

# DAT300 - Compulsory assignment 2

## Group 2

Fight Club Goofy Edition

## Orion username:

dat300-22-9

## Members

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## Introduction

The problem that we are going to solve is to differentiate between roads and everything else using pictures of roads as training data. The pictures have three channels; red, green and blue. The different parts in the pictures are already classified, therefore we have to make this a binary problem where roads are categorised as one thing, while everything else falls under another category called 'other'.

We are then going to use U-net and tune the parameters to then train the model. After that we are going to use VGG16 and compare that method with the manual U-net to see which model performed the best.

And last, but not least, we are going to upload these models to Orion and see if there is any difference in accuracy and total time used.

## Data handling and visualisation

```
In [1]: # Import and extraction of data.
import numpy as np
import h5py
import matplotlib.pyplot as plt
import tensorflow as tf
import pandas as pd

from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Input, Conv2D, BatchNormalization, Activation, MaxPool2D
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint, LearningRateScheduler, EarlyStopping
from keras import backend as K
from keras.applications.vgg16 import VGG16 as vg, preprocess_input
```

As seen below, we are defining the training and testing data

```
In [2]: train_data = h5py.File("../input/ca2-test-and-train/train.h5")
test_data = h5py.File("../input/ca2-test-and-train/test.h5")
```

```
In [3]: print(train_data.keys())  
print(test_data.keys())
```

```
<KeysViewHDF5 ['X', 'y']>  
<KeysViewHDF5 ['X']>
```

```
In [4]: X = train_data["X"][:]  
y = train_data["y"][:]  
  
X_test_final = test_data["X"][:]
```

```
In [38]: print("Shape of X: ", X.shape)  
print("Shape of y: ", y.shape)  
print("Shape of X_test_final: ", X_test_final.shape)
```

```
Shape of X: (2780, 128, 128, 3)  
Shape of y: (2780, 128, 128, 1)  
Shape of X_test_final: (695, 128, 128, 3)
```

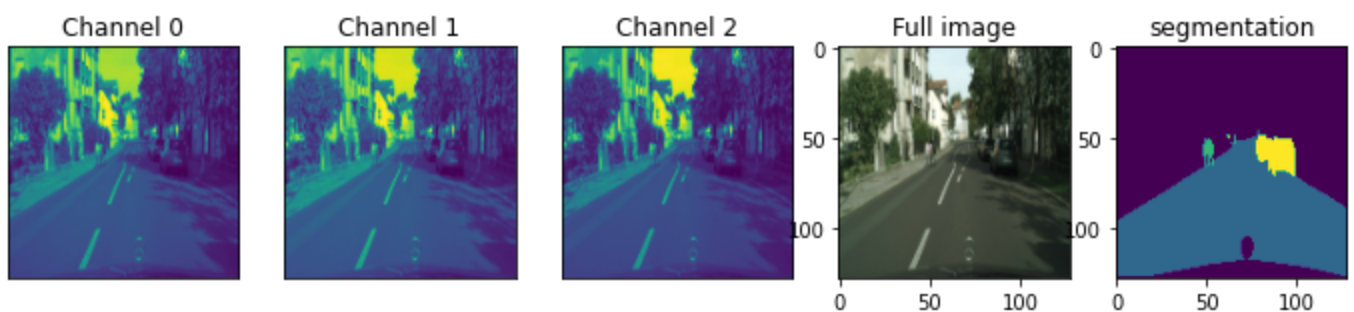
As seen on shape of X, the pictures are all 128 x 128 with 3 channels.

```
In [6]: # Short exploration and visualisation of dataset (point 1 in Canvas).  
print("Height of image: ",X.shape[1])  
print("Width of image: ",X.shape[2])  
print("Channels of image: ",X.shape[3])
```

```
Height of image: 128  
Width of image: 128  
Channels of image: 3
```

The code below is to show the three channels, the original picture and how the different parts are segmented.

```
In [7]: fig, ax = plt.subplots(1,5, figsize=(12,12))  
  
for i , axis in enumerate(ax[:3]):  
    axis.imshow(X[0][:,:,i])  
    axis.title.set_text(f'Channel {i}')  
    axis.set_xticks([])  
    axis.set_yticks([])  
  
ax[3].imshow(X[0])  
ax[3].title.set_text("Full image")  
  
ax[4].imshow(y[0])  
ax[4].title.set_text("segmentation")  
  
plt.show()
```



In channel 0, we see where there are most reds, in channel 1 the same but with greens, and channel 2 with blues. The last picture shows the segmentation of the different parts (cars, roads, people and other things).

# Methods

Since the dataset was particularly large, we did not perform gridsearch and such strategies to get better tuned hyperparameters. Other than splitting the dataset for training and testing, we did not use much advanced methods for this task.

We first tried a 2D U-Net, then we combined our U-Net with the pretrained VGG16 for a better result. The last method we used was multiclass segmentation with U-Net, we had to convert our U-Net function to a 3D approach.

