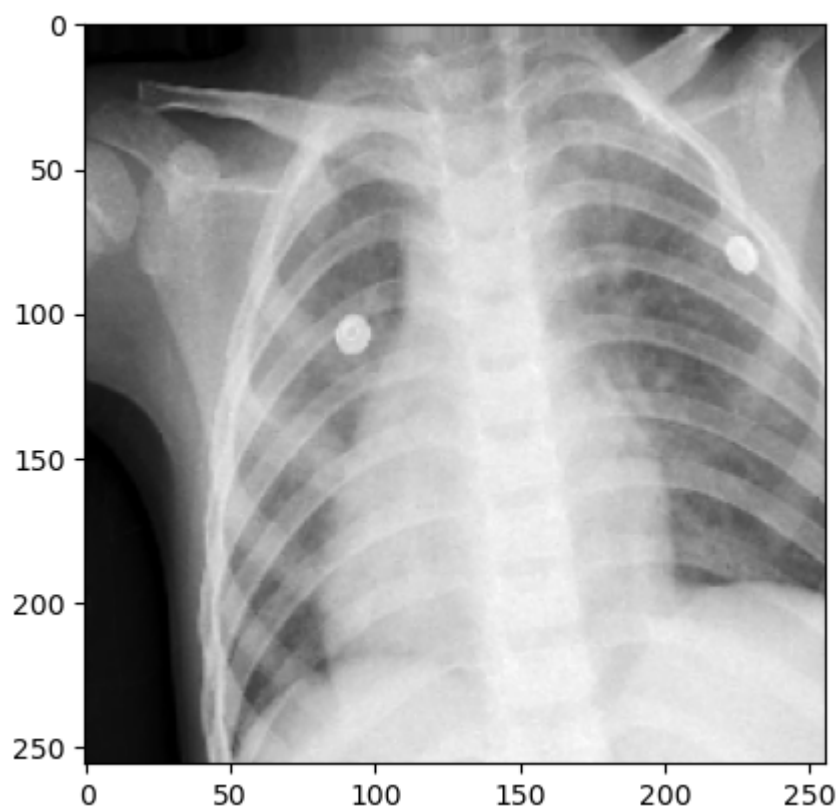
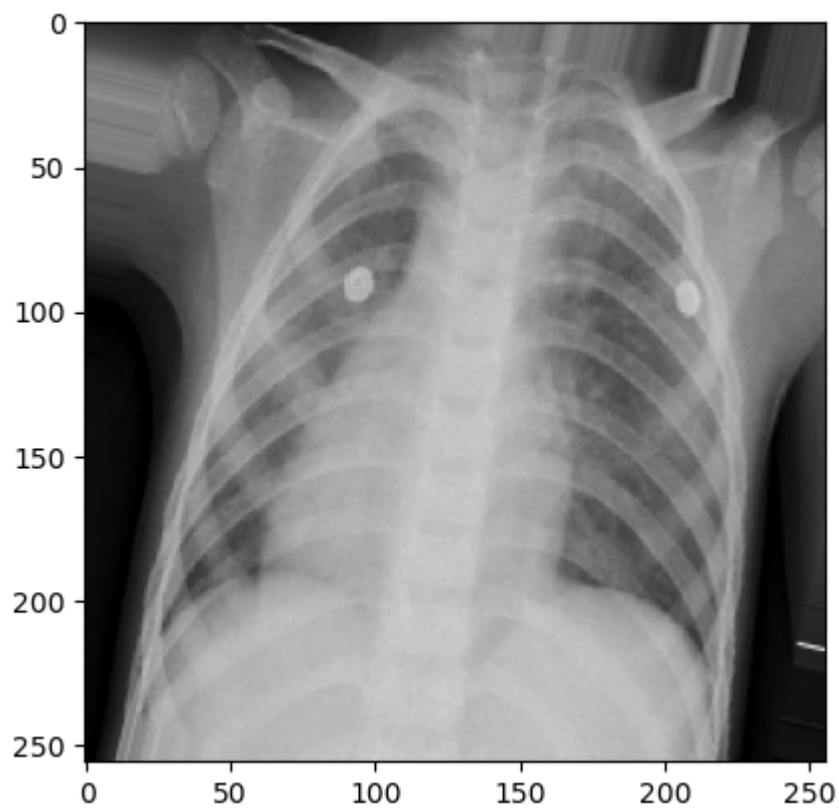
x = np.reshape(img, (256, 256, 3))

x = x.reshape((1,) + x.shape)

i = 0
for batch in datagen.flow(x, batch_size=1):
    plt.figure(i)
    imgplot = plt.imshow(image.array_to_img(batch[0]))
    i += 1
    if i % 4 == 0:
        break
```







**Ba**

