In [28]:
```
import pandas as pd
import numpy as np
import os, shutil
import tensorflow as tf

from tensorflow.keras.preprocessing.image import ImageDataGenerator, a
from tensorflow.keras.models import Model, load_model, Sequential
from tensorflow.keras.layers import GlobalAveragePooling2D, Dropout, D
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.applications import VGG16
from tensorflow.keras.metrics import Recall as recall
from keras import layers, models
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStoppir
from sklearn.metrics import plot_confusion_matrix, classification_repo
from PIL import Image

import matplotlib.pyplot as plt
%matplotlib inline
```

Business Problem

Pneumonia kills more children than any other infectious disease. Every year it claimes the live of more then 700,000 children under the age of five globally. These deaths are preventable with early diagnostic and treatment.

Stakeholders

The Doctors Without Borders, who are currently have a mission in Central and West Africa, where according to the UNICEF's 2019 statistics, the mortality rate for this infection for 5 years old and younger was between 21-24%. They would like to get help in their effort to speed up xray evaluation and detect pneumonia so they can start early treatment to save these lives. Just for comparison this rate in the developed countries runs between

Splitting the dataset - shutil images

The kaggle dataset has more then 89% of the images in the train set, 10 % in the test and only 0.3% in the validation, so I will move some of the images from the train folder to the test and validation, to get 70-20-10% split between the 3 folders. The dataset is imbalance, this I will address this later on with augmentation, to create more images to balance out the .

In [3]:
```
train_p = "data/chest_xray/train/PNEUMONIA"
train_n = "data/chest_xray/train/NORMAL"
test_p = "data/chest_xray/test/PNEUMONIA"
test_n = "data/chest_xray/test/NORMAL"
val_p = "data/chest_xray/val/PNEUMONIA"
val_n = "data/chest_xray/val/NORMAL"
```

In [3]:
```
#images_p = [file for file in os.listdir(train_p) if file.endswith('.j
```

In [4]:
```
#images_n = [file for file in os.listdir(train_n) if file.endswith('.j
```

In [5]:
```
# checking images
#images_p[0:10]
```

In [6]:
```
#test images pneumonia shutil
#imgs_pneumonia = images_p[:404]
#for img in imgs_pneumonia:
#    origin = os.path.join(train_p, img)
#    destination = os.path.join(test_p, img)
#    shutil.move(origin, destination)
```

In [7]:
```
# test images normal shutil
#imgs_normal = images_n[:206]
#for img in imgs_normal:
#    origin = os.path.join(train_n, img)
#    destination = os.path.join(test_n, img)
#    shutil.move(origin, destination)
```

In [8]:
```
# validation images pneumonia shutil
#imgs_pneumonia = images_p[404:825]
#for img in imgs_pneumonia:
#    origin = os.path.join(train_p, img)
#    destination = os.path.join(val_p, img)
#    shutil.move(origin, destination)
```

In [9]:
```
# validation images normal shutil
#imgs_normal = images_n[206:490]
#for img in imgs_normal:
#    origin = os.path.join(train_n, img)
#    destination = os.path.join(val_n, img)
#    shutil.move(origin, destination)
```

Preprocessing

In [4]:
```
# image folder path
train_path = "data/chest_xray/train"
test_path = "data/chest_xray/test"
val_path = "data/chest_xray/val"
```

In [5]:
```
# normalizing the images
train_datagen = ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom
test_datagen = ImageDataGenerator(rescale = 1./255)
val_datagen = ImageDataGenerator(rescale = 1.255)
```

In [6]:
```
# intentiating the generators for train, test and validation
train_generator = train_datagen.flow_from_directory(
    train_path,
    target_size=(200,200),
    batch_size = 6100,
    color_mode = 'grayscale',
    class_mode = 'categorical')

test_generator = test_datagen.flow_from_directory(
    test_path,
    target_size = (200, 200),
    batch_size = 1588,
    color_mode = 'grayscale',
    class_mode = 'categorical')

val_generator = test_datagen.flow_from_directory(
    val_path,
    target_size = (200, 200),
    batch_size = 858,
    color_mode = 'grayscale',
    class_mode = 'categorical')
```

```
Found 6100 images belonging to 2 classes.
Found 1588 images belonging to 2 classes.
Found 858 images belonging to 2 classes.
```

In [18]:
```
#train_class_names = list(train_generator.class_indices.keys())
#train_class_names
```

In [7]:
```
# create the data sets
train_images, train_labels = next(train_generator)
test_images, test_labels = next(test_generator)
val_images, val_labels = next(val_generator)
```

In [8]:
```
# creating the labels for the confusion matrix
test_labels_c = np.argmax(test_labels, axis =-1)
```

In [9]:
```
# workaround to plot confusion matrix, seting up the estimator
labels = list(train_generator.class_indices.keys())
class estimator:
    _estimator_type = ''
    classes_ = []
    def __init__(self, model, classes):
        self.model = model
        self._estimator_type = 'classifier'
        self.classes_ = classes
    def predict(self, X):
        y_prob = self.model.predict(X)
        y_pred = y_prob.argmax(axis=1)
        return y_pred
```

In [10]:
```
# Explore the dataset
m_train = train_images.shape[0]
num_px = train_images.shape[1]
m_test = test_images.shape[0]
m_val = val_images.shape[0]

print ("Number of training samples: " + str(m_train))
print ("Number of testing samples: " + str(m_test))
print ("Number of validation samples: " + str(m_val))
```

```
Number of training samples: 6100
Number of testing samples: 1588
Number of validation samples: 858
```

In [11]:

```
# reshaping label arrays for modeling
train_y = np.reshape(train_labels[:,0], (6100,1))
test_y = np.reshape(test_labels[:,0], (1588,1))
val_y = np.reshape(val_labels[:,0], (858,1))
```

Model1

In [41]:

```
### Ridge regularization
#reg = l2(1e-4)
#reg = l2(3e-3)
reg= l2(1e-6)
```

In [42]:
```
# basic sequential model, with adam optimizer, batch normalization and
model1 = Sequential()
# input layer : 64 filters, 4 by 4 shape for each stride, image size 2
model1.add(layers.Conv2D(64, (4,4),input_shape=(200,200,1), activation
model1.add(BatchNormalization())
model1.add(MaxPooling2D(pool_size=(3,3)))

# flatten the model for the dense layer
model1.add(Flatten())

# fully conected dense layers
model1.add(Dense(64, activation ='relu'))
model1.add(Dense(1, activation = 'sigmoid'))

# compiling the model
model1.compile(optimizer = 'adam', loss = 'binary_crossentropy', metri

# fitting the model
history1 = model1.fit(train_images, train_y, batch_size = 32, epochs =

model1.summary()
```

```
Epoch 1/50

2022-12-12 00:28:29.035094: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - ETA: 0s - loss: 0.7654 - r
ecall_5: 0.8797 - acc: 0.8795

2022-12-12 00:29:00.497815: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - 35s 182ms/step - loss: 0.7
654 - recall_5: 0.8797 - acc: 0.8795 - val_loss: 0.6184 - val_recall_
5: 0.9953 - val_acc: 0.5746
Epoch 2/50
191/191 [==============================] - 34s 177ms/step - loss: 0.1
578 - recall_5: 0.9361 - acc: 0.9375 - val_loss: 0.3913 - val_recall_
5: 0.7855 - val_acc: 0.8438
```

In [44]:
```
# evaluating model1 train
results_train = model1.evaluate(train_images, train_y)
results_train
```

```
191/191 [==============================] - 25s 130ms/step - loss: 4.9
209e-06 - recall_5: 1.0000 - acc: 1.0000
```

Out[44]:
```
[4.920911123917904e-06, 1.0, 1.0]
```

In [45]:
```
# evaluating model1 validation
results_val = model1.evaluate(val_images, val_y)
results_val
```

```
27/27 [==============================] - 4s 130ms/step - loss: 0.3815
- recall_5: 0.9627 - acc: 0.9569
```