## Preprocessing

Splitting into train and test using the train data before transforming the train labels into a binary problem.

```
In [8]: # Code for preprocessing of the data and transformation of labels for the binary problem

y = np.where(y != 0, 1, 0) # Transform the train labels into a binary problem

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.1, random_state=69)
```

## Results

Functions of U-net below:

```
In [9]: # Code and model training for your best Basic U-Net model (point 3 in Canvas)

def conv2d_block(input_tensor, n_filters, kernel_size = 3, batchnorm = True):
    """Function to add 2 convolutional layers with the parameters passed to it"""
    # first layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size),\
               kernel_initializer = 'he_normal', padding = 'same')(input_tensor)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    # second layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size),\
               kernel_initializer = 'he_normal', padding = 'same')(x)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    return x

def get_unet(input_img, n_filters = 16, dropout = 0.1, batchnorm = True, n_classes = 2):

    # Contracting Path
    c1 = conv2d_block(input_img, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)
    p1 = MaxPooling2D((2, 2))(c1)
    p1 = Dropout(dropout)(p1)

    c2 = conv2d_block(p1, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)
    p2 = MaxPooling2D((2, 2))(c2)
    p2 = Dropout(dropout)(p2)

    c3 = conv2d_block(p2, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)
```

```

p3 = MaxPooling2D((2, 2))(c3)
p3 = Dropout(dropout)(p3)

c4 = conv2d_block(p3, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)
p4 = MaxPooling2D((2, 2))(c4)
p4 = Dropout(dropout)(p4)

c5 = conv2d_block(p4, n_filters = n_filters * 16, kernel_size = 3, batchnorm = batchnorm)

# Expansive Path
u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides = (2, 2), padding = 'same')(c5)
u6 = concatenate([u6, c4])
u6 = Dropout(dropout)(u6)
c6 = conv2d_block(u6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)

u7 = Conv2DTranspose(n_filters * 4, (3, 3), strides = (2, 2), padding = 'same')(c6)
u7 = concatenate([u7, c3])
u7 = Dropout(dropout)(u7)
c7 = conv2d_block(u7, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)

u8 = Conv2DTranspose(n_filters * 2, (3, 3), strides = (2, 2), padding = 'same')(c7)
u8 = concatenate([u8, c2])
u8 = Dropout(dropout)(u8)
c8 = conv2d_block(u8, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)

u9 = Conv2DTranspose(n_filters * 1, (3, 3), strides = (2, 2), padding = 'same')(c8)
u9 = concatenate([u9, c1])
u9 = Dropout(dropout)(u9)
c9 = conv2d_block(u9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)

outputs = Conv2D(n_classes, (1, 1), activation='sigmoid')(c9)
model = Model(inputs=[input_img], outputs=[outputs])
return model

```

In [10]:

```

input_img = Input(shape=(128,128,3))
model = get_unet(input_img, n_filters = 32, dropout = 0.1, batchnorm = True, n_classes = 1)
model.summary()

```

```

2022-11-09 12:04:05.515727: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.516780: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.864303: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.865158: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.865920: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.866666: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2022-11-09 12:04:05.868073: I tensorflow/core/platform/cpu_feature_guard.cc:142] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations: AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2022-11-09 12:04:06.120224: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero

```

```

2022-11-09 12:04:06.121124: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:06.121890: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:06.122654: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:06.123347: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:06.124018: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.873350: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.874342: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.875145: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.875884: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.876608: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.877318: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1510] Creat
ed device /job:localhost/replica:0/task:0/device:GPU:0 with 13789 MB memory:  -> device:
0, name: Tesla T4, pci bus id: 0000:00:04.0, compute capability: 7.5
2022-11-09 12:04:10.882349: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:937] su
ccessful NUMA node read from SysFS had negative value (-1), but there must be at least one
NUMA node, so returning NUMA node zero
2022-11-09 12:04:10.883113: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1510] Creat
ed device /job:localhost/replica:0/task:0/device:GPU:1 with 13789 MB memory:  -> device:
1, name: Tesla T4, pci bus id: 0000:00:05.0, compute capability: 7.5
Model: "model"

```

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 128, 128, 3) 0		
=====			
conv2d (Conv2D)	(None, 128, 128, 32) 896		input_1[0][0]
=====			
batch_normalization (BatchNorma	(None, 128, 128, 32) 128		conv2d[0][0]
=====			
activation (Activation)	(None, 128, 128, 32) 0		batch_normalization[0][0]
=====			
conv2d_1 (Conv2D)	(None, 128, 128, 32) 9248		activation[0][0]
=====			