```
In [14]: model_DA = models.Sequential()
model_DA.add(layers.Conv2D(32, (3, 3), activation='relu',
                           input_shape=(256, 256, 3)))
model_DA.add(layers.MaxPooling2D((2, 2)))
model_DA.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_DA.add(layers.MaxPooling2D((2, 2)))
model_DA.add(layers.Conv2D(128, (3, 3), activation='relu'))
model_DA.add(layers.MaxPooling2D((2, 2)))
model_DA.add(layers.Conv2D(128, (3, 3), activation='relu'))
model_DA.add(layers.MaxPooling2D((2, 2)))
model_DA.add(layers.Flatten())
model_DA.add(layers.Dropout(0.35))
model_DA.add(layers.Dense(512, activation='relu'))
model_DA.add(layers.Dropout(0.25))
```

In [15]:

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_4 (MaxPooling 2D)	(None, 127, 127, 32)	0
conv2d_5 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_5 (MaxPooling 2D)	(None, 62, 62, 64)	0
conv2d_6 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_6 (MaxPooling 2D)	(None, 30, 30, 128)	0
conv2d_7 (Conv2D)	(None, 28, 28, 128)	147584
max_pooling2d_7 (MaxPooling 2D)	(None, 14, 14, 128)	0
flatten_1 (Flatten)	(None, 25088)	0
dropout_2 (Dropout)	(None, 25088)	0
dense_2 (Dense)	(None, 512)	12845568
dropout_3 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 1)	513
=====		
Total params: 13,086,913		
Trainable params: 13,086,913		
Non-trainable params: 0		

In [16]:

```
model_DA.compile(loss='binary_crossentropy',  
                  optimizer='adam',
```

In [17]:

```
history_DA = model_DA.fit(train,
                           epochs=10,
                           #steps_per_epoch=4192/batch_size,
```

Epoch 1/10

131/131 [=====] - 120s 898ms/step - loss: 0.4225 - acc: 0.8099 - val\_loss: 0.2160 - val\_acc: 0.9240

Epoch 2/10

131/131 [=====] - 120s 917ms/step - loss: 0.2824 - acc: 0.8845 - val\_loss: 0.2452 - val\_acc: 0.9038

Epoch 3/10

131/131 [=====] - 119s 907ms/step - loss: 0.2647 - acc: 0.8857 - val\_loss: 0.2573 - val\_acc: 0.9375

Epoch 4/10

131/131 [=====] - 118s 903ms/step - loss: 0.2363 - acc: 0.8991 - val\_loss: 0.1980 - val\_acc: 0.9317

Epoch 5/10

131/131 [=====] - 118s 903ms/step - loss: 0.2468 - acc: 0.8955 - val\_loss: 0.1627 - val\_acc: 0.9433

Epoch 6/10

131/131 [=====] - 118s 901ms/step - loss: 0.2148 - acc: 0.9098 - val\_loss: 0.1757 - val\_acc: 0.9423

Epoch 7/10

131/131 [=====] - 118s 902ms/step - loss: 0.2002 - acc: 0.9151 - val\_loss: 0.2088 - val\_acc: 0.9221

Epoch 8/10

131/131 [=====] - 117s 897ms/step - loss: 0.2051 - acc: 0.9172 - val\_loss: 0.1705 - val\_acc: 0.9385

Epoch 9/10

131/131 [=====] - 118s 904ms/step - loss: 0.1846 - acc: 0.9210 - val\_loss: 0.1493 - val\_acc: 0.9433

Epoch 10/10

131/131 [=====] - 118s 901ms/step - loss: 0.1778 - acc: 0.9315 - val\_loss: 0.1510 - val\_acc: 0.9452

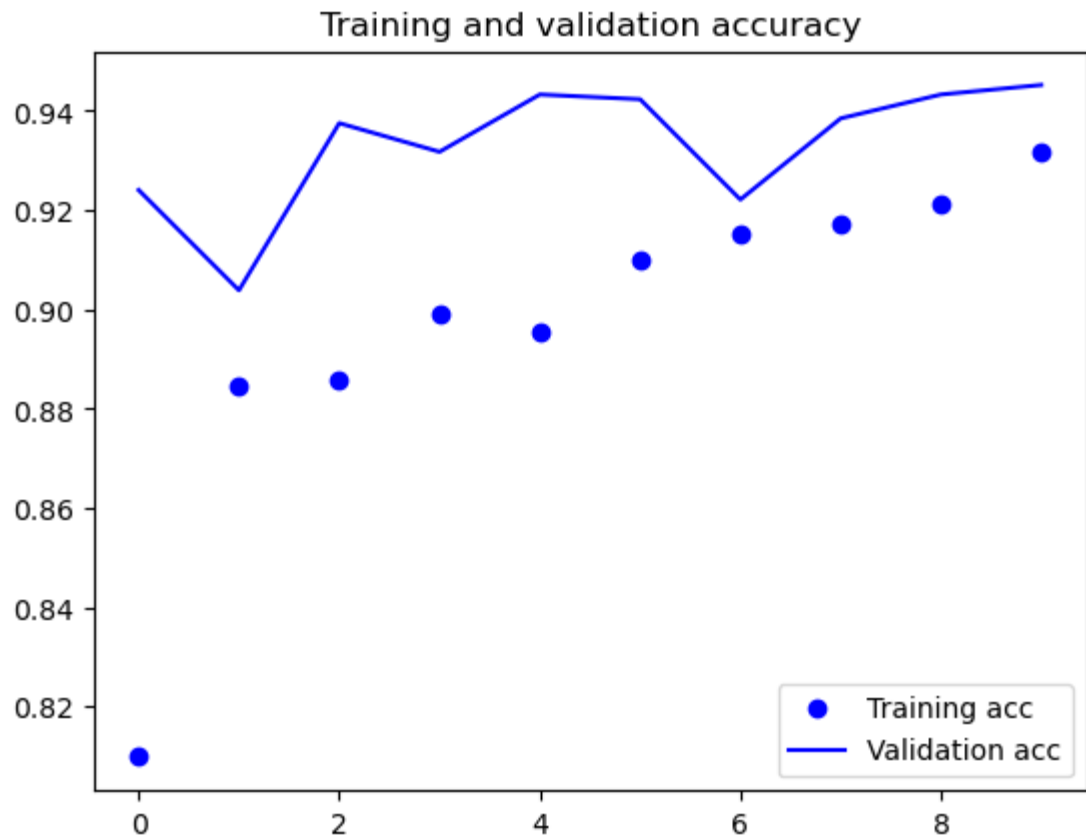
```
In [18]: import matplotlib.pyplot as plt

