

## ▼ Import

```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import tensorflow as tf
import keras

from keras.models import Sequential
from keras import regularizers
from keras.layers import Dense, Dropout, Activation, Flatten, Conv2D, MaxPooling2D, AvgPool2D
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import RMSprop
```

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## ▼ Deep/Reinforcement Learning with Convoluted Neural Networks on Covid-19 X-Ray Images

In this project, I shall be performing analysis on covid-19 x-ray images, using three distinct convoluted neural networks.

- LeNet
- AlexNet
- VGG

The dataset is available at; <https://www.kaggle.com/khoongweihao/covid19-xray-dataset-train-test-sets> which has a total of 188 pictures, split into 40 images for testing and 148 for training. Let's get started with importing the images and splitting them into their validation and test sets.

We first define the directories which point to the train folder and test folder, then labeling which are the "NORMAL" and "PNEUMONIA" sets.

```
#point to train/test directories.
train_dir = '/content/drive/MyDrive/xray_dataset_covid19/train'
validation_dir = '/content/drive/MyDrive/xray_dataset_covid19/test'

train_normal_dir = os.path.join(train_dir, 'NORMAL')
train_pneumonia_dir = os.path.join(train_dir, 'PNEUMONIA')
validation_normal_dir = os.path.join(validation_dir, 'NORMAL')
validation_pneumonia_dir = os.path.join(validation_dir, 'PNEUMONIA')

train_normal_names = os.listdir(train_normal_dir)
print(train_normal_names[0:10])
```

```
print(train_normal_names[:10])

train_pneumonia_names = os.listdir(train_pneumonia_dir)
print(train_pneumonia_names[:10])

['IM-0005-0001.jpeg', 'IM-0001-0001.jpeg', 'IM-0006-0001.jpeg', 'IM-0003-0001.jpeg',
['2C26F453-AF3B-4517-BB9E-802CF2179543.jpeg', '1-s2.0-S1684118220300682-main.pdf-002
```

Above, we can see a subset of images in each directory for our training sets. This is quite like that of the test set. While below, we can see our train/test split count.

```
print('total training normal-rays:', len(os.listdir(train_normal_dir)))
print('total training Pneumonia x-rays:', len(os.listdir(train_pneumonia_dir)))
print('total validation normal-rays:', len(os.listdir(validation_normal_dir)))
print('total validation Pneumonia x-rays:', len(os.listdir(validation_pneumonia_dir)))

total training normal-rays : 74
total training Pneumonia x-rays: 74
total validation normal-rays : 20
total validation Pneumonia x-rays: 20
```

Lastly, we will need to scale our image sets down from their original sizing, and setting up our batch size.

```
#data generate
train_data_generator = ImageDataGenerator(rescale = 1/255)
validation_data_generator = ImageDataGenerator(rescale = 1/255)

train_generator = train_data_generator.flow_from_directory(
    train_dir, target_size = (150,150), batch_size = 16, class_mode = 'binary')

validation_generator = validation_data_generator.flow_from_directory(
    validation_dir, target_size = (150,150), batch_size = 16, class_mode = 'binary')

Found 148 images belonging to 2 classes.
Found 40 images belonging to 2 classes.
```

---

## ➤ Model One - CNN: LeNet

[http://d2l.ai/chapter\\_convolutional-neural-networks/lenet.html](http://d2l.ai/chapter_convolutional-neural-networks/lenet.html)

LeNet, among the first published CNNs to capture wide attention for its performance on computer vision tasks. The model was introduced by (and named for) Yann LeCun, then a researcher at AT&T Bell Labs, for the purpose of recognizing handwritten digits in images. This

work represented the culmination of a decade of research developing the technology. In 1989, LeCun published the first study to successfully train CNNs via backpropagation.