batch_normalization_1 (BatchNor	(None, 128, 128, 32)	128	conv2d_1[0][0]
activation_1 (Activation)	(None, 128, 128, 32)	0	batch_normalization_1[0][0]
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0	activation_1[0][0]
dropout (Dropout)	(None, 64, 64, 32)	0	max_pooling2d[0][0]
conv2d_2 (Conv2D)	(None, 64, 64, 64)	18496	dropout[0][0]
batch_normalization_2 (BatchNor	(None, 64, 64, 64)	256	conv2d_2[0][0]
activation_2 (Activation)	(None, 64, 64, 64)	0	batch_normalization_2[0][0]
conv2d_3 (Conv2D)	(None, 64, 64, 64)	36928	activation_2[0][0]
batch_normalization_3 (BatchNor	(None, 64, 64, 64)	256	conv2d_3[0][0]
activation_3 (Activation)	(None, 64, 64, 64)	0	batch_normalization_3[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0	activation_3[0][0]
dropout_1 (Dropout)	(None, 32, 32, 64)	0	max_pooling2d_1[0][0]
conv2d_4 (Conv2D)	(None, 32, 32, 128)	73856	dropout_1[0][0]
batch_normalization_4 (BatchNor	(None, 32, 32, 128)	512	conv2d_4[0][0]
activation_4 (Activation)	(None, 32, 32, 128)	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D)	(None, 32, 32, 128)	147584	activation_4[0][0]
batch_normalization_5 (BatchNor	(None, 32, 32, 128)	512	conv2d_5[0][0]

activation_5 (Activation)	(None, 32, 32, 128)	0	batch_normalization_5[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 128)	0	activation_5[0][0]
dropout_2 (Dropout)	(None, 16, 16, 128)	0	max_pooling2d_2[0][0]
conv2d_6 (Conv2D)	(None, 16, 16, 256)	295168	dropout_2[0][0]
batch_normalization_6 (BatchNor	(None, 16, 16, 256)	1024	conv2d_6[0][0]
activation_6 (Activation)	(None, 16, 16, 256)	0	batch_normalization_6[0][0]
conv2d_7 (Conv2D)	(None, 16, 16, 256)	590080	activation_6[0][0]
batch_normalization_7 (BatchNor	(None, 16, 16, 256)	1024	conv2d_7[0][0]
activation_7 (Activation)	(None, 16, 16, 256)	0	batch_normalization_7[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 8, 8, 256)	0	activation_7[0][0]
dropout_3 (Dropout)	(None, 8, 8, 256)	0	max_pooling2d_3[0][0]
conv2d_8 (Conv2D)	(None, 8, 8, 512)	1180160	dropout_3[0][0]
batch_normalization_8 (BatchNor	(None, 8, 8, 512)	2048	conv2d_8[0][0]
activation_8 (Activation)	(None, 8, 8, 512)	0	batch_normalization_8[0][0]
conv2d_9 (Conv2D)	(None, 8, 8, 512)	2359808	activation_8[0][0]
batch_normalization_9 (BatchNor	(None, 8, 8, 512)	2048	conv2d_9[0][0]

activation_9 (Activation)	(None, 8, 8, 512)	0	batch_normalization_9[0][0]
conv2d_transpose (Conv2DTranspo	(None, 16, 16, 256)	1179904	activation_9[0][0]
concatenate (Concatenate)	(None, 16, 16, 512)	0	conv2d_transpose[0][0] activation_7[0][0]
dropout_4 (Dropout)	(None, 16, 16, 512)	0	concatenate[0][0]
conv2d_10 (Conv2D)	(None, 16, 16, 256)	1179904	dropout_4[0][0]
batch_normalization_10 (BatchNo	(None, 16, 16, 256)	1024	conv2d_10[0][0]
activation_10 (Activation)	(None, 16, 16, 256)	0	batch_normalization_10[0][0]
conv2d_11 (Conv2D)	(None, 16, 16, 256)	590080	activation_10[0][0]
batch_normalization_11 (BatchNo	(None, 16, 16, 256)	1024	conv2d_11[0][0]
activation_11 (Activation)	(None, 16, 16, 256)	0	batch_normalization_11[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 32, 32, 128)	295040	activation_11[0][0]
concatenate_1 (Concatenate)	(None, 32, 32, 256)	0	conv2d_transpose_1[0][0] activation_5[0][0]
dropout_5 (Dropout)	(None, 32, 32, 256)	0	concatenate_1[0][0]
conv2d_12 (Conv2D)	(None, 32, 32, 128)	295040	dropout_5[0][0]
batch_normalization_12 (BatchNo	(None, 32, 32, 128)	512	conv2d_12[0][0]
activation_12 (Activation)	(None, 32, 32, 128)	0	batch_normalization_12[0][0]



conv2d_13 (Conv2D)	(None, 32, 32, 128)	147584	activation_12[0][0]
batch_normalization_13 (Batch Normalization)	(None, 32, 32, 128)	512	conv2d_13[0][0]
activation_13 (Activation)	(None, 32, 32, 128)	0	batch_normalization_13[0][0]
conv2d_transpose_2 (Conv2DTranspose)	(None, 64, 64, 64)	73792	activation_13[0][0]
concatenate_2 (Concatenate)	(None, 64, 64, 128)	0	conv2d_transpose_2[0][0] activation_3[0][0]
dropout_6 (Dropout)	(None, 64, 64, 128)	0	concatenate_2[0][0]
conv2d_14 (Conv2D)	(None, 64, 64, 64)	73792	dropout_6[0][0]
batch_normalization_14 (Batch Normalization)	(None, 64, 64, 64)	256	conv2d_14[0][0]
activation_14 (Activation)	(None, 64, 64, 64)	0	batch_normalization_14[0][0]
conv2d_15 (Conv2D)	(None, 64, 64, 64)	36928	activation_14[0][0]
batch_normalization_15 (Batch Normalization)	(None, 64, 64, 64)	256	conv2d_15[0][0]
activation_15 (Activation)	(None, 64, 64, 64)	0	batch_normalization_15[0][0]
conv2d_transpose_3 (Conv2DTranspose)	(None, 128, 128, 32)	18464	activation_15[0][0]
concatenate_3 (Concatenate)	(None, 128, 128, 64)	0	conv2d_transpose_3[0][0] activation_1[0][0]
dropout_7 (Dropout)	(None, 128, 128, 64)	0	concatenate_3[0][0]