Out[45]:
```
[0.38153010606765747, 0.9627040028572083, 0.9568764567375183]
```

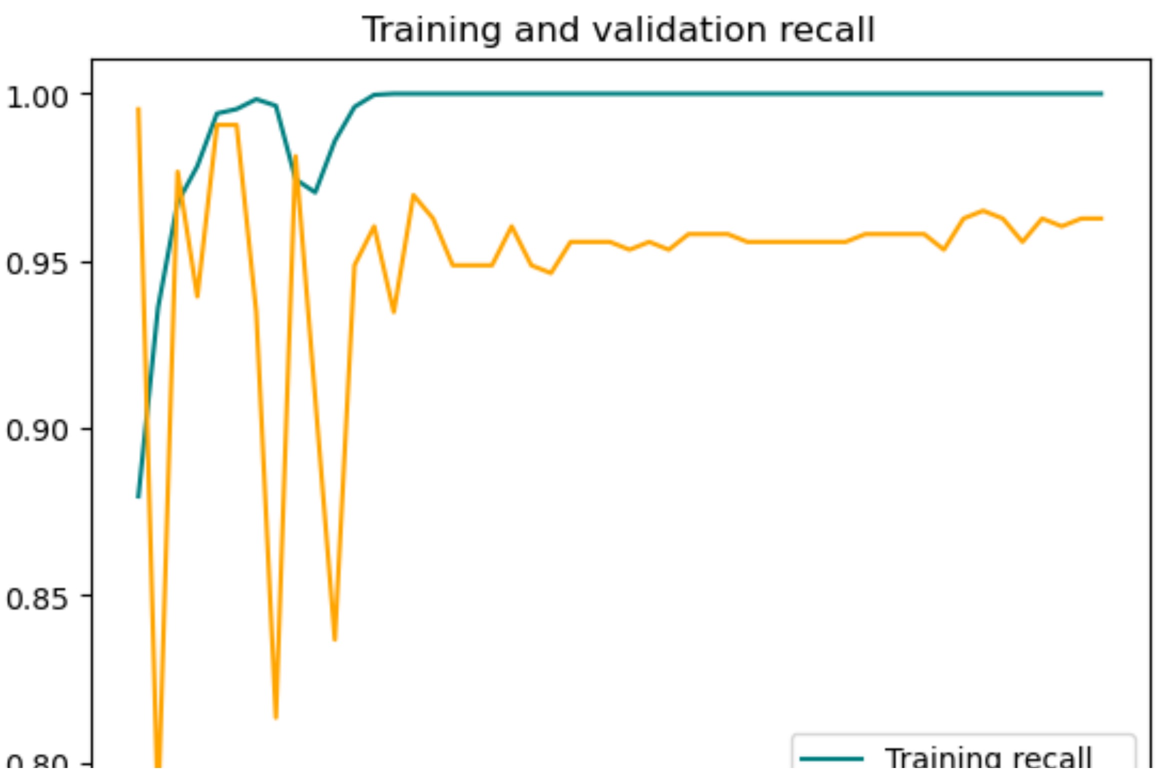
In [46]:
```
# evaluating model1 test
results_test = model1.evaluate(test_images, test_y)
results_test
```

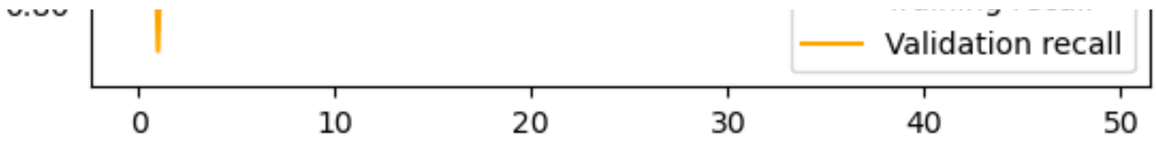
```
50/50 [==============================] - 6s 129ms/step - loss: 1.2063
- recall_5: 0.8615 - acc: 0.9093
```

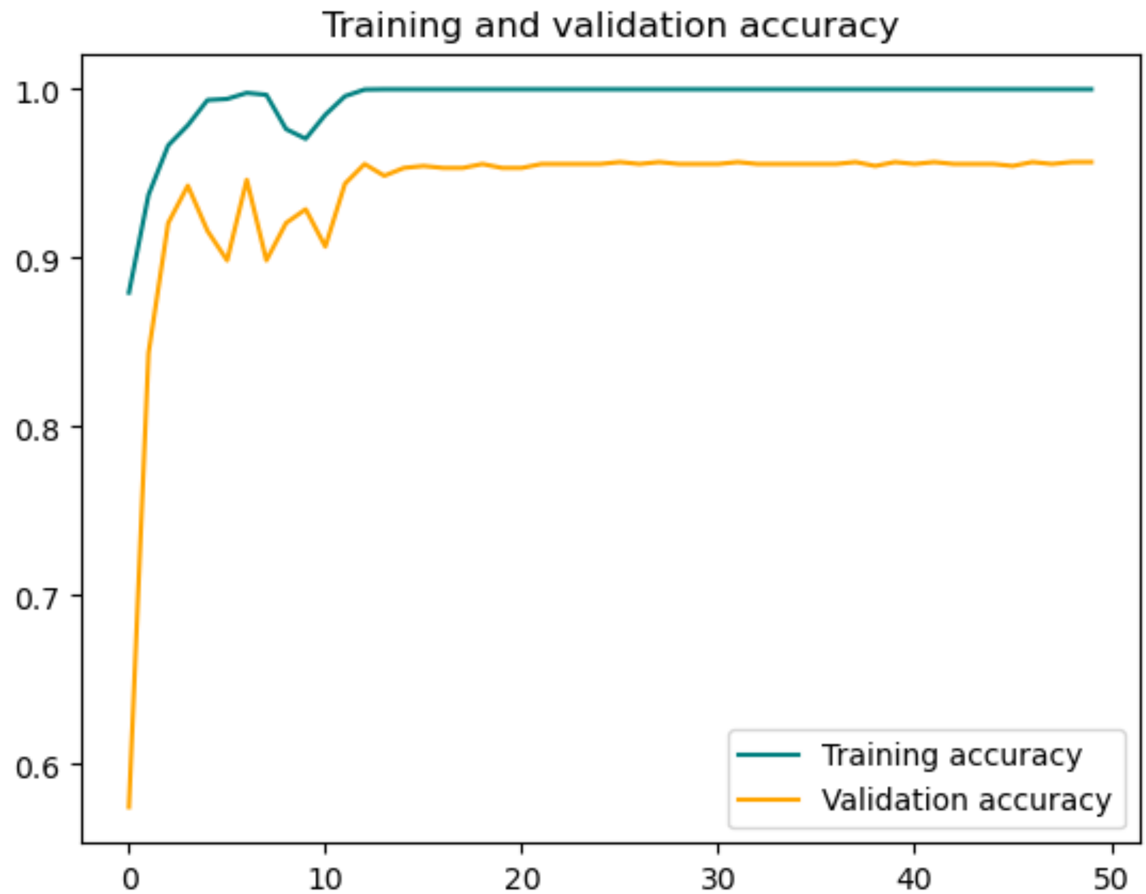
Out[46]:
```
[1.2063026428222656, 0.8614609837532043, 0.9093199372291565]
```

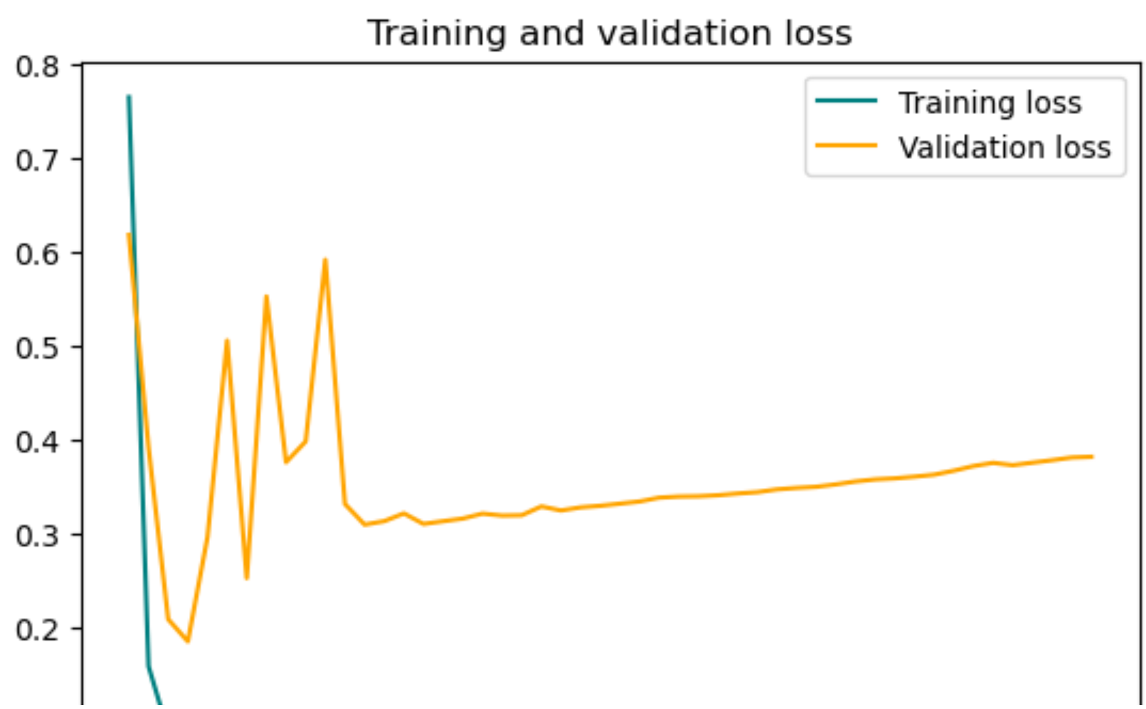
In [47]:

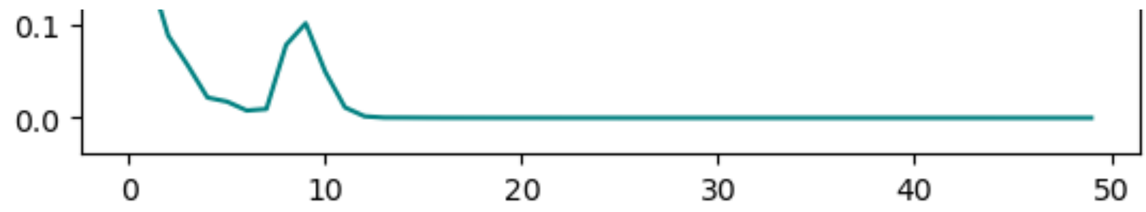
```
# evaluating model1 recall, accuracy and
acc = history1.history['acc']
val_acc = history1.history['val_acc']
loss = history1.history['loss']
val_loss = history1.history['val_loss']
epochs = range(len(acc))
epochsv = range(len(loss))
rec = history1.history['recall_5']
val_rec = history1.history['val_recall_5']

epochsr = range(len(rec))

plt.plot(epochsr, rec, color='teal', label= 'Training recall')
plt.plot(epochsr, val_rec, color='orange', label='Validation recall')
plt.title('Training and validation recall')
plt.legend()
plt.figure()

plt.plot(epochs, acc, color='teal', label= 'Training accuracy')
plt.plot(epochs, val_acc, color='orange', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochsv, loss, color='teal', label='Training loss')
plt.plot(epochsv, val_loss, color='orange', label = 'Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```




Validation recall
0
10
20
30
40
50


Training and validation accuracy
1.0
0.9
0.8
0.7
0.6
Training accuracy
Validation accuracy
0
10
20
30
40
50


Training and validation loss
0.8
0.7
0.6
0.5
0.4
0.3
0.2
Training loss
Validation loss



The first neural networks model is doing pretty well, with high recall score for validation (96.27%) and for the test (86.15%). This is a good result, and it shows that the neural networks model is able to learn from data and generalize well. The high recall score for the validation set suggests that the model is correctly classifing most of the examples in the validation set. The validation score and the training score were very high. The loss also decreasing, however the validation loss starts to separate and increase, this might be an indication that the model is overfitting. To stop the model from overfitting I will try to apply regularization in the next model with more Conv2D layer.

In case the training loss is not decreasing or going weird, it would be time to potentially consider a larger neural network or to make a more sophisticated neural network model. Thankfully this is not the case for my model. As I mentioned earlier the increase in validation loss might be an indicator for overfitting, so I will try to apply the following methods which can help with this: apply regularization, introduce early stopping, hyperparameter tunning, and last but not least increasing the increasing and modifying the images we already have in the training data with some data augmentation.

Model2 - CNN1

In [19]:
```
### Ridge regularization
#reg = l2(1e-4)
#reg = l2(3e-3)
reg= l2(1e-6)
```

In [20]:

```
# Initializing the CNN
model2 = Sequential()

# 1st convolution layer and pooling
model2.add(layers.Conv2D(32, (3, 3), input_shape=(200, 200, 1), activa
model2.add(MaxPooling2D(pool_size = (3, 3)))

# 2nd convolution layer and pooling
model2.add(layers.Conv2D(32, (3, 3), activation = 'relu'))
model2.add(MaxPooling2D(pool_size = (3, 3)))
model2.add(Dropout(0.3))

# 3rd
model2.add(layers.Conv2D(64, (3,3), activation ='relu'))
model2.add(MaxPooling2D(pool_size = (3, 3)))

# plattening the layers
model2.add(Flatten())

# adding the fully connected dense layer
model2.add(Dense(64, activation = 'relu'))
#model2.add(Dropout(0.3))
# output layer
model2.add(Dense(1, activation = 'sigmoid')) # is it 1 or 2 for binary

# compiler
model2.compile(optimizer = 'adam', loss = 'binary_crossentropy', metri

# earlystop
# callback in the fit
history2 = model2.fit(train_images,
                        train_y, # changed train_generator and added t
                        batch_size = 32,
                        epochs = 150,
                        validation_data = (val_images, val_y))
```

```
Epoch 1/150

2022-12-11 23:11:17.183922: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - ETA: 0s - loss: 0.4237 - r
ecall_2: 0.8610 - acc: 0.7905

2022-12-11 23:11:22.071639: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - 6s 27ms/step - loss: 0.423
```

```
7 - recall_2: 0.8610 - acc: 0.7905 - val_loss: 0.3082 - val_recall_2:
0.7669 - val_acc: 0.8578
Epoch 2/150
191/191 [==============================] - 4s 23ms/step - loss: 0.267
2 - recall_2: 0.8816 - acc: 0.8918 - val_loss: 0.1875 - val_recall_2:
0.9464 - val_acc: 0.9301
```

In [21]:
```
model2.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 198, 198, 32)      320

 max_pooling2d_2 (MaxPooling  (None, 66, 66, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 64, 64, 32)        9248

 max_pooling2d_3 (MaxPooling  (None, 21, 21, 32)       0
 2D)

 dropout (Dropout)           (None, 21, 21, 32)        0

 conv2d_4 (Conv2D)           (None, 19, 19, 64)        18496

 max_pooling2d_4 (MaxPooling  (None, 6, 6, 64)         0
 2D)

 flatten_2 (Flatten)         (None, 2304)              0

 dense_4 (Dense)             (None, 64)                147520

 dense_5 (Dense)             (None, 1)                 65

=================================================================
Total params: 175,649
Trainable params: 175,649
Non-trainable params: 0
_________________________________________________________________
```

In [22]:
```
results_train = model2.evaluate(train_images, train_y)
results_train
```

```
191/191 [==============================] - 2s 12ms/step - loss: 0.004
2 - recall_2: 0.9977 - acc: 0.9985
```

Out[22]:
```
[0.004154770169407129, 0.9977049231529236, 0.9985246062278748]
```

In [23]:
```
results_val = model2.evaluate(val_images, val_y)
results_val
```