acc = history_DA.history['acc']
val_acc = history_DA.history['val_acc']

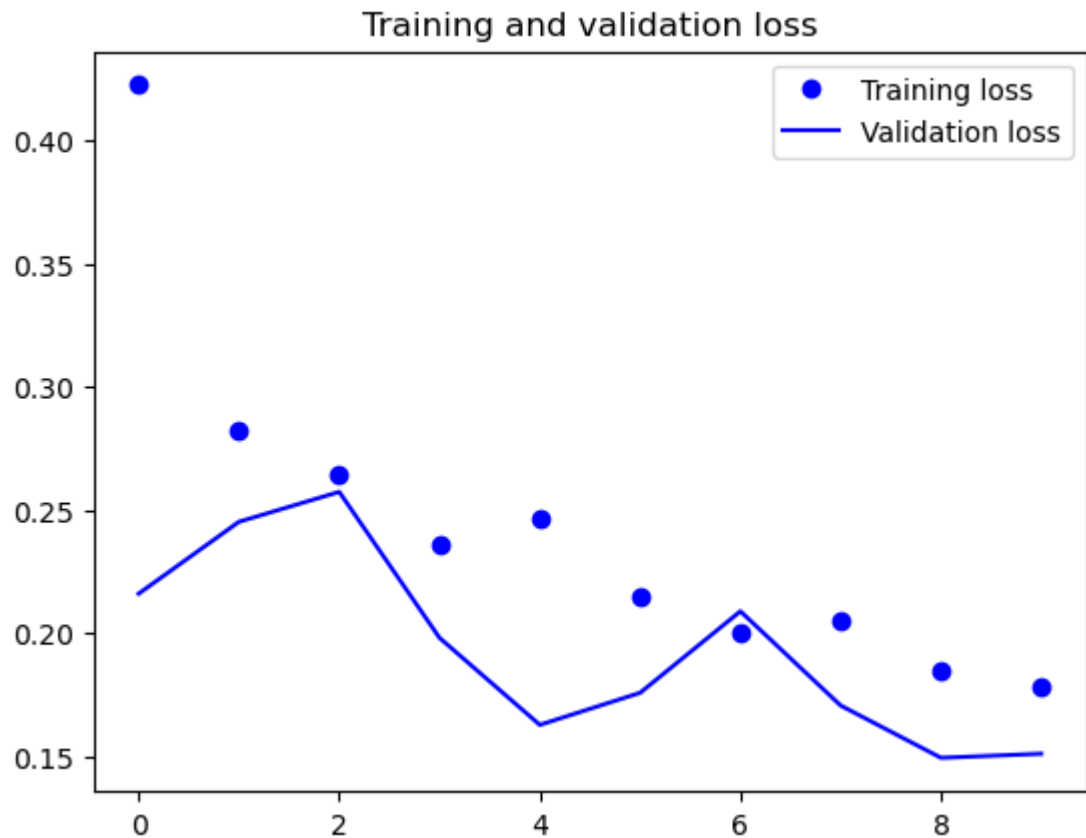
epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
```

Out[18]: <matplotlib.legend.Legend at 0x7f55e463ed50>



```
In [19]: ▶ loss = history_DA.history['loss']  
val_loss = history_DA.history['val_loss']  
  
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()
```



```
In [20]: ▶ 20/20 [=====] - 8s 377ms/step - loss: 0.3199  
- acc: 0.8734
```

## Transfer Learning

```
In [21]: ▶ from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.imagenet_utils import preprocess_input

batch_size = 32
datagen = ImageDataGenerator(rescale = 1/255,
                             rotation_range=15,
                             width_shift_range=0.1,
                             height_shift_range=0.1,
                             shear_range=0.05,
                             zoom_range=0.2,
                             horizontal_flip=True,
                             fill_mode='nearest')

train = datagen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(1)')
val_gen = ImageDataGenerator(rescale = 1/255)
val = val_gen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(2)')
test_gen = ImageDataGenerator(rescale = 1/255)
test = test_gen.flow_from_directory('C:/Users/Xhensil/Downloads/archive(3)')