conv2d_16 (Conv2D)	(None, 128, 128, 32)	18464	dropout_7[0][0]
<hr/>			
batch_normalization_16 (Batch Normalization)	(None, 128, 128, 32)	128	conv2d_16[0][0]
<hr/>			
activation_16 (Activation)	(None, 128, 128, 32)	0	batch_normalization_16[0][0]
<hr/>			
conv2d_17 (Conv2D)	(None, 128, 128, 32)	9248	activation_16[0][0]
<hr/>			
batch_normalization_17 (Batch Normalization)	(None, 128, 128, 32)	128	conv2d_17[0][0]
<hr/>			
activation_17 (Activation)	(None, 128, 128, 32)	0	batch_normalization_17[0][0]
<hr/>			
conv2d_18 (Conv2D)	(None, 128, 128, 1)	33	activation_17[0][0]
<hr/>			
=====			
Total params: 8,642,273			
Trainable params: 8,636,385			
Non-trainable params: 5,888			
<hr/>			

In [11]:

```
def recall_m(y_true, y_pred):
    true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
    possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
    recall = true_positives / (possible_positives + K.epsilon())
    return recall

def precision_m(y_true, y_pred):
    true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
    predicted_positives = K.sum(K.round(K.clip(y_pred, 0, 1)))
    precision = true_positives / (predicted_positives + K.epsilon())
    return precision

def f1_m(y_true, y_pred):
    precision = precision_m(y_true, y_pred)
    recall = recall_m(y_true, y_pred)
    return 2*((precision*recall)/(precision+recall+K.epsilon()))
```

In [12]:

```
model.compile(optimizer = "Adam", loss = "binary_crossentropy", metrics = ['acc', f1_m]) #
callback = EarlyStopping(monitor="loss", patience=5)
```