At the time LeNet achieved outstanding results matching the performance of support vector machines, then a dominant approach in supervised learning. LeNet was eventually adapted to recognize digits for processing deposits in ATM machines. To this day, some ATMs still run the code that Yann and his colleague Leon Bottou wrote in the 1990s!

```
#making our LeNet Model
model_leNet = Sequential()

model_leNet.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, activation='sigmoid', ir
model_leNet.add(tf.keras.layers.AvgPool2D(pool_size=2, strides=2))
model_leNet.add(tf.keras.layers.Conv2D(filters=32, kernel_size=5, activation='sigmoid'))
model_leNet.add(tf.keras.layers.AvgPool2D(pool_size=2, strides=2))

model_leNet.add(Flatten())

model_leNet.add(tf.keras.layers.Dense(100, activation='sigmoid'))
model_leNet.add(tf.keras.layers.Dense(50, activation='sigmoid'))
model_leNet.add(tf.keras.layers.Dense(1))

model_leNet.compile(loss='binary_crossentropy', optimizer=RMSprop(learning_rate=0.1), metr

history1 = model_leNet.fit_generator(generator=train_generator, epochs = 15, validation_da

/usr/local/lib/python3.7/dist-packages/keras/engine/training.py:1972: UserWarning: `
  warnings.warn("`Model.fit_generator` is deprecated and `
Epoch 1/15
10/10 [=====] - 17s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 2/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 3/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 4/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 5/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 6/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 7/15
10/10 [=====] - 16s 1s/step - loss: 7.6246 - accuracy: 0.50
Epoch 8/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 9/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 10/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 11/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 12/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 13/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
Epoch 14/15
10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50
```

Epoch 15/15

10/10 [=====] - 16s 2s/step - loss: 7.6246 - accuracy: 0.50

```
model_leNet.build()
model_leNet.summary()
```

Model: "sequential\_18"

Layer (type)	Output Shape	Param #
conv2d_99 (Conv2D)	(None, 150, 150, 64)	1792
average_pooling2d_8 (Average)	(None, 75, 75, 64)	0
conv2d_100 (Conv2D)	(None, 71, 71, 32)	51232
average_pooling2d_9 (Average)	(None, 35, 35, 32)	0
flatten_11 (Flatten)	(None, 39200)	0
dense_30 (Dense)	(None, 100)	3920100
dense_31 (Dense)	(None, 50)	5050
dense_32 (Dense)	(None, 1)	51
Total params: 3,978,225		
Trainable params: 3,978,225		
Non-trainable params: 0		

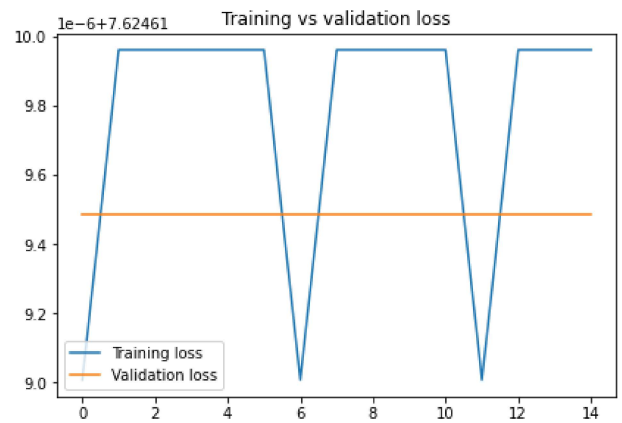
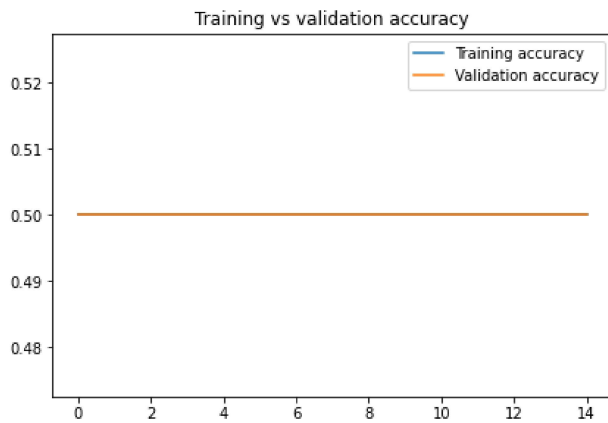
```
accuracy = history1.history['accuracy']
val_accuracy = history1.history['val_accuracy']
```

```
loss = history1.history['loss']
val_loss = history1.history['val_loss']
plt.figure(figsize=(15,10))
```

```
plt.subplot(2, 2, 1)
plt.plot(accuracy, label = "Training accuracy")
plt.plot(val_accuracy, label="Validation accuracy")
plt.legend()
plt.title("Training vs validation accuracy")
```

```
plt.subplot(2,2,2)
plt.plot(loss, label = "Training loss")
plt.plot(val_loss, label="Validation loss")
plt.legend()
plt.title("Training vs validation loss")
```

```
plt.show()
```