Found 4192 images belonging to 2 classes.
Found 1040 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

In [22]: `from tensorflow.keras.applications import VGG16`

```
conv_base = VGG16(weights='imagenet',
                    include_top=False,
                    input_shape=(256, 256, 3))
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels\\_notop.h5](https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5)  
 (https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16\_weights\_tf\_dim\_ordering\_tf\_kernels\_notop.h5)  
 58889256/58889256 [=====] - 0s 0us/step  
 Model: "vgg16"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 256, 256, 3)]	0
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1180160
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block5_pool (MaxPooling2D)	(None, 8, 8, 512)	0
=====		
Total params: 14,714,688		



Trainable params: 14,714,688  
Non-trainable params: 0

```
In [23]: model_TL = models.Sequential()
model_TL.add(conv_base)
model_TL.add(layers.Flatten())
model_TL.add(layers.Dense(512, activation='relu'))
model_TL.add(layers.Dropout(0.4))
model_TL.add(layers.Dense(1, activation='sigmoid'))
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 8, 8, 512)	14714688
flatten_2 (Flatten)	(None, 32768)	0
dense_4 (Dense)	(None, 512)	16777728
dropout_4 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 1)	513

=====  
Total params: 31,492,929  
Trainable params: 31,492,929  
Non-trainable params: 0  
=====

```
In [24]: print('This is the number of trainable weights ')
```

This is the number of trainable weights before freezing the conv base:  
30

```
In [25]:
```

```
In [26]: print('This is the number of trainable weights ')
```

This is the number of trainable weights before freezing the conv base:  
4

```
In [27]: model_TL.compile(optimizer='adam',  
                        loss='binary_crossentropy',  
                        metrics=['accuracy'])  
  
history_TL = model_TL.fit(train,  
                        epochs=10,
```

```
Epoch 1/10  
66/66 [=====] - 137s 2s/step - loss: 5.7719 -  
accuracy: 0.8721 - val_loss: 0.1235 - val_accuracy: 0.9644  
Epoch 2/10  
66/66 [=====] - 126s 2s/step - loss: 0.1441 -  
accuracy: 0.9401 - val_loss: 0.0964 - val_accuracy: 0.9702  
Epoch 3/10  
66/66 [=====] - 126s 2s/step - loss: 0.1399 -  
accuracy: 0.9463 - val_loss: 0.0765 - val_accuracy: 0.9779  
Epoch 4/10  
66/66 [=====] - 126s 2s/step - loss: 0.1158 -  
accuracy: 0.9549 - val_loss: 0.1040 - val_accuracy: 0.9683  
Epoch 5/10  
66/66 [=====] - 126s 2s/step - loss: 0.1061 -  
accuracy: 0.9583 - val_loss: 0.0875 - val_accuracy: 0.9779  
Epoch 6/10  
66/66 [=====] - 126s 2s/step - loss: 0.1091 -  
accuracy: 0.9594 - val_loss: 0.0702 - val_accuracy: 0.9760  
Epoch 7/10  
66/66 [=====] - 126s 2s/step - loss: 0.0873 -  
accuracy: 0.9654 - val_loss: 0.0865 - val_accuracy: 0.9692  
Epoch 8/10  
66/66 [=====] - 126s 2s/step - loss: 0.0921 -  
accuracy: 0.9640 - val_loss: 0.0706 - val_accuracy: 0.9760  
Epoch 9/10  
66/66 [=====] - 127s 2s/step - loss: 0.0870 -  
accuracy: 0.9661 - val_loss: 0.1157 - val_accuracy: 0.9721  
Epoch 10/10  
66/66 [=====] - 126s 2s/step - loss: 0.0953 -  
accuracy: 0.9637 - val_loss: 0.0910 - val_accuracy: 0.9644
```