```
27/27 [==============================] - 0s 11ms/step - loss: 0.3007
- recall_2: 0.9394 - acc: 0.9499
```

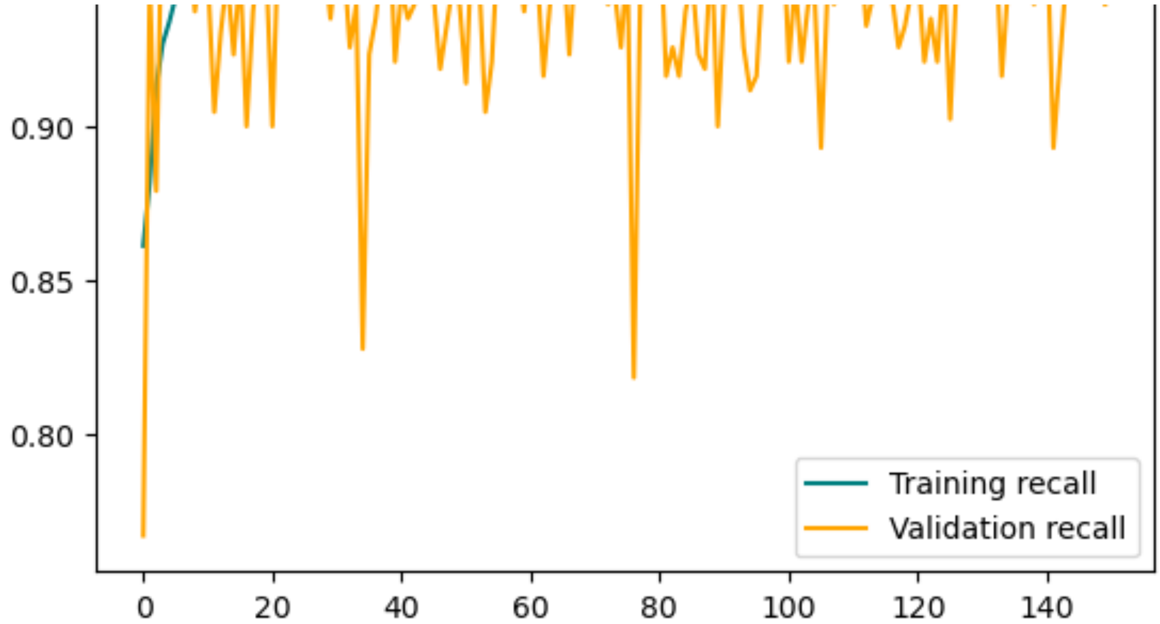
Out[23]:
```
[0.30073633790016174, 0.939393937587738, 0.9498834609985352]
```

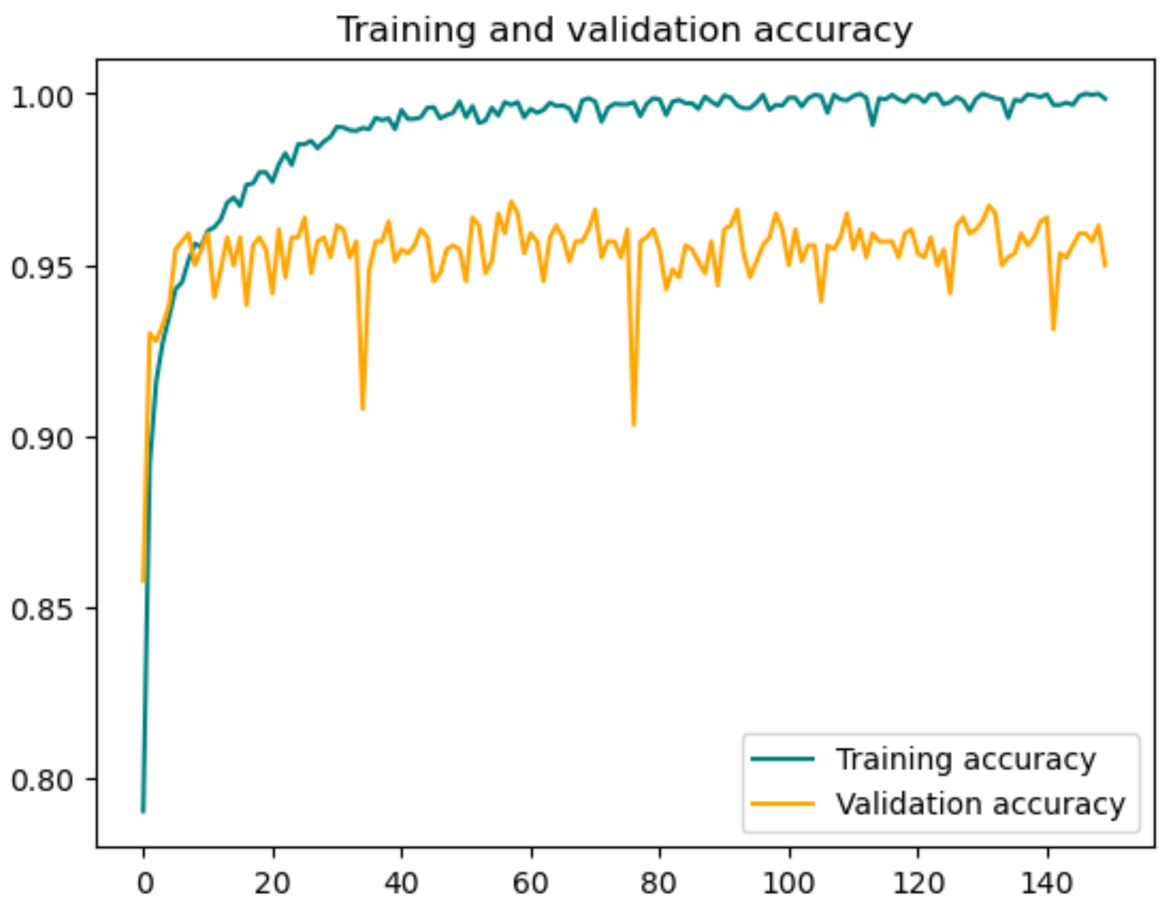
In [24]:
```
results_test = model2.evaluate(test_images, test_y)
results_test
```

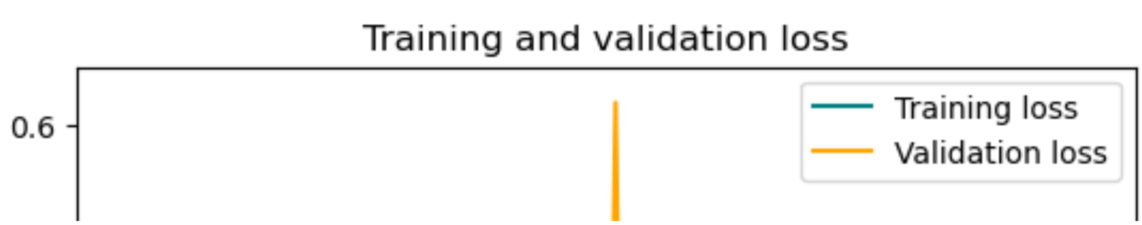
```
50/50 [==============================] - 1s 11ms/step - loss: 0.5917
- recall_2: 0.8778 - acc: 0.9282
```

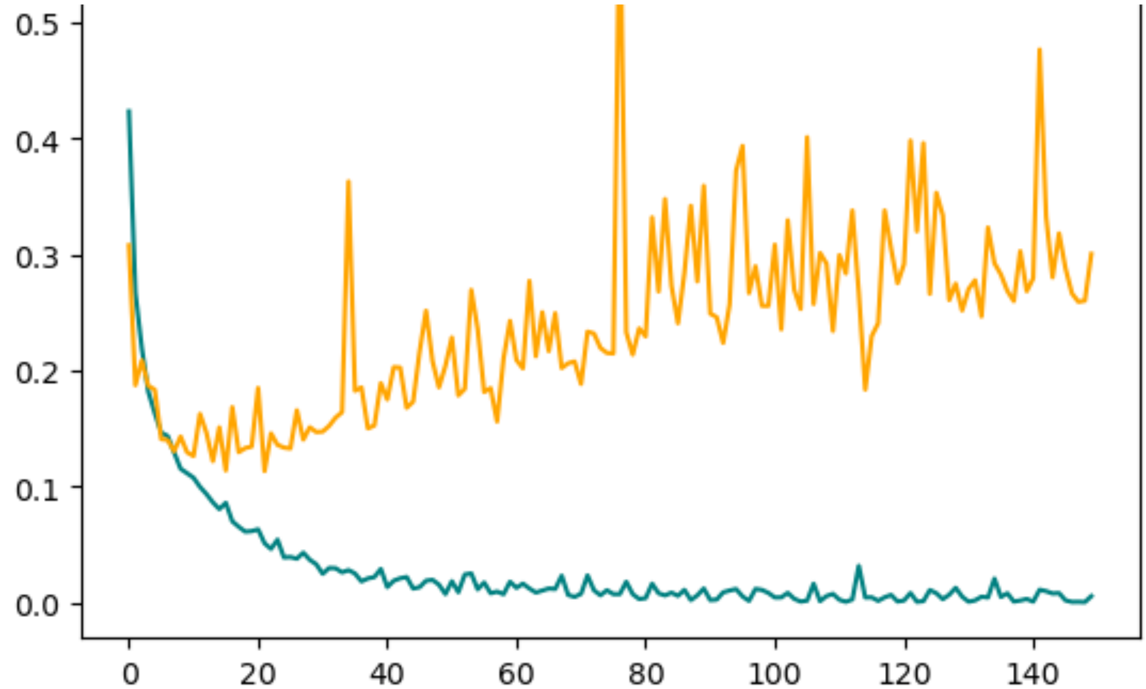
Out[24]:
```
[0.5917469263076782, 0.8778337836265564, 0.9282116293907166]
```

In [35]:
```
acc = history2.history['acc']
val_acc = history2.history['val_acc']
rec = history2.history['recall_2']
val_rec = history2.history['val_recall_2']
loss = history2.history['loss']
val_loss = history2.history['val_loss']
epochsr = range(len(rec))
epochs = range(len(acc))
epochsv = range(len(loss))

plt.plot(epochsr, rec, color='teal', label= 'Training recall')
plt.plot(epochsr, val_rec, color='orange', label='Validation recall')
plt.title('Training and validation recall')
plt.legend()
plt.figure()
plt.plot(epochs, acc, color='teal', label= 'Training accuracy')
plt.plot(epochs, val_acc, color='orange', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochsv, loss, color='teal', label='Training loss')
plt.plot(epochsv, val_loss, color='orange', label = 'Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```


0.90
0.85
0.80
Training recall
Validation recall
0
20
40
60
80
100
120
140


Training and validation accuracy
1.00
0.95
0.90
0.85
0.80
Training accuracy
Validation accuracy
0
20
40
60
80
100
120
140


Training and validation loss
0.6
Training loss
Validation loss



I applied an Ridge regularization of `l2(1e-6)` . The training recall and the validation recall still not converging. There are still an oscillation in both. The validation recall is 93.94% , and the test is 87,78%. As a next step I will change the L2 regularization and add early stopping to the model. I will also try to run it with a larger epoch size (200) and change the L2 regularization to control the models complexity, thus prevent it from overfitting. In addition I will also apply early stopping with a patience of 10 on the validation loss.