## ▼ Model Two - CNN: AlexNet

[http://d2l.ai/chapter\\_convolutional-modern/alexnet.html?highlight=alexnet](http://d2l.ai/chapter_convolutional-modern/alexnet.html?highlight=alexnet)

Although LeNet achieved good results on early small datasets, the performance and feasibility of training CNNs on larger, more realistic datasets had yet to be established. AlexNet was named after Alex Krizhevsky, in the lowest layers of the network, the model learned feature extractors that resembled some traditional filters. Higher layers in the network might build upon these representations to represent larger structures, like eyes, noses, blades of grass, and so on. Even higher layers might represent whole objects like people, airplanes, dogs, or frisbees. Ultimately, the final hidden state learns a compact representation of the image that summarizes its contents such that data belonging to different categories can be easily separated.

Below, the AlexNet model is established;

```
# Making our AlexNet
model_alexNet = Sequential()

# Here, we use a larger 11 x 11 window to capture objects.
# At the same time, we use a stride of 4 to greatly reduce the height and width of the out
# Here, the number of output channels is much larger than that in LeNet
model_alexNet.add(tf.keras.layers.Conv2D(filters=96, kernel_size=11, strides=4, activation='relu'))
model_alexNet.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

# Make the convolution window smaller, set padding to 2 for consistent
# height and width across the input and output, and increase the number of output channels
model_alexNet.add(tf.keras.layers.Conv2D(filters=64, kernel_size=5, padding='same', activation='relu'))
model_alexNet.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

# Use three successive convolutional layers and a smaller convolution window.
# Except for the final convolutional layer, the number of output channels is further increased
# Pooling layers are not used to reduce the height and width of input after the first two
model_alexNet.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, padding='same', activation='relu'))
model_alexNet.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, padding='same', activation='relu'))
```

```

model_alexNet.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, padding='same', activation='relu'))
model_alexNet.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
model_alexNet.add(tf.keras.layers.Flatten())

# Here, the number of outputs of the fully-connected layer is several times larger than the number of inputs.
# Use the dropout layer to mitigate overfitting.
model_alexNet.add(tf.keras.layers.Dense(128, activation='relu'))
model_alexNet.add(tf.keras.layers.Dropout(0.25))
model_alexNet.add(tf.keras.layers.Dense(1, activation='relu'))
model_alexNet.add(tf.keras.layers.Dropout(0.25))

# Output layer. Since we are using Fashion-MNIST, the number of classes is 10, instead of 1000.
model_alexNet.add(tf.keras.layers.Dense(10))

model_alexNet.compile(loss='binary_crossentropy', optimizer=RMSprop(learning_rate=0.1), metrics=['accuracy'])

history2 = model_alexNet.fit_generator(generator=train_generator, epochs = 15, validation_data=(test_images, test_labels))

/usr/local/lib/python3.7/dist-packages/keras/engine/training.py:1972: UserWarning: `Model.fit_generator` is deprecated and will be removed from Keras in version 3.0.
warnings.warn("`Model.fit_generator` is deprecated and will be removed from Keras in version 3.0.")
Epoch 1/15
10/10 [=====] - 10s 932ms/step - loss: 6.7254 - accuracy: 0.0000
Epoch 2/15
10/10 [=====] - 9s 930ms/step - loss: 7.1589 - accuracy: 0.0000
Epoch 3/15
10/10 [=====] - 9s 830ms/step - loss: 6.9314 - accuracy: 0.0000
Epoch 4/15
10/10 [=====] - 9s 833ms/step - loss: 6.8747 - accuracy: 0.0000
Epoch 5/15
10/10 [=====] - 9s 830ms/step - loss: 6.8083 - accuracy: 0.0000
Epoch 6/15
10/10 [=====] - 9s 809ms/step - loss: 7.0813 - accuracy: 0.0000
Epoch 7/15
10/10 [=====] - 9s 850ms/step - loss: 6.8841 - accuracy: 0.0000
Epoch 8/15
10/10 [=====] - 9s 844ms/step - loss: 7.0919 - accuracy: 0.0000
Epoch 9/15
10/10 [=====] - 9s 856ms/step - loss: 7.0374 - accuracy: 0.0000
Epoch 10/15
10/10 [=====] - 9s 864ms/step - loss: 6.9205 - accuracy: 0.0000
Epoch 11/15
10/10 [=====] - 9s 873ms/step - loss: 6.8101 - accuracy: 0.0000
Epoch 12/15
10/10 [=====] - 9s 868ms/step - loss: 6.9741 - accuracy: 0.0000
Epoch 13/15
10/10 [=====] - 9s 849ms/step - loss: 7.0092 - accuracy: 0.0000
Epoch 14/15
10/10 [=====] - 9s 842ms/step - loss: 7.0155 - accuracy: 0.0000
Epoch 15/15
10/10 [=====] - 9s 858ms/step - loss: 6.9665 - accuracy: 0.0000

model_alexNet.build()
model_alexNet.summary()