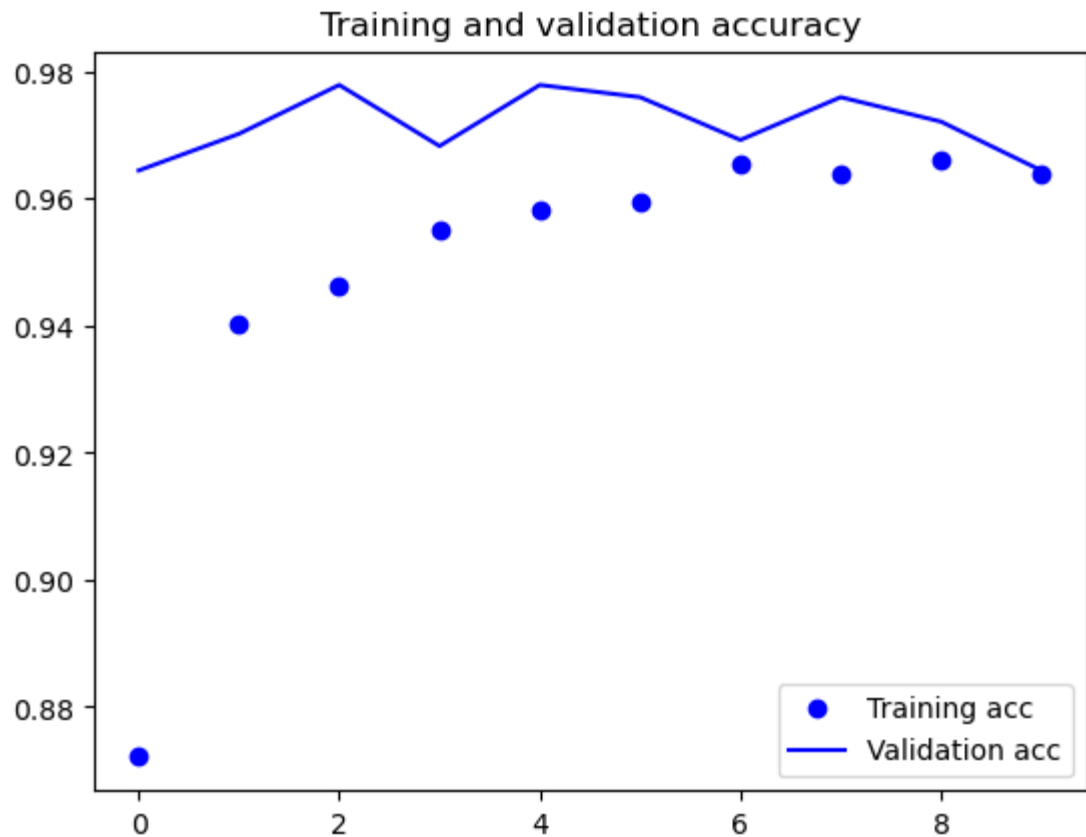
```
In [28]: import matplotlib.pyplot as plt

acc = history_TL.history['accuracy']
val_acc = history_TL.history['val_accuracy']

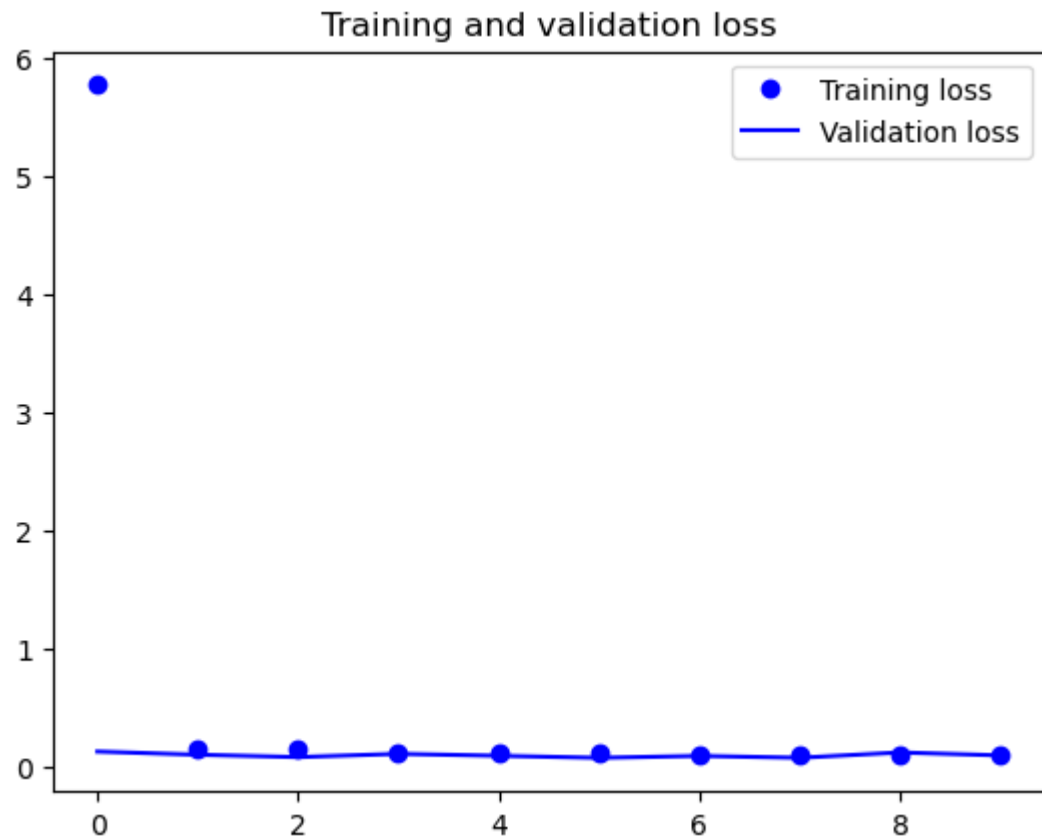
epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
```

Out[28]: <matplotlib.legend.Legend at 0x7f55e40d0e50>



```
In [29]: ▶ loss = history_TL.history['loss']  
val_loss = history_TL.history['val_loss']  
  
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()
```



```
In [30]: ▶ 10/10 [=====] - 14s 1s/step - loss: 0.3148 -  
accuracy: 0.9199
```

```
In [32]: ▶ conv_base.trainable = True

set_trainable = False
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 8, 8, 512)	14714688
flatten_2 (Flatten)	(None, 32768)	0
dense_4 (Dense)	(None, 512)	16777728
dropout_4 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 1)	513
=====		
Total params: 31,492,929		
Trainable params: 23,857,665		
Non-trainable params: 7,635,264		