In [13]:

```
var = model.fit(X_train, y_train, epochs=50, callbacks = callback, validation_data=(X_test,
```

```
2022-11-09 12:04:11.891639: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 491913216 exceeds 10% of free system memory.
2022-11-09 12:04:12.424395: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 327942144 exceeds 10% of free system memory.
2022-11-09 12:04:12.827627: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 491913216 exceeds 10% of free system memory.
```

```
2022-11-09 12:04:13.219286: W tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 327942144 exceeds 10% of free system memory.
2022-11-09 12:04:13.522752: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)
Epoch 1/50

2022-11-09 12:04:17.909853: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cuDNN version 8005
79/79 [=====] - 37s 234ms/step - loss: 0.2396 - acc: 0.9032 - f1_m: 0.9277 - val_loss: 0.9053 - val_acc: 0.7464 - val_f1_m: 0.8364
Epoch 2/50
79/79 [=====] - 15s 194ms/step - loss: 0.1500 - acc: 0.9415 - f1_m: 0.9568 - val_loss: 1.2142 - val_acc: 0.7168 - val_f1_m: 0.8260
Epoch 3/50
79/79 [=====] - 15s 195ms/step - loss: 0.1215 - acc: 0.9531 - f1_m: 0.9655 - val_loss: 0.2202 - val_acc: 0.9163 - val_f1_m: 0.9392
Epoch 4/50
79/79 [=====] - 16s 198ms/step - loss: 0.1140 - acc: 0.9563 - f1_m: 0.9678 - val_loss: 0.1820 - val_acc: 0.9407 - val_f1_m: 0.9567
Epoch 5/50
79/79 [=====] - 16s 200ms/step - loss: 0.0984 - acc: 0.9615 - f1_m: 0.9717 - val_loss: 0.1435 - val_acc: 0.9513 - val_f1_m: 0.9640
Epoch 6/50
79/79 [=====] - 16s 203ms/step - loss: 0.0925 - acc: 0.9642 - f1_m: 0.9733 - val_loss: 0.1041 - val_acc: 0.9640 - val_f1_m: 0.9730
Epoch 7/50
79/79 [=====] - 16s 206ms/step - loss: 0.0866 - acc: 0.9665 - f1_m: 0.9752 - val_loss: 0.1088 - val_acc: 0.9611 - val_f1_m: 0.9710
Epoch 8/50
79/79 [=====] - 16s 208ms/step - loss: 0.0830 - acc: 0.9681 - f1_m: 0.9764 - val_loss: 0.0980 - val_acc: 0.9628 - val_f1_m: 0.9730
Epoch 9/50
79/79 [=====] - 16s 207ms/step - loss: 0.0821 - acc: 0.9681 - f1_m: 0.9763 - val_loss: 0.1128 - val_acc: 0.9650 - val_f1_m: 0.9737
Epoch 10/50
79/79 [=====] - 16s 206ms/step - loss: 0.0762 - acc: 0.9704 - f1_m: 0.9783 - val_loss: 0.0842 - val_acc: 0.9692 - val_f1_m: 0.9768
Epoch 11/50
79/79 [=====] - 16s 206ms/step - loss: 0.0689 - acc: 0.9737 - f1_m: 0.9807 - val_loss: 0.0819 - val_acc: 0.9701 - val_f1_m: 0.9774
Epoch 12/50
79/79 [=====] - 16s 207ms/step - loss: 0.0671 - acc: 0.9744 - f1_m: 0.9812 - val_loss: 0.0845 - val_acc: 0.9703 - val_f1_m: 0.9780
Epoch 13/50
79/79 [=====] - 16s 208ms/step - loss: 0.0654 - acc: 0.9747 - f1_m: 0.9812 - val_loss: 0.0808 - val_acc: 0.9722 - val_f1_m: 0.9793
Epoch 14/50
79/79 [=====] - 16s 207ms/step - loss: 0.0621 - acc: 0.9761 - f1_m: 0.9824 - val_loss: 0.0965 - val_acc: 0.9671 - val_f1_m: 0.9753
Epoch 15/50
79/79 [=====] - 16s 207ms/step - loss: 0.0591 - acc: 0.9771 - f1_m: 0.9831 - val_loss: 0.1061 - val_acc: 0.9673 - val_f1_m: 0.9753
Epoch 16/50
79/79 [=====] - 16s 206ms/step - loss: 0.0577 - acc: 0.9778 - f1_m: 0.9837 - val_loss: 0.0833 - val_acc: 0.9647 - val_f1_m: 0.9743
Epoch 17/50
79/79 [=====] - 16s 207ms/step - loss: 0.0534 - acc: 0.9797 - f1_m: 0.9850 - val_loss: 0.0803 - val_acc: 0.9716 - val_f1_m: 0.9789
Epoch 18/50
79/79 [=====] - 16s 206ms/step - loss: 0.0541 - acc: 0.9794 - f1_m: 0.9849 - val_loss: 0.0676 - val_acc: 0.9748 - val_f1_m: 0.9814
Epoch 19/50
79/79 [=====] - 16s 208ms/step - loss: 0.0482 - acc: 0.9817 - f1_m: 0.9866 - val_loss: 0.0782 - val_acc: 0.9707 - val_f1_m: 0.9783
Epoch 20/50
79/79 [=====] - 16s 207ms/step - loss: 0.0472 - acc: 0.9820 - f1_m:
```