```

Model: "sequential\_21"

Layer (type)	Output Shape	Param #
conv2d_118 (Conv2D)	(None, 35, 35, 96)	34944
max_pooling2d_100 (MaxPoolin	(None, 17, 17, 96)	0
conv2d_119 (Conv2D)	(None, 17, 17, 64)	153664
max_pooling2d_101 (MaxPoolin	(None, 8, 8, 64)	0
conv2d_120 (Conv2D)	(None, 8, 8, 128)	73856
conv2d_121 (Conv2D)	(None, 8, 8, 128)	147584
conv2d_122 (Conv2D)	(None, 8, 8, 64)	73792
max_pooling2d_102 (MaxPoolin	(None, 4, 4, 64)	0
flatten_14 (Flatten)	(None, 1024)	0
dense_39 (Dense)	(None, 128)	131200
dropout_24 (Dropout)	(None, 128)	0
dense_40 (Dense)	(None, 1)	129
dropout_25 (Dropout)	(None, 1)	0
dense_41 (Dense)	(None, 10)	20
Total params: 615,189		
Trainable params: 615,189		
Non-trainable params: 0		

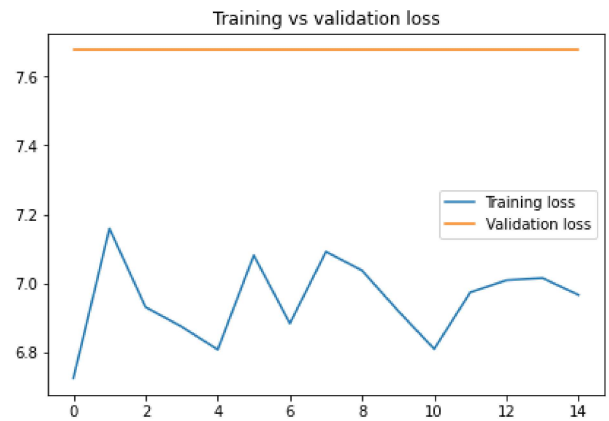
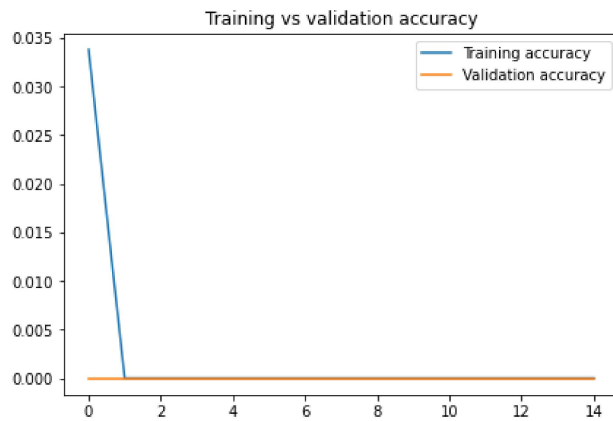
```
accuracy = history2.history['accuracy']  
val_accuracy = history2.history['val_accuracy']
```

```
loss = history2.history['loss']  
val_loss = history2.history['val_loss']  
plt.figure(figsize=(15,10))
```

```
plt.subplot(2, 2, 1)  
plt.plot(accuracy, label = "Training accuracy")  
plt.plot(val_accuracy, label="Validation accuracy")  
plt.legend()  
plt.title("Training vs validation accuracy")
```

```
plt.subplot(2,2,2)  
plt.plot(loss, label = "Training loss")  
plt.plot(val_loss, label="Validation loss")  
plt.legend()  
plt.title("Training vs validation loss")
```

```
plt.show()
```