Model3 - CNN2 with L2 regularization and Early Stopping

In [26]:
```
### Ridge regularization
reg = l2(1e-4)
#reg = l2(3e-3)
#reg= l2(1e-6)
```

In [29]:
```
```

```
# Initializing the CNN
model3 = Sequential()

# 1st convolution layer and pooling
model3.add(layers.Conv2D(128, (3, 3), input_shape=(200, 200, 1), activ
model3.add(MaxPooling2D(pool_size = (3, 3)))

# 2nd convolution layer and pooling
model3.add(layers.Conv2D(64, (3, 3), activation = 'relu'))
model3.add(MaxPooling2D(pool_size = (3, 3)))
model3.add(Dropout(0.2))

# 3rd
model3.add(layers.Conv2D(64, (3,3), activation ='relu'))
model3.add(MaxPooling2D(pool_size = (3, 3)))

# 4th
model3.add(layers.Conv2D(32, (3,3), activation ='relu'))
model3.add(MaxPooling2D(pool_size = (3, 3)))

# plattening the layers
model3.add(Flatten())

# adding the fully connected dense layer
model3.add(Dense(64, activation = 'relu'))
#model2.add(Dropout(0.1))
# output layer
model3.add(Dense(1, activation = 'sigmoid'))

# compiler
model3.compile(optimizer = 'adam', loss = 'binary_crossentropy', metri

# fit the model
history3 = model3.fit(train_images,
                        train_y,
                        batch_size = 16,
                        epochs = 200,
                        validation_data = (val_images, val_y),
                        callbacks = [early_stopping])
```

```
Epoch 1/300

2022-12-11 23:34:38.272746: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - ETA: 0s - loss: 0.5297 - r
ecall_3: 0.7666 - acc: 0.7133

2022-12-11 23:34:50.595135: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
```

```
GPU is enabled.

191/191 [==============================] - 14s 69ms/step - loss: 0.52
97 - recall_3: 0.7666 - acc: 0.7133 - val_loss: 0.3988 - val_recall_3
: 0.6807 - val_acc: 0.8054
Epoch 2/300
191/191 [==============================] - 11s 58ms/step - loss: 0.31
83 - recall_3: 0.8377 - acc: 0.8620 - val_loss: 0.3946 - val_recall_3
: 0.6364 - val_acc: 0.8089
Epoch 3/300
191/191 [==============================] - 11s 58ms/step - loss: 0.25
21 - recall_3: 0.8813 - acc: 0.8941 - val_loss: 0.2399 - val_recall_3
: 0.8858 - val_acc: 0.9068
Epoch 4/300

191/191 [==============================] - 11s 58ms/step - loss: 0.21
66 - recall_3: 0.8993 - acc: 0.9103 - val_loss: 0.2347 - val_recall_3
: 0.8485 - val_acc: 0.9068
Epoch 5/300
191/191 [==============================] - 11s 58ms/step - loss: 0.19
46 - recall_3: 0.9115 - acc: 0.9190 - val_loss: 0.1802 - val_recall_3
: 0.9371 - val_acc: 0.9359
Epoch 6/300
191/191 [==============================] - 11s 59ms/step - loss: 0.16
27 - recall_3: 0.9275 - acc: 0.9325 - val_loss: 0.2062 - val_recall_3
: 0.8741 - val_acc: 0.9242
Epoch 7/300
191/191 [==============================] - 11s 59ms/step - loss: 0.16
10 - recall_3: 0.9311 - acc: 0.9343 - val_loss: 0.1653 - val_recall_3
: 0.9604 - val_acc: 0.9394
Epoch 8/300
191/191 [==============================] - 11s 59ms/step - loss: 0.14
31 - recall_3: 0.9387 - acc: 0.9423 - val_loss: 0.2338 - val_recall_3
: 0.8392 - val_acc: 0.9103
Epoch 9/300
191/191 [==============================] - 11s 59ms/step - loss: 0.12
78 - recall_3: 0.9475 - acc: 0.9482 - val_loss: 0.1667 - val_recall_3
: 0.9371 - val_acc: 0.9336
Epoch 10/300
191/191 [==============================] - 11s 58ms/step - loss: 0.12
69 - recall_3: 0.9492 - acc: 0.9505 - val_loss: 0.1844 - val_recall_3
: 0.9021 - val_acc: 0.9324
Epoch 11/300
191/191 [==============================] - 11s 58ms/step - loss: 0.11
45 - recall_3: 0.9557 - acc: 0.9557 - val_loss: 0.1649 - val_recall_3
: 0.9464 - val_acc: 0.9441
Epoch 12/300
191/191 [==============================] - 11s 58ms/step - loss: 0.10
09 - recall_3: 0.9597 - acc: 0.9608 - val_loss: 0.1577 - val_recall_3
: 0.9394 - val_acc: 0.9371
Epoch 13/300
```

```
191/191 [==============================] - 11s 59ms/step - loss: 0.09
98 - recall_3: 0.9626 - acc: 0.9618 - val_loss: 0.2257 - val_recall_3
: 0.9021 - val_acc: 0.9347
Epoch 14/300
191/191 [==============================] - 11s 58ms/step - loss: 0.09
07 - recall_3: 0.9623 - acc: 0.9646 - val_loss: 0.1822 - val_recall_3
: 0.9161 - val_acc: 0.9382
Epoch 15/300
191/191 [==============================] - 11s 58ms/step - loss: 0.08
65 - recall_3: 0.9649 - acc: 0.9654 - val_loss: 0.2001 - val_recall_3
: 0.9674 - val_acc: 0.9336
Epoch 16/300
191/191 [==============================] - 11s 59ms/step - loss: 0.08
56 - recall_3: 0.9666 - acc: 0.9680 - val_loss: 0.1655 - val_recall_3
: 0.9510 - val_acc: 0.9464
Epoch 17/300
191/191 [==============================] - 11s 58ms/step - loss: 0.07
98 - recall_3: 0.9669 - acc: 0.9687 - val_loss: 0.1834 - val_recall_3
: 0.9301 - val_acc: 0.9406
Epoch 18/300
191/191 [==============================] - 11s 58ms/step - loss: 0.07
91 - recall_3: 0.9711 - acc: 0.9693 - val_loss: 0.1799 - val_recall_3
: 0.9184 - val_acc: 0.9452
Epoch 19/300
191/191 [==============================] - 11s 59ms/step - loss: 0.06
16 - recall_3: 0.9767 - acc: 0.9777 - val_loss: 0.1910 - val_recall_3
: 0.9441 - val_acc: 0.9429
Epoch 20/300
191/191 [==============================] - 11s 58ms/step - loss: 0.05
29 - recall_3: 0.9793 - acc: 0.9800 - val_loss: 0.2136 - val_recall_3
: 0.9347 - val_acc: 0.9441
Epoch 21/300
191/191 [==============================] - 11s 58ms/step - loss: 0.05
69 - recall_3: 0.9767 - acc: 0.9774 - val_loss: 0.2004 - val_recall_3
: 0.9231 - val_acc: 0.9429
Epoch 22/300
191/191 [==============================] - 11s 59ms/step - loss: 0.05
74 - recall_3: 0.9764 - acc: 0.9775 - val_loss: 0.2302 - val_recall_3
: 0.9114 - val_acc: 0.9371
```

In [30]:

```
results_train = model3.evaluate(train_images, train_y)
results_train
```

```
191/191 [==============================] - 5s 22ms/step - loss: 0.037
5 - recall_3: 0.9784 - acc: 0.9887
```

Out[30]:

```
[0.03750944510102272, 0.978360652923584, 0.9886885285377502]
```

In [31]:
```
results_val = model3.evaluate(val_images, val_y)
results_val
```

```
27/27 [==============================] - 1s 22ms/step - loss: 0.2302
- recall_3: 0.9114 - acc: 0.9371
```

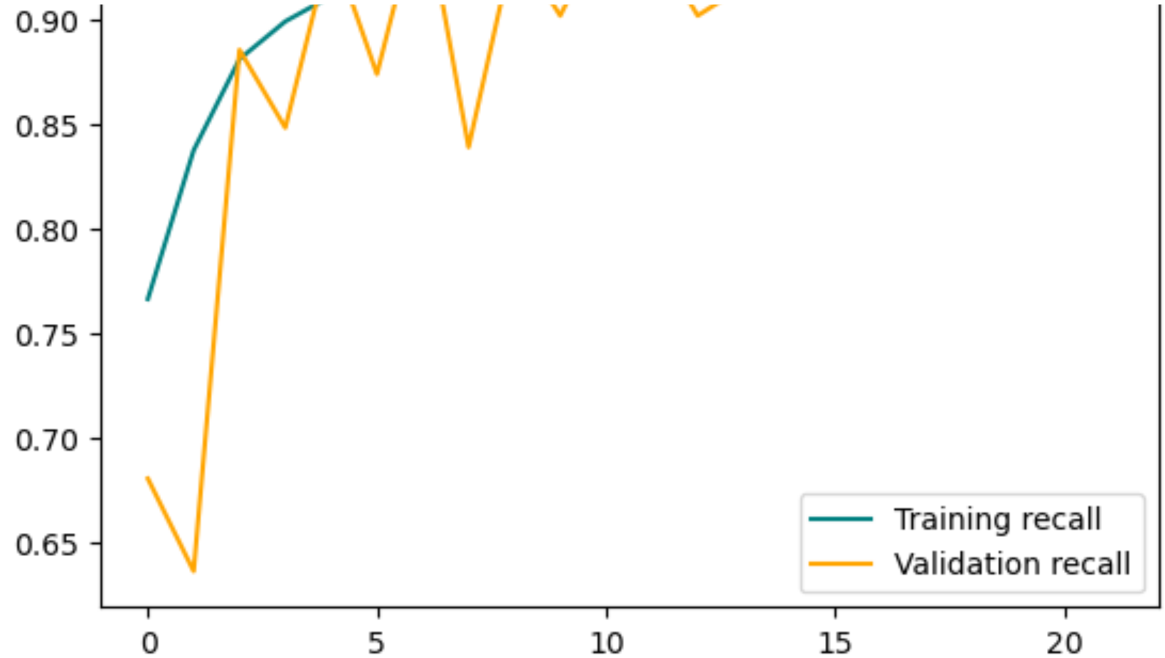
Out[31]:
```
[0.23018981516361237, 0.9114219546318054, 0.9370629787445068]
```