m: 0.9867 - val\_loss: 0.0723 - val\_acc: 0.9744 - val\_f1\_m: 0.9811  
Epoch 21/50  
79/79 [=====] - 16s 207ms/step - loss: 0.0456 - acc: 0.9824 - f1\_m: 0.9870 - val\_loss: 0.0810 - val\_acc: 0.9720 - val\_f1\_m: 0.9790  
Epoch 22/50  
79/79 [=====] - 16s 207ms/step - loss: 0.0431 - acc: 0.9834 - f1\_m: 0.9878 - val\_loss: 0.0649 - val\_acc: 0.9757 - val\_f1\_m: 0.9820  
Epoch 23/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0408 - acc: 0.9844 - f1\_m: 0.9885 - val\_loss: 0.0651 - val\_acc: 0.9761 - val\_f1\_m: 0.9823  
Epoch 24/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0371 - acc: 0.9857 - f1\_m: 0.9895 - val\_loss: 0.0796 - val\_acc: 0.9748 - val\_f1\_m: 0.9812  
Epoch 25/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0387 - acc: 0.9851 - f1\_m: 0.9890 - val\_loss: 0.0773 - val\_acc: 0.9734 - val\_f1\_m: 0.9804  
Epoch 26/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0433 - acc: 0.9833 - f1\_m: 0.9876 - val\_loss: 0.0975 - val\_acc: 0.9708 - val\_f1\_m: 0.9780  
Epoch 27/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0515 - acc: 0.9801 - f1\_m: 0.9853 - val\_loss: 0.1519 - val\_acc: 0.9654 - val\_f1\_m: 0.9739  
Epoch 28/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0412 - acc: 0.9842 - f1\_m: 0.9884 - val\_loss: 0.0671 - val\_acc: 0.9782 - val\_f1\_m: 0.9837  
Epoch 29/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0367 - acc: 0.9858 - f1\_m: 0.9896 - val\_loss: 0.0670 - val\_acc: 0.9770 - val\_f1\_m: 0.9829  
Epoch 30/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0360 - acc: 0.9861 - f1\_m: 0.9897 - val\_loss: 0.0691 - val\_acc: 0.9763 - val\_f1\_m: 0.9823  
Epoch 31/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0365 - acc: 0.9857 - f1\_m: 0.9895 - val\_loss: 0.0673 - val\_acc: 0.9766 - val\_f1\_m: 0.9827  
Epoch 32/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0328 - acc: 0.9873 - f1\_m: 0.9907 - val\_loss: 0.0683 - val\_acc: 0.9768 - val\_f1\_m: 0.9828  
Epoch 33/50  
79/79 [=====] - 16s 207ms/step - loss: 0.0522 - acc: 0.9805 - f1\_m: 0.9856 - val\_loss: 0.1832 - val\_acc: 0.9602 - val\_f1\_m: 0.9688  
Epoch 34/50  
79/79 [=====] - 16s 207ms/step - loss: 0.0359 - acc: 0.9861 - f1\_m: 0.9897 - val\_loss: 0.0884 - val\_acc: 0.9728 - val\_f1\_m: 0.9800  
Epoch 35/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0312 - acc: 0.9880 - f1\_m: 0.9912 - val\_loss: 0.0663 - val\_acc: 0.9769 - val\_f1\_m: 0.9828  
Epoch 36/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0294 - acc: 0.9885 - f1\_m: 0.9915 - val\_loss: 0.0876 - val\_acc: 0.9694 - val\_f1\_m: 0.9771  
Epoch 37/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0324 - acc: 0.9874 - f1\_m: 0.9908 - val\_loss: 0.0645 - val\_acc: 0.9775 - val\_f1\_m: 0.9833  
Epoch 38/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0282 - acc: 0.9890 - f1\_m: 0.9918 - val\_loss: 0.0646 - val\_acc: 0.9783 - val\_f1\_m: 0.9838  
Epoch 39/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0311 - acc: 0.9878 - f1\_m: 0.9910 - val\_loss: 0.1280 - val\_acc: 0.9642 - val\_f1\_m: 0.9739  
Epoch 40/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0381 - acc: 0.9854 - f1\_m: 0.9892 - val\_loss: 0.1251 - val\_acc: 0.9705 - val\_f1\_m: 0.9778  
Epoch 41/50  
79/79 [=====] - 16s 209ms/step - loss: 0.0310 - acc: 0.9879 - f1\_m: 0.9910 - val\_loss: 0.0700 - val\_acc: 0.9779 - val\_f1\_m: 0.9835  
Epoch 42/50  
79/79 [=====] - 16s 208ms/step - loss: 0.0278 - acc: 0.9891 - f1\_m:

```

m: 0.9920 - val_loss: 0.0667 - val_acc: 0.9797 - val_f1_m: 0.9847
Epoch 43/50
79/79 [=====] - 16s 208ms/step - loss: 0.0243 - acc: 0.9904 - f1_
m: 0.9929 - val_loss: 0.0655 - val_acc: 0.9797 - val_f1_m: 0.9848
Epoch 44/50
79/79 [=====] - 16s 207ms/step - loss: 0.0235 - acc: 0.9908 - f1_
m: 0.9932 - val_loss: 0.0659 - val_acc: 0.9802 - val_f1_m: 0.9852
Epoch 45/50
79/79 [=====] - 16s 208ms/step - loss: 0.0244 - acc: 0.9904 - f1_
m: 0.9929 - val_loss: 0.0701 - val_acc: 0.9795 - val_f1_m: 0.9847
Epoch 46/50
79/79 [=====] - 16s 208ms/step - loss: 0.0233 - acc: 0.9908 - f1_
m: 0.9931 - val_loss: 0.0676 - val_acc: 0.9797 - val_f1_m: 0.9848
Epoch 47/50
79/79 [=====] - 16s 208ms/step - loss: 0.0240 - acc: 0.9905 - f1_
m: 0.9930 - val_loss: 0.0863 - val_acc: 0.9786 - val_f1_m: 0.9839
Epoch 48/50
79/79 [=====] - 16s 208ms/step - loss: 0.0228 - acc: 0.9910 - f1_
m: 0.9933 - val_loss: 0.0698 - val_acc: 0.9797 - val_f1_m: 0.9849
Epoch 49/50
79/79 [=====] - 16s 207ms/step - loss: 0.0222 - acc: 0.9912 - f1_
m: 0.9935 - val_loss: 0.0669 - val_acc: 0.9808 - val_f1_m: 0.9857
Epoch 50/50
79/79 [=====] - 16s 208ms/step - loss: 0.0209 - acc: 0.9917 - f1_
m: 0.9939 - val_loss: 0.0715 - val_acc: 0.9799 - val_f1_m: 0.9849