## ▼ Model Three - CNN: VGG

[http://d2l.ai/chapter\\_convolutional-modern/vgg.html?highlight=vgg](http://d2l.ai/chapter_convolutional-modern/vgg.html?highlight=vgg)

While AlexNet offered empirical evidence that deep CNNs can achieve good results, it did not provide a general template to guide subsequent researchers in designing new networks. The idea of using blocks first emerged from the Visual Geometry Group (VGG) at Oxford University, in their eponymously-named VGG network. It is easy to implement these repeated structures in code with any modern deep learning framework by using loops and subroutines.

Below, the VGG model is established;

```
# Making our VGG
```

```
num_convs = 11
num_channels = 20
```

```
model_VGG = Sequential()
```

```
#first layer
```

```
model_VGG.add(tf.keras.layers.Conv2D(num_channels, kernel_size=3, padding='same', activation='relu'))
model_VGG.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

```
# The convulational part
```

```
for _ in range(num_convs):
    model_VGG.add(tf.keras.layers.Conv2D(num_channels, kernel_size=3, padding='same', activation='relu'))
    model_VGG.add(tf.keras.layers.MaxPool2D(pool_size=1, strides=2))
```

```
# The fully-connected part
```

```
model_VGG.add(tf.keras.layers.Flatten())
model_VGG.add(tf.keras.layers.Dense(32, activation='relu'))
model_VGG.add(tf.keras.layers.Dropout(0.1))
model_VGG.add(tf.keras.layers.Dense(32, activation='relu'))
```



```

model_VGG.add(tf.keras.layers.Dense(1024, activation='relu'))
model_VGG.add(tf.keras.layers.Dropout(0.1))
model_VGG.add(tf.keras.layers.Dense(1))

model_VGG.compile(loss='binary_crossentropy', optimizer=RMSprop(learning_rate=0.1), metrics=['accuracy'])

history3 = model_VGG.fit_generator(generator=train_generator, epochs = 15, validation_data=

```

```

/usr/local/lib/python3.7/dist-packages/keras/engine/training.py:1972: UserWarning: `
    warnings.warn("`Model.fit_generator` is deprecated and
Epoch 1/15
10/10 [=====] - 12s 985ms/step - loss: 7.8010 - accuracy: 0.0000
Epoch 2/15
10/10 [=====] - 9s 914ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 3/15
10/10 [=====] - 9s 983ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 4/15
10/10 [=====] - 9s 922ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 5/15
10/10 [=====] - 9s 897ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 6/15
10/10 [=====] - 9s 896ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 7/15
10/10 [=====] - 9s 909ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 8/15
10/10 [=====] - 9s 920ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 9/15
10/10 [=====] - 9s 895ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 10/15
10/10 [=====] - 9s 875ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 11/15
10/10 [=====] - 9s 897ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 12/15
10/10 [=====] - 9s 900ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 13/15
10/10 [=====] - 9s 887ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 14/15
10/10 [=====] - 9s 854ms/step - loss: 7.6246 - accuracy: 0.0000
Epoch 15/15
10/10 [=====] - 9s 908ms/step - loss: 7.6246 - accuracy: 0.0000

```