```
In [33]: model_TL.compile(optimizer=optimizers.Adam(learning_rate=1e-5),
                        loss='binary_crossentropy',
                        metrics=['accuracy'])

history_FT = model_TL.fit(train,
                        epochs=10,
                        # steps_per_epoch=100, # Run same number of steps we would if
```

Epoch 1/10

66/66 [=====] - 129s 2s/step - loss: 0.0919 - accuracy: 0.9688 - val\_loss: 0.0645 - val\_accuracy: 0.9760

Epoch 2/10

66/66 [=====] - 125s 2s/step - loss: 0.0742 - accuracy: 0.9742 - val\_loss: 0.1274 - val\_accuracy: 0.9577

Epoch 3/10

66/66 [=====] - 125s 2s/step - loss: 0.0729 - accuracy: 0.9716 - val\_loss: 0.1069 - val\_accuracy: 0.9644

Epoch 4/10

66/66 [=====] - 127s 2s/step - loss: 0.0637 - accuracy: 0.9790 - val\_loss: 0.4936 - val\_accuracy: 0.8500

Epoch 5/10

66/66 [=====] - 125s 2s/step - loss: 0.0628 - accuracy: 0.9802 - val\_loss: 0.1228 - val\_accuracy: 0.9596

Epoch 6/10

66/66 [=====] - 125s 2s/step - loss: 0.0451 - accuracy: 0.9845 - val\_loss: 0.1269 - val\_accuracy: 0.9654

Epoch 7/10

66/66 [=====] - 126s 2s/step - loss: 0.0464 - accuracy: 0.9840 - val\_loss: 0.1258 - val\_accuracy: 0.9625

Epoch 8/10

66/66 [=====] - 126s 2s/step - loss: 0.0470 - accuracy: 0.9823 - val\_loss: 0.2018 - val\_accuracy: 0.9423

Epoch 9/10

66/66 [=====] - 125s 2s/step - loss: 0.0438 - accuracy: 0.9838 - val\_loss: 0.1478 - val\_accuracy: 0.9567

Epoch 10/10

66/66 [=====] - 127s 2s/step - loss: 0.0501 - accuracy: 0.9843 - val\_loss: 0.0746 - val\_accuracy: 0.9798

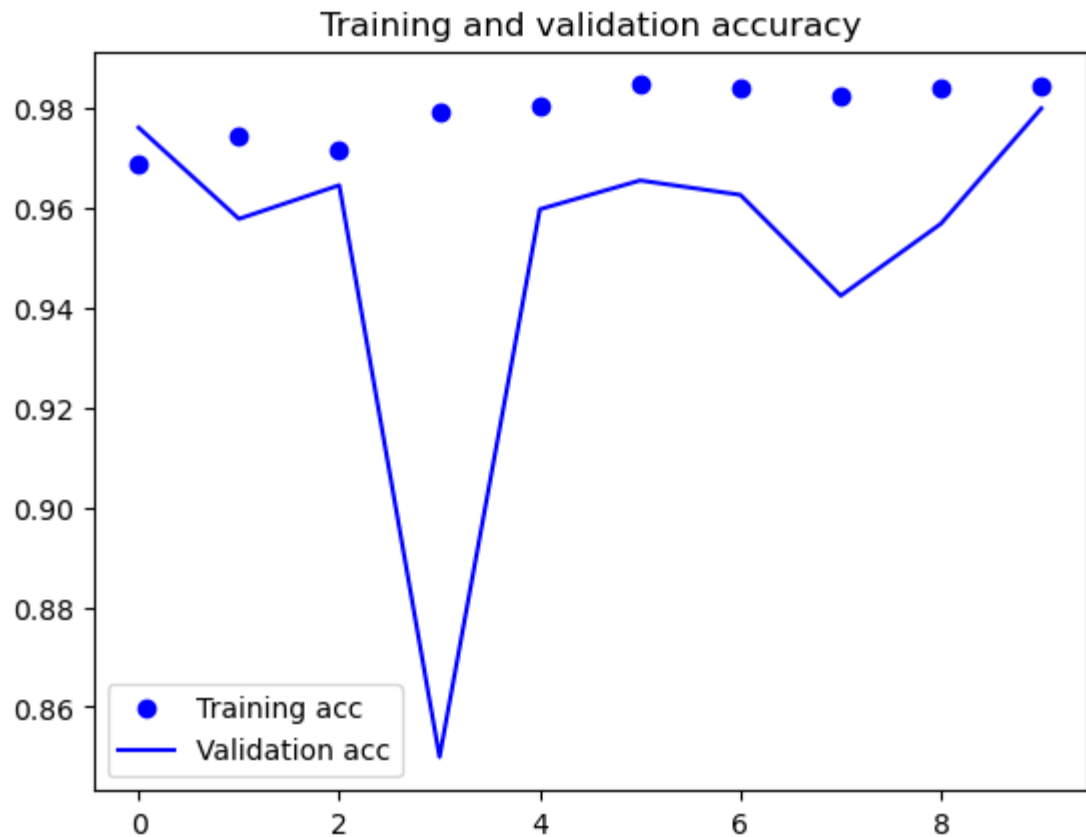
```
In [34]: import matplotlib.pyplot as plt

acc = history_FT.history['accuracy']
val_acc = history_FT.history['val_accuracy']

epochs = range(len(acc))