```

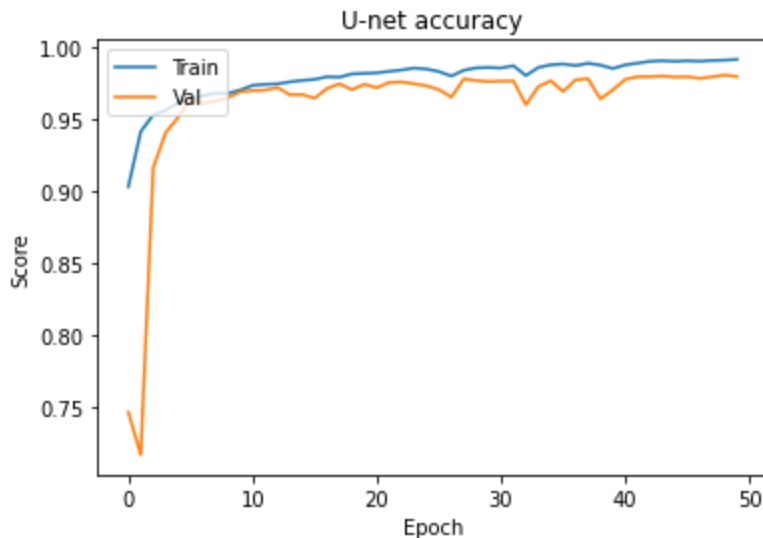
In [14]:

```
# Plot of the accuracy of the U-net model over each epoch
```

```

plt.plot(var.history['acc'])
plt.plot(var.history['val_acc'])
plt.title('U-net accuracy')
plt.ylabel('Score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()

```



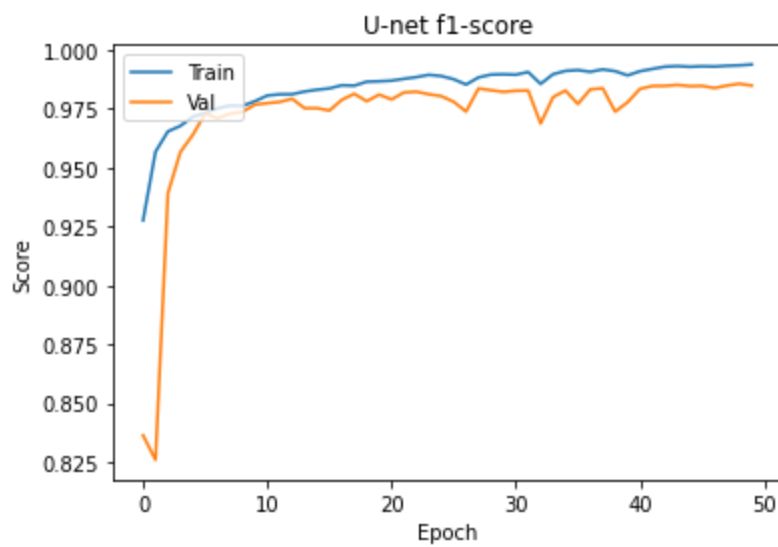
In [15]:

```
# Plot of the f1-score of the U-net model over each epoch
```

```

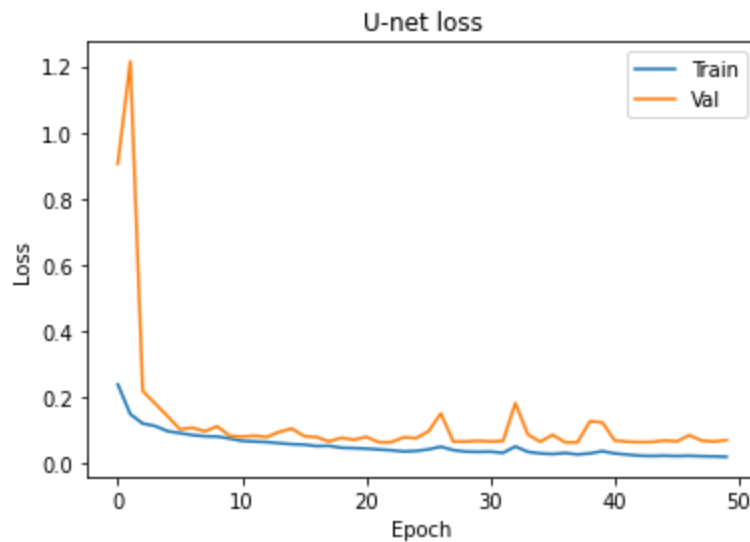
plt.plot(var.history['f1_m'])
plt.plot(var.history['val_f1_m'])
plt.title('U-net f1-score')
plt.ylabel('Score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()

```



In [16]: *#Plot of the loss of the U-net model over each epoch*

```
plt.plot(var.history['loss'])
plt.plot(var.history['val_loss'])
plt.title('U-net loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



One can see that the training accuracy and f1-score is a small bit higher than the validation score. This means that the manual U-net model overfits a tiny bit. Furthermore, one can see that the loss gets smaller for each epoch.

In [17]: *# Code and model training for your best transfer learning model (point 4 in Canvas)*

```
def get_unet_vg16(input_img, n_filters = 16, dropout = 0.1, batchnorm = True, n_classes = 2):
    encode_model = vg(input_tensor=input_img, include_top = False, weights="imagenet")

    for layer in encode_model.layers:
        layer.trainable = False

    encoder_output = encode_model.get_layer("block5_conv3").output

    # Expansive Path
    u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides = (2, 2), padding = 'same')(encoder_output)
```