```

model_VGG.summary()

```

-----		
max_pooling2d_104 (MaxPoolin	(None, 38, 38, 20)	0
conv2d_125 (Conv2D)	(None, 38, 38, 20)	3620
max_pooling2d_105 (MaxPoolin	(None, 19, 19, 20)	0
conv2d_126 (Conv2D)	(None, 19, 19, 20)	3620
max_pooling2d_106 (MaxPoolin	(None, 10, 10, 20)	0
conv2d_127 (Conv2D)	(None, 10, 10, 20)	3620
max_pooling2d_107 (MaxPoolin	(None, 5, 5, 20)	0

conv2d_128 (Conv2D)	(None, 5, 5, 20)	3620
max_pooling2d_108 (MaxPoolin	(None, 3, 3, 20)	0
conv2d_129 (Conv2D)	(None, 3, 3, 20)	3620
max_pooling2d_109 (MaxPoolin	(None, 2, 2, 20)	0
conv2d_130 (Conv2D)	(None, 2, 2, 20)	3620
max_pooling2d_110 (MaxPoolin	(None, 1, 1, 20)	0
conv2d_131 (Conv2D)	(None, 1, 1, 20)	3620
max_pooling2d_111 (MaxPoolin	(None, 1, 1, 20)	0
conv2d_132 (Conv2D)	(None, 1, 1, 20)	3620
max_pooling2d_112 (MaxPoolin	(None, 1, 1, 20)	0
conv2d_133 (Conv2D)	(None, 1, 1, 20)	3620
max_pooling2d_113 (MaxPoolin	(None, 1, 1, 20)	0
conv2d_134 (Conv2D)	(None, 1, 1, 20)	3620
max_pooling2d_114 (MaxPoolin	(None, 1, 1, 20)	0
flatten_15 (Flatten)	(None, 20)	0
dense_42 (Dense)	(None, 32)	672
dropout_26 (Dropout)	(None, 32)	0
dense_43 (Dense)	(None, 32)	1056
dropout_27 (Dropout)	(None, 32)	0
dense_44 (Dense)	(None, 1)	33
=====		
Total params: 42,141		
Trainable params: 42,141		
Non-trainable params: 0		

```

accuracy = history3.history['accuracy']
val_accuracy = history3.history['val_accuracy']

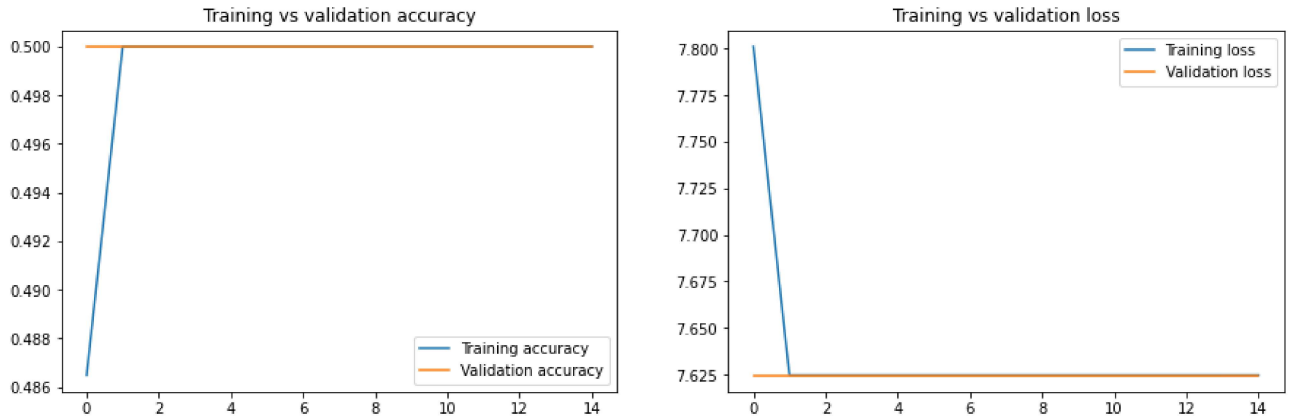
loss = history3.history['loss']
val_loss = history3.history['val_loss']
plt.figure(figsize=(15,10))

plt.subplot(2, 2, 1)
plt.plot(accuracy, label = "Training accuracy")
plt.plot(val_accuracy, label="Validation accuracy")
plt.legend()
plt.title("Training vs validation accuracy")

```