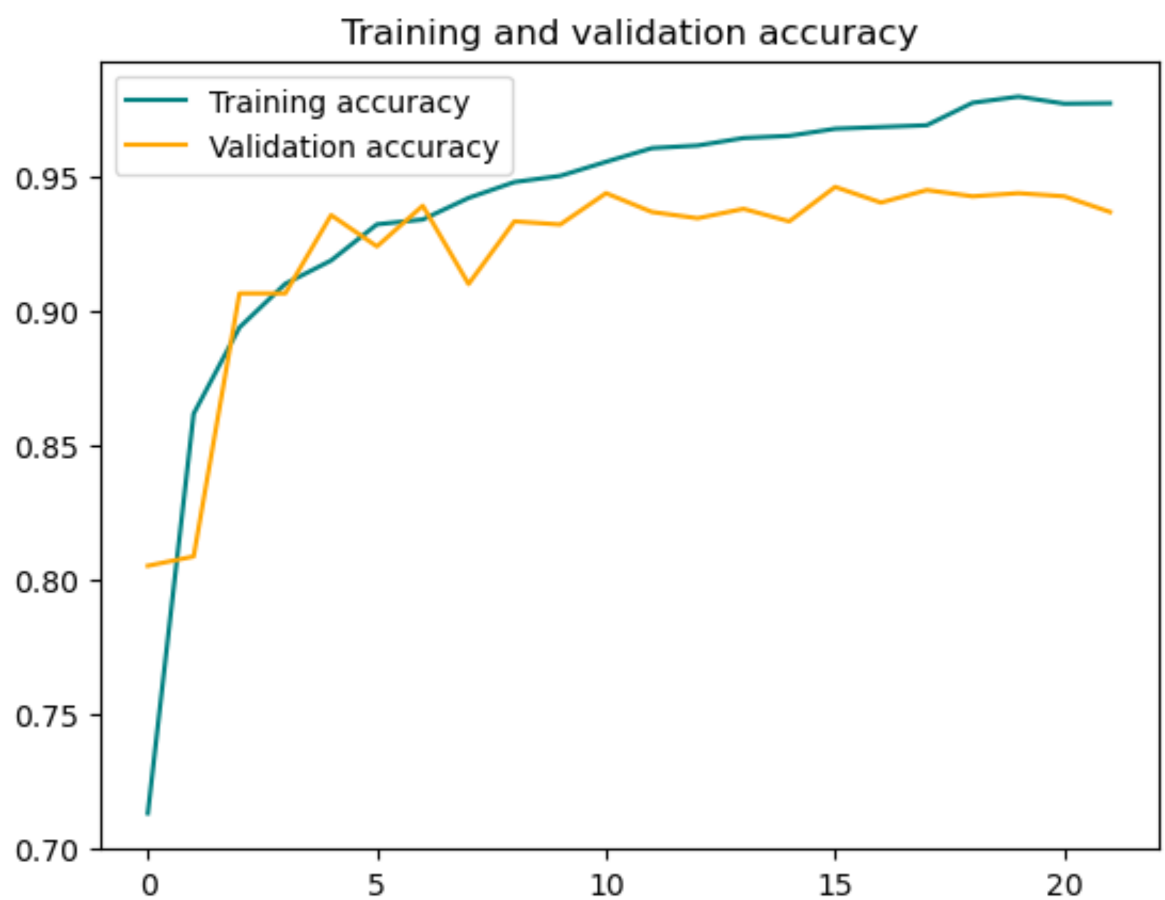
In [32]:
```
results_test = model3.evaluate(test_images, test_y)
results_test
```

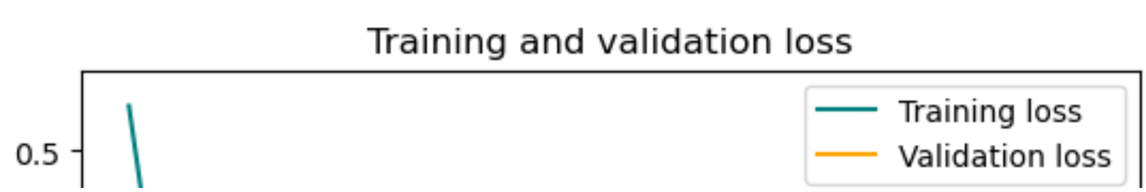
```
50/50 [==============================] - 1s 21ms/step - loss: 0.3246
- recall_3: 0.8627 - acc: 0.9194
```

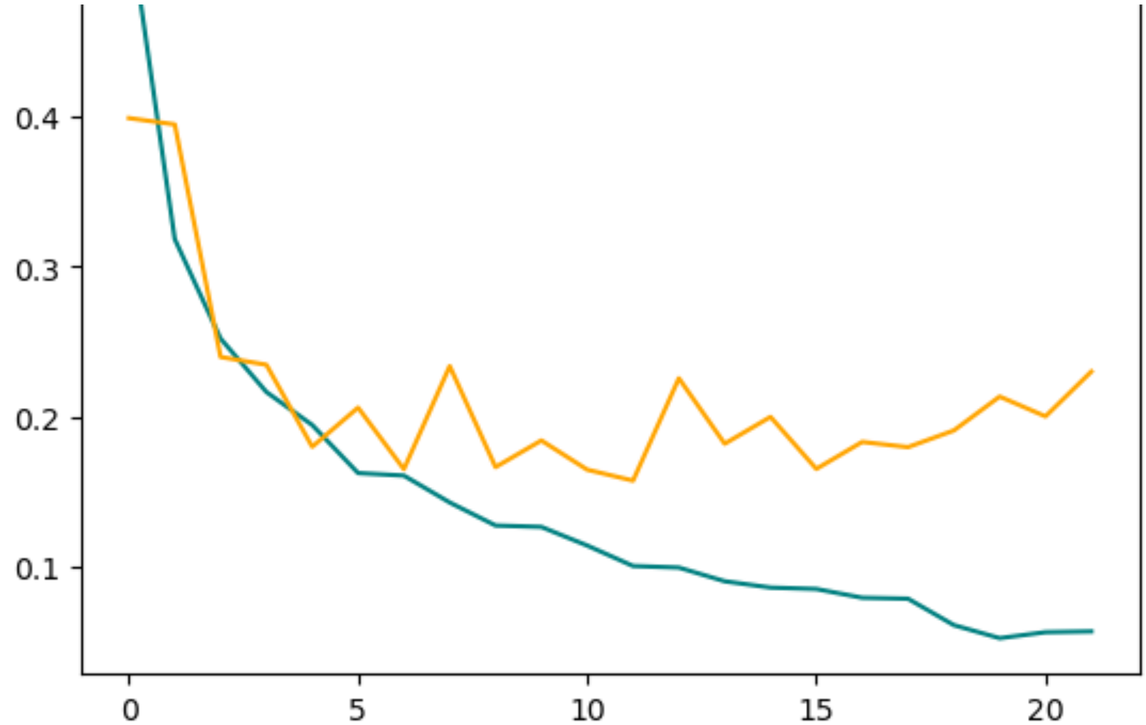
Out[32]:
```
[0.3246440291404724, 0.8627204298973083, 0.9193955063819885]
```