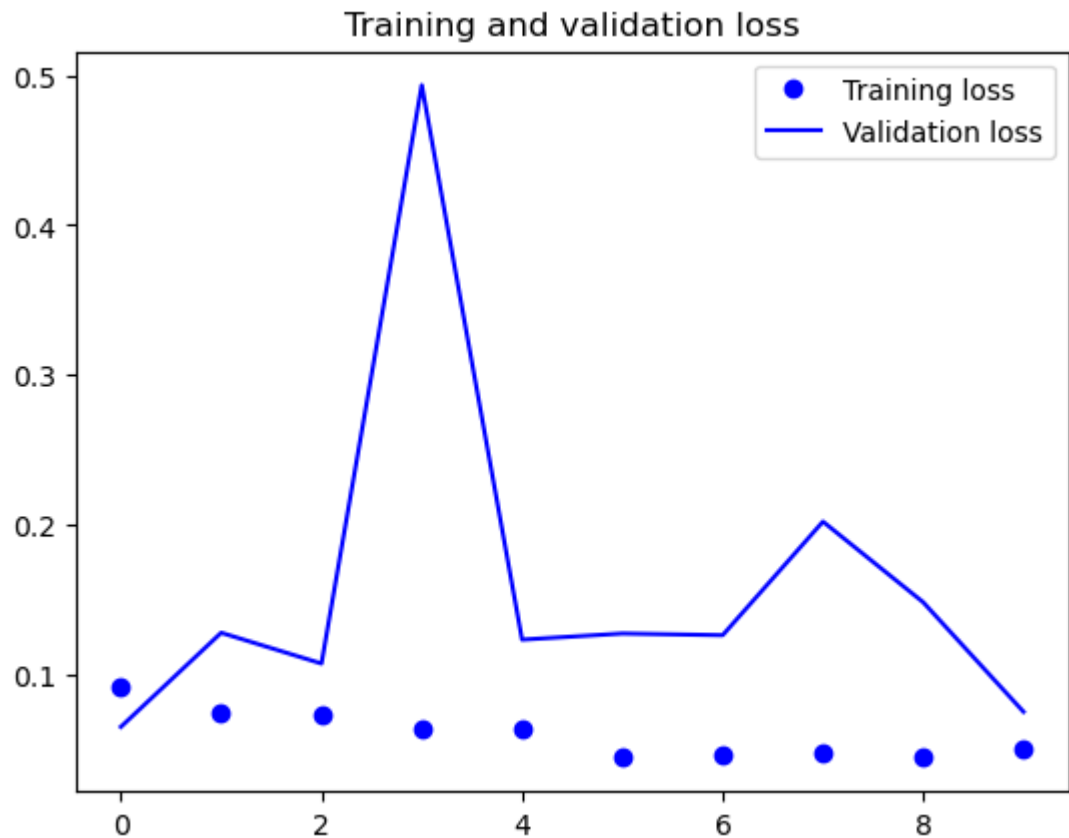
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
```

Out[34]: <matplotlib.legend.Legend at 0x7f55e45c6890>



```
In [35]: ▶ loss = history_FT.history['loss']
val_loss = history_FT.history['val_loss']

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()
```



```
In [36]: ▶ 10/10 [=====] - 9s 925ms/step - loss: 0.3591
- accuracy: 0.9199
```

```
In [48]: ▶ from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
# Make predictions on the batches of images
y_pred = model_TL.predict_generator(test)