```
plt.subplot(2,2,2)
plt.plot(loss, label = "Training loss")
plt.plot(val_loss, label="Validation loss")
plt.legend()
plt.title("Training vs validation loss")

plt.show()
```



## ▼ Summery

With all models, the validation accuracy has been capped to 0.5, with high loss values under validation. With the exception of AlexNet which actually reduced in accuracy from the first epoch and never increased through the proceeding cycles.

This to me indicates a potential of overly complex models for the problem at hand. I feel that non of the above models fit the problem, and this can be proven with the model below.

```
model_sum = Sequential()

model_sum.add(tf.keras.layers.Conv2D(64, (3,3), activation='relu', input_shape=(150, 150,
model_sum.add(tf.keras.layers.MaxPooling2D(2, 2))
model_sum.add(tf.keras.layers.Dropout(0.25))
model_sum.add(tf.keras.layers.Conv2D(32, (3,3), activation='relu'))
model_sum.add(tf.keras.layers.MaxPooling2D(2,2))
model_sum.add(tf.keras.layers.Dropout(0.25))
model_sum.add(tf.keras.layers.Conv2D(16, (3,3), activation='relu'))
model_sum.add(tf.keras.layers.MaxPooling2D(2,2))
model_sum.add(tf.keras.layers.Dropout(0.25))
model_sum.add(tf.keras.layers.Flatten())
model_sum.add(tf.keras.layers.Dense(512, activation='relu'))
model_sum.add(tf.keras.layers.Dropout(0.25))
model_sum.add(tf.keras.layers.Dense(1, activation='sigmoid'))
```

```
model_sum.compile(loss='binary_crossentropy', optimizer=RMSprop(learning_rate=0.001), metr
```

```
history_sum = model_sum.fit_generator(generator=train_generator, epochs = 15, validation_c
```

```
/usr/local/lib/python3.7/dist-packages/keras/engine/training.py:1972: UserWarning: `
  warnings.warn("`Model.fit_generator` is deprecated and '
```

```
Epoch 1/15
10/10 [=====] - 14s 1s/step - loss: 1.9109 - accuracy: 0.50
Epoch 2/15
10/10 [=====] - 13s 1s/step - loss: 0.6568 - accuracy: 0.63
Epoch 3/15
10/10 [=====] - 13s 1s/step - loss: 0.5125 - accuracy: 0.76
Epoch 4/15
10/10 [=====] - 13s 1s/step - loss: 0.4322 - accuracy: 0.80
Epoch 5/15
10/10 [=====] - 13s 1s/step - loss: 0.5569 - accuracy: 0.72
Epoch 6/15
10/10 [=====] - 13s 1s/step - loss: 0.2558 - accuracy: 0.89
Epoch 7/15
10/10 [=====] - 13s 1s/step - loss: 0.3508 - accuracy: 0.85
Epoch 8/15
10/10 [=====] - 13s 1s/step - loss: 0.2350 - accuracy: 0.92
Epoch 9/15
10/10 [=====] - 13s 1s/step - loss: 0.2479 - accuracy: 0.89
Epoch 10/15
10/10 [=====] - 13s 1s/step - loss: 0.4025 - accuracy: 0.85
Epoch 11/15
10/10 [=====] - 13s 1s/step - loss: 0.1569 - accuracy: 0.95
Epoch 12/15
10/10 [=====] - 13s 1s/step - loss: 0.1471 - accuracy: 0.95
Epoch 13/15
10/10 [=====] - 13s 1s/step - loss: 0.1288 - accuracy: 0.95
Epoch 14/15
10/10 [=====] - 13s 1s/step - loss: 0.4639 - accuracy: 0.83
Epoch 15/15
10/10 [=====] - 12s 1s/step - loss: 0.1209 - accuracy: 0.96
```