In [34]:
```
# plot model3 scores
acc = history3.history['acc']
val_acc = history3.history['val_acc']
rec = history3.history['recall_3']
val_rec = history3.history['val_recall_3']
loss = history3.history['loss']
val_loss = history3.history['val_loss']
epochsr = range(len(rec))
epochs = range(len(acc))
epochsv = range(len(loss))

plt.plot(epochsr, rec, color='teal', label= 'Training recall')
plt.plot(epochsr, val_rec, color='orange', label='Validation recall')
plt.title('Training and validation recall')
plt.legend()
plt.figure()
plt.plot(epochs, acc, color='teal', label= 'Training accuracy')
plt.plot(epochs, val_acc, color='orange', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochsv, loss, color='teal', label='Training loss')
plt.plot(epochsv, val_loss, color='orange', label = 'Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```


0.90
0.85
0.80
0.75
0.70
0.65
0
5
10
15
20
Training recall
Validation recall


Training and validation accuracy
Training accuracy
Validation accuracy
0.95
0.90
0.85
0.80
0.75
0.70
0
5
10
15
20


Training and validation loss
Training loss
Validation loss
0.5



The early stopping with a patience of 10 did stop the model after the 22nd epochs. The test recall is 86.27% and the validation is 91,14%. Which is still good. The loss starts to separate and increase over 10 epochs. In general you want to see the loss decreasing steadily and the accuracy increasing for both the train and validation.

To increase the dataset and to prevent overfitting besides handling the data imbalance, I will try data augmentation. With small transformations such as rotating the images and zooming in on them, we can increase the number of images in our dataset.

In [ ]:
```
#ImageDataGenerator??
```

Data Augmentation

In [49]:

```
# generating more data with ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,
                                   rotation_range = 40,
                                   width_shift_range = 0.2,
                                   height_shift_range = 0.2,
                                   shear_range = 0.3,
                                   zoom_range = 0.2,
                                   horizontal_flip=True)

#train_datagen.fit(train_images)
```

Data Augmentation allows to add more data to the training set, similar to the data we just had but it is reasonably modified to some degrees so it's not exactly the same. I used the following data augmentation arguments:

- rescaling the images after transformation
- rotation_range: rotating images by 40 degrees
- width_shift_range: shifting images horizontally (by 0.2 of total width)
- height_shift_range: shifting images vertically(by 0.2 of total height)
- shear_range: shear angle by 30 degrees
- zoom_range: zoom images by 20%
- horizontal_flip: flip images horizontally

names = [os.path.join(train_n, name) for name in os.listdir(train_n)] names

loop through each image in the normal train folder

for i in names: if i.endswith('.jpeg'): # open up each image img = Image.open(i) # make it into an array arr = img_to_array(img) # reshape the input image arr = arr.reshape((1,) + arr.shape) n = 0 # creating the new images for m in train_datagen.flow(arr, batch_size = 1, save_to_dir = './data/chest_xray/train/NORMAL', save_prefix = 'augmented -', save_format = 'jpeg'): n += 1 if n > 3: break

loop through each image in the normal test folder and augment some more images

names_test = [os.path.join(test_n, name) for name in os.listdir(test_n)] names_test

loop through each image in the normal train folder

for i in names_test: if i.endswith('.jpeg'): # open up each image img = Image.open(i) # make it into an array arr = img_to_array(img) # reshape the input image arr = arr.reshape((1,) + arr.shape) n = 0 # creating the new images for m in train_datagen.flow(arr, batch_size = 1, save_to_dir = './data/test_aug/normal', save_prefix = 'augmented -', save_format = 'jpeg'): break

creating new images for the validation normal

names_val = [os.path.join(val_n, name) for name in os.listdir(val_n)] names_val

for i in names_val: if i.endswith('.jpeg'): # open up each image img = Image.open(i) # make it into an array arr = img_to_array(img) # reshape the input image arr = arr.reshape((1,) + arr.shape) n = 0 # creating the new images for m in train_datagen.flow(arr, batch_size = 1, save_to_dir = './data/val_aug/normal', save_prefix = 'aug-', save_format = 'jpeg'): break

Model4 -Augmented CNN with L2 regularization, BatchNormalization and Dropout

In [36]:

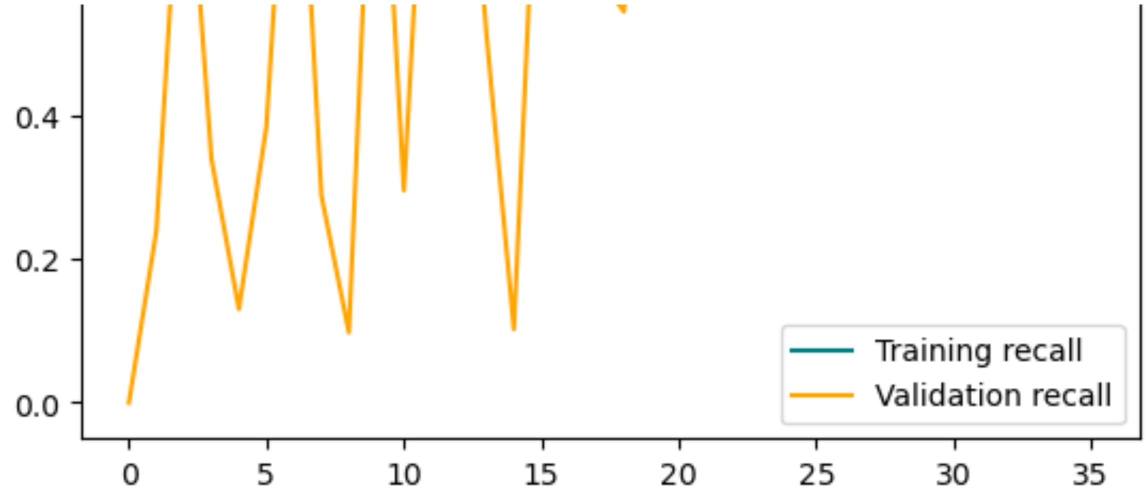
```
model4 = Sequential()
#1st conv layer
model4.add(layers.Conv2D(32, (3, 3),strides = 1, padding='same', activ
                        input_shape=(200 ,200,  1)))
model4.add(BatchNormalization())
model4.add(layers.MaxPooling2D((2, 2), strides = 2, padding ='same'))

#2nd conv layer
model4.add(layers.Conv2D(64, (3, 3), strides = 1, padding = 'same', ac
model4.add(Dropout(0.1))
model4.add(BatchNormalization())
model4.add(layers.MaxPooling2D((2, 2), strides = 2, padding = 'same'))

#3rd conv layer
model4.add(layers.Conv2D(64, (3, 3),strides = 1, padding = 'same', act
model4.add(layers.MaxPooling2D((2, 2),strides = 2, padding = 'same'))

# 4th conv layer
model4.add(layers.Conv2D(64, (3, 3),strides = 1, padding = 'same', act
model4.add(Dropout(0.1))
model4.add(BatchNormalization())
model4.add(layers.MaxPooling2D((2, 2),strides = 2, padding = 'same'))

model4.add(layers.Flatten())
model4.add(layers.Dense(64, activation='relu'))#, kernel_regularizer =
model4.add(layers.Dense(1, activation='sigmoid'))

adam = tf.keras.optimizers.Adam(learning_rate = 0.01)
model4.compile(loss='binary_crossentropy',
              optimizer= adam,
              metrics=[recall(), 'acc'])

# fitting model 4
history4 = model4.fit(train_images,
                        train_y,
                        batch_size = 32,
                        epochs = 200,
                        validation_data = (val_images, val_y),
                        callbacks = [early_stopping])