# Convert predicted probabilities to predicted labels
y_pred_labels = np.where(y_pred > 0.5, 1, 0)

# Get true labels
```

/opt/conda/lib/python3.7/site-packages/ipykernel\_launcher.py:3: UserWarning: `Model.predict\_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generator s.

This is separate from the ipykernel package so we can avoid doing imports until



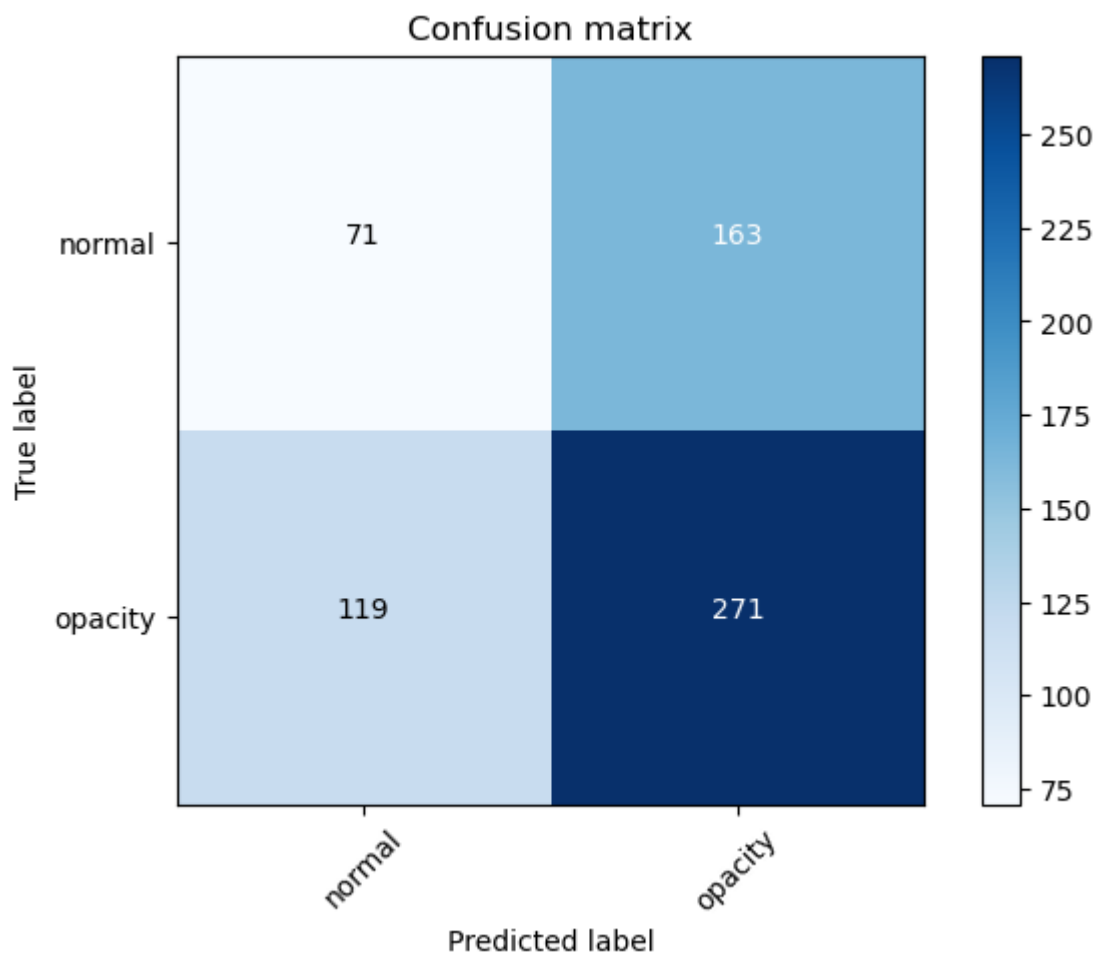
```
In [49]: import matplotlib.pyplot as plt
import itertools

# Define the classes
classes = ['normal', 'opacity']

# Calculate the confusion matrix
confusion_mtx = confusion_matrix(y_true_labels, y_pred_labels)

# Define a function to plot the confusion matrix
def plot_confusion_matrix(cm, classes, title='Confusion matrix', cmap=plt.cm.Blues):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)
    fmt = 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt), horizontalalignment="center", color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

# Plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes)
plt.show()
```



```
In [38]: # CNN model
acc2=history_CNN.history['acc'][-1]
vacc2=history_CNN.history['val_acc'][-1]
loss2=history_CNN.history['loss'][-2]
vloss2=history_CNN.history['val_loss'][-2]

# Data Augmentation
acc3=history_DA.history['acc'][-1]
vacc3=history_DA.history['val_acc'][-1]
loss3=history_DA.history['loss'][-2]
vloss3=history_DA.history['val_loss'][-2]

# ResNet50
acc4=history_TL.history['accuracy'][-1]
vacc4=history_TL.history['val_accuracy'][-1]
loss4=history_TL.history['loss'][-2]
vloss4=history_TL.history['val_loss'][-2]

# ResNet50 Fine Tune
acc5=history_FT.history['accuracy'][-1]
vacc5=history_FT.history['val_accuracy'][-1]
loss5=history_FT.history['loss'][-2]
```

```
In [39]: ► results = pd.DataFrame([["CNN",acc2*100,vacc2*100,loss2,vloss2],
                                   ["CNN_data_augmentation",acc3*100,vacc3*100,loss3,vloss3],
                                   ["Transfer Learning model",acc4*100,vacc4*100,loss4,vloss4],
                                   ["Transfer Learning model_FT",acc5*100,vacc5*100,loss5,vloss5],
                                   columns = ["Model","Training Accuracy %","Validation Accuracy %","Loss","Validation Loss"])
```

Out[39]:

	Model	Training Accuracy %	Validation Accuracy %	Loss	Validation Loss
0	CNN	98.759544	97.307694	0.027386	0.050128
1	CNN_data_augmentation	93.153626	94.519234	0.184610	0.149308
2	Transfer Learning model	96.374047	96.442306	0.087022	0.115681
3	Transfer Learning model_FT	98.425573	97.980767	0.043833	0.147835

In [ ]: ►