```
model_sum.summary()
```

```
Model: "sequential_6"
```

Layer (type)	Output Shape	Param #
=====		
conv2d_17 (Conv2D)	(None, 148, 148, 64)	1792
max_pooling2d_9 (MaxPooling2	(None, 74, 74, 64)	0
dropout_10 (Dropout)	(None, 74, 74, 64)	0
conv2d_18 (Conv2D)	(None, 72, 72, 32)	18464
max_pooling2d_10 (MaxPooling	(None, 36, 36, 32)	0
dropout_11 (Dropout)	(None, 36, 36, 32)	0
conv2d_19 (Conv2D)	(None, 34, 34, 16)	4624

max_pooling2d_11 (MaxPooling)	(None, 17, 17, 16)	0
dropout_12 (Dropout)	(None, 17, 17, 16)	0
flatten_6 (Flatten)	(None, 4624)	0
dense_16 (Dense)	(None, 512)	2368000
dropout_13 (Dropout)	(None, 512)	0
dense_17 (Dense)	(None, 1)	513
=====		
Total params: 2,393,393		
Trainable params: 2,393,393		
Non-trainable params: 0		

Already we can see high accuracy scores with low validation losses. This is what I was expecting from the above three models. Though, I think there is scope of improvement regarding these two models could be adapted, given more time, thorough exploration of the appropriate variables of the models could help yield an understanding of what's optimal and what's not. Though, fundamentally, less complex models are the way forward for this issue.

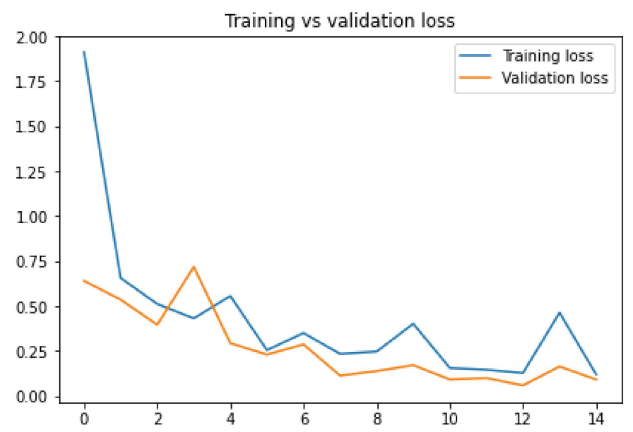
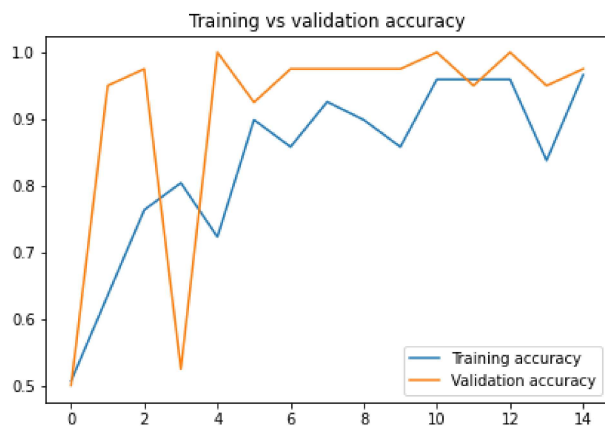
```
accuracy = history_sum.history['accuracy']
val_accuracy = history_sum.history['val_accuracy']

loss = history_sum.history['loss']
val_loss = history_sum.history['val_loss']
plt.figure(figsize=(15,10))

plt.subplot(2, 2, 1)
plt.plot(accuracy, label = "Training accuracy")
plt.plot(val_accuracy, label="Validation accuracy")
plt.legend()
plt.title("Training vs validation accuracy")

plt.subplot(2,2,2)
plt.plot(loss, label = "Training loss")
plt.plot(val_loss, label="Validation loss")
plt.legend()
plt.title("Training vs validation loss")

plt.show()
```



✓ 0s completed at 13:23