model4.summary()
```

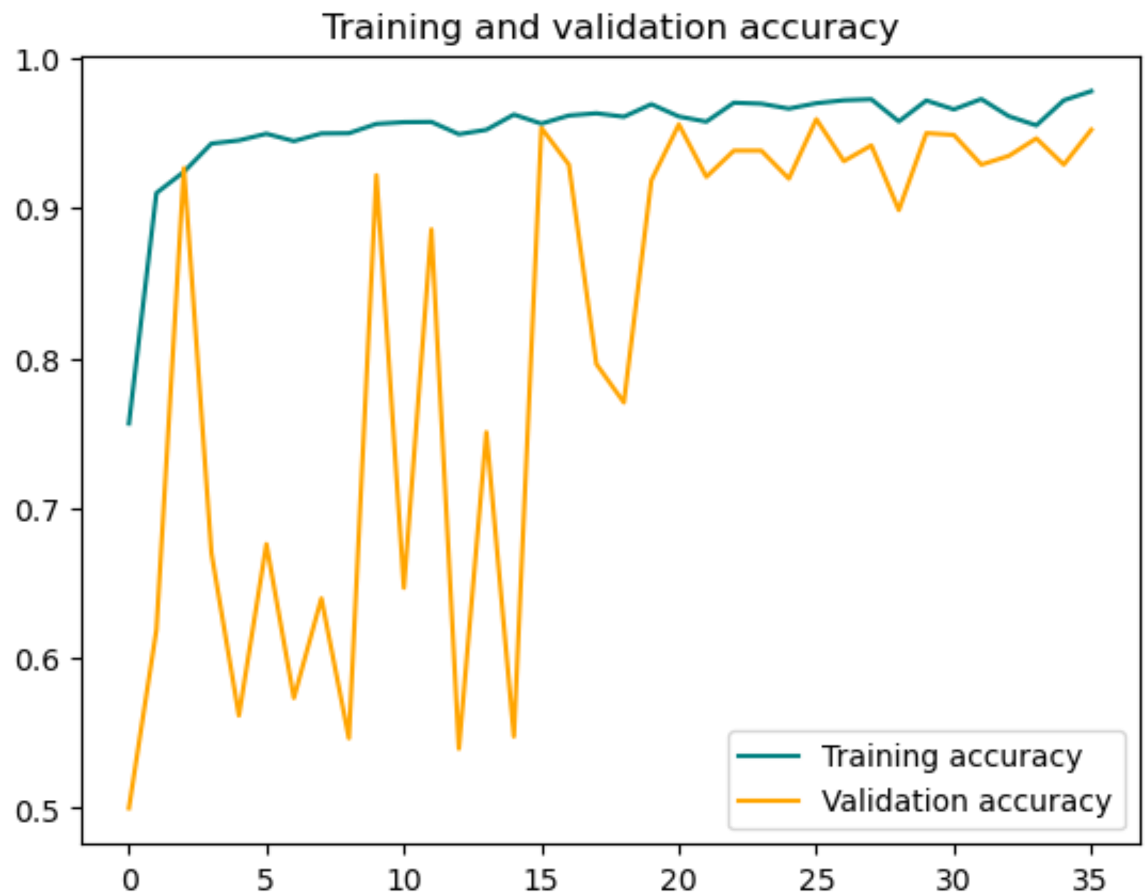
```
Epoch 1/200

2022-12-12 00:10:19.974078: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - ETA: 0s - loss: 0.7654 - r
ecall_4: 0.6056 - acc: 0.7564
```

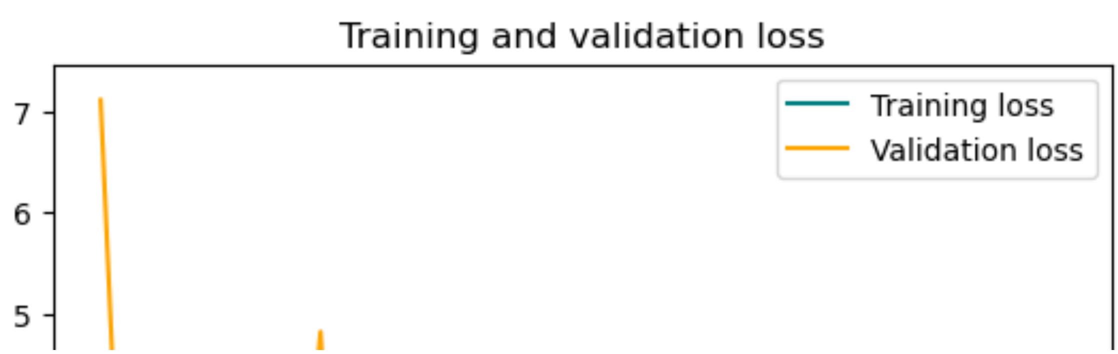
```
2022-12-12 00:10:30.484132: I tensorflow/core/grappler/optimizers/cus
tom_graph_optimizer_registry.cc:113] Plugin optimizer for device_type
GPU is enabled.

191/191 [==============================] - 11s 54ms/step - loss: 0.76
54 - recall_4: 0.6056 - acc: 0.7564 - val_loss: 7.1104 - val_recall_4
: 0.0000e+00 - val_acc: 0.5000
Epoch 2/200
191/191 [==============================] - 9s 48ms/step - loss: 0.220
5 - recall_4: 0.9289 - acc: 0.9100 - val_loss: 1.1257 - val_recall_4:
0.2401 - val_acc: 0.6189
```

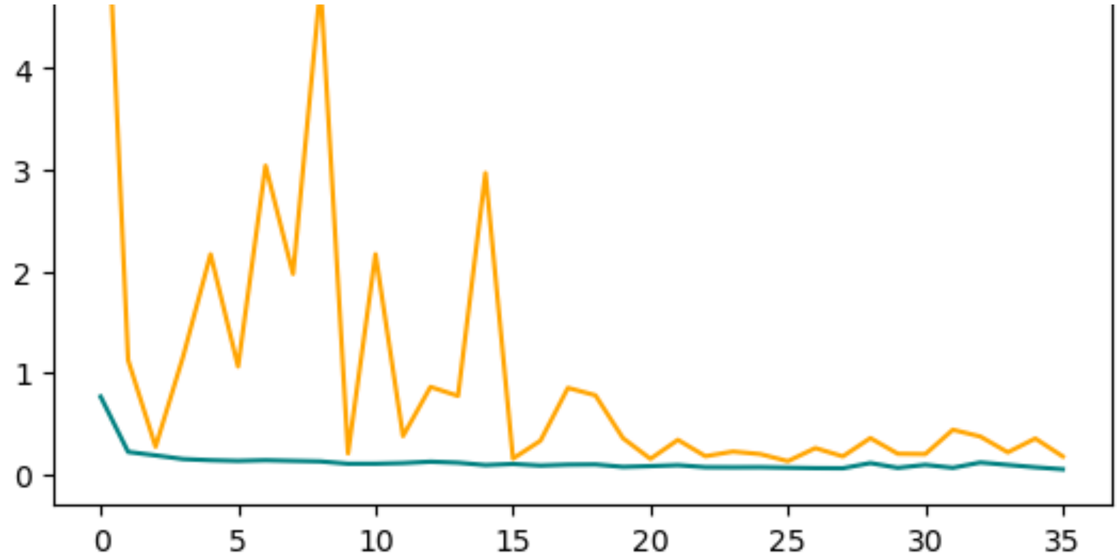
In [37]:

```python
# creating visualization
acc = history4.history['acc']
val_acc = history4.history['val_acc']
rec = history4.history['recall_4']
val_rec = history4.history['val_recall_4']
loss = history4.history['loss']
val_loss = history4.history['val_loss']
epochs = range(len(acc))
epochsr = range(len(rec))
epochsv = range(len(loss))

plt.plot(epochs, rec, color='teal', label= 'Training recall')
plt.plot(epochs, val_rec, color='orange', label='Validation recall')
plt.title('Training and validation recall')
plt.legend()
plt.figure()
plt.plot(epochs, acc, color='teal', label= 'Training accuracy')
plt.plot(epochs, val_acc, color='orange', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, loss, color='teal', label='Training loss')
plt.plot(epochs, val_loss, color='orange', label = 'Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```


0.4
0.2
0.0
Training recall
Validation recall
0
5
10
15
20
25
30
35


Training and validation accuracy
1.0
0.9
0.8
0.7
0.6
0.5
Training accuracy
Validation accuracy
0
5
10
15
20
25
30
35


Training and validation loss
7
6
5
Training loss
Validation loss



Model4 does not perform that well. There is a fluctuation in the recall. The validation score is 94.40% and the test score is 86.02% . The loss is approaching zero after 20 epochs. The early stopping stop the model at 36 epochs.

In [38]:
```
results_train = model4.evaluate(train_images, train_y)
results_train
```

```
191/191 [==============================] - 3s 17ms/step - loss: 0.046
8 - recall_4: 0.9816 - acc: 0.9798
```

Out[38]:
```
[0.04676535725593567, 0.9816393256187439, 0.9798360466957092]
```

In [39]:
```
results_val = model4.evaluate(val_images, val_y)
results_val
```

```
27/27 [==============================] - 0s 15ms/step - loss: 0.1759
- recall_4: 0.9441 - acc: 0.9522
```

Out[39]:
```
[0.17590372264385223, 0.94405597448349, 0.9522144794464111]
```

In [40]:
```
results_test = model4.evaluate(test_images, test_y)
results_test
```

```
50/50 [==============================] - 1s 15ms/step - loss: 0.5000
- recall_4: 0.8602 - acc: 0.9175
```

Out[40]:
```
[0.5000172853469849, 0.8602015376091003, 0.9175063371658325]
```

Evaluation

Best Model Results: Model1

- `Test Recall:` 86.14%
- `Test Accuracy:` 96.27%

This model only has 1 convolution layer with L2 regularization, BatchNormalization and two dense layers. It has high accuracy and high recall scores, which indicates that the model can correctly identify whether a patient has pneumonia or not.

Conclusion

Model1 performed the best out of all the models. It only had 1 convolution layer with L2 regularization, BatchNormalization and two dense layers. In the Conv2D with 64 layers, I used relu optimizer and Ridge regularization of l2(1e-6) with relu and sigmoid optimizer and loss set to binary crossentrophy. After fitting the model I used the batch size of 32 with 50 epochs.

The selected model has high accuracy and high recall scores, which indicates that the model can correctly identify whether a patient has pneumonia or not after checking the X-Ray images. With this model any organization would cut down on time spent evaluating these images, it would also speed up the process of diagnostic, which would lead more availably doctors for the patients and after diagnosis they could start early treatment. Which would directly lead to more pediatric patient recovering from this infection and this also decreases the mortality rate.

In [ ]:

```
```