```

u6 = concatenate([u6, encode_model.get_layer("block4_conv3").output])
u6 = Dropout(dropout)(u6)
c6 = conv2d_block(u6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)

u7 = Conv2DTranspose(n_filters * 4, (3, 3), strides = (2, 2), padding = 'same')(c6)
u7 = concatenate([u7, encode_model.get_layer("block3_conv3").output])
u7 = Dropout(dropout)(u7)
c7 = conv2d_block(u7, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)

u8 = Conv2DTranspose(n_filters * 2, (3, 3), strides = (2, 2), padding = 'same')(c7)
u8 = concatenate([u8, encode_model.get_layer("block2_conv2").output])
u8 = Dropout(dropout)(u8)
c8 = conv2d_block(u8, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)

u9 = Conv2DTranspose(n_filters * 1, (3, 3), strides = (2, 2), padding = 'same')(c8)
u9 = concatenate([u9, encode_model.get_layer("block1_conv2").output])
u9 = Dropout(dropout)(u9)
c9 = conv2d_block(u9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)

outputs_vg = Conv2D(n_classes, (1, 1), padding = 'same', activation='sigmoid')(c9)
vg_model = Model(inputs=[encode_model.input], outputs=[outputs_vg])
return vg_model

```

In [18]:

```

input_img = Input(shape=(128,128,3))
model_vg = get_unet_vg16(input_img, n_filters = 64, dropout = 0.2, batchnorm = True, n_classes=1000)
model_vg.summary()

```

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)  
58892288/58889256 [=====] - 0s 0us/step  
58900480/58889256 [=====] - 0s 0us/step  
Model: "model\_1"

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[ (None, 128, 128, 3) 0		
block1_conv1 (Conv2D)	(None, 128, 128, 64) 1792		input_2[0][0]
block1_conv2 (Conv2D)	(None, 128, 128, 64) 36928		block1_conv1[0][0]
block1_pool (MaxPooling2D)	(None, 64, 64, 64) 0		block1_conv2[0][0]
block2_conv1 (Conv2D)	(None, 64, 64, 128) 73856		block1_pool[0][0]
block2_conv2 (Conv2D)	(None, 64, 64, 128) 147584		block2_conv1[0][0]
block2_pool (MaxPooling2D)	(None, 32, 32, 128) 0		block2_conv2[0][0]

block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168	block2_pool[0][0]
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080	block3_conv1[0][0]
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080	block3_conv2[0][0]
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0	block3_conv3[0][0]
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160	block3_pool[0][0]
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808	block4_conv1[0][0]
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808	block4_conv2[0][0]
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0	block4_conv3[0][0]
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808	block4_pool[0][0]
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808	block5_conv1[0][0]
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808	block5_conv2[0][0]
conv2d_transpose_4 (Conv2DTrans	(None, 16, 16, 512)	2359808	block5_conv3[0][0]
concatenate_4 (Concatenate)	(None, 16, 16, 1024)	0	conv2d_transpose_4[0][0] block4_conv3[0][0]
dropout_8 (Dropout)	(None, 16, 16, 1024)	0	concatenate_4[0][0]
conv2d_19 (Conv2D)	(None, 16, 16, 512)	4719104	dropout_8[0][0]
batch_normalization_18 (BatchNo	(None, 16, 16, 512)	2048	conv2d_19[0][0]



activation_18 (Activation)	(None, 16, 16, 512)	0	batch_normalization_18[0][0]
conv2d_20 (Conv2D)	(None, 16, 16, 512)	2359808	activation_18[0][0]
batch_normalization_19 (Batch Normalization)	(None, 16, 16, 512)	2048	conv2d_20[0][0]
activation_19 (Activation)	(None, 16, 16, 512)	0	batch_normalization_19[0][0]
conv2d_transpose_5 (Conv2DTranspose)	(None, 32, 32, 256)	1179904	activation_19[0][0]
concatenate_5 (Concatenate)	(None, 32, 32, 512)	0	conv2d_transpose_5[0][0] block3_conv3[0][0]
dropout_9 (Dropout)	(None, 32, 32, 512)	0	concatenate_5[0][0]
conv2d_21 (Conv2D)	(None, 32, 32, 256)	1179904	dropout_9[0][0]
batch_normalization_20 (Batch Normalization)	(None, 32, 32, 256)	1024	conv2d_21[0][0]
activation_20 (Activation)	(None, 32, 32, 256)	0	batch_normalization_20[0][0]
conv2d_22 (Conv2D)	(None, 32, 32, 256)	590080	activation_20[0][0]
batch_normalization_21 (Batch Normalization)	(None, 32, 32, 256)	1024	conv2d_22[0][0]
activation_21 (Activation)	(None, 32, 32, 256)	0	batch_normalization_21[0][0]
conv2d_transpose_6 (Conv2DTranspose)	(None, 64, 64, 128)	295040	activation_21[0][0]
concatenate_6 (Concatenate)	(None, 64, 64, 256)	0	conv2d_transpose_6[0][0] block2_conv2[0][0]

dropout_10 (Dropout)	(None, 64, 64, 256)	0	concatenate_6[0][0]
conv2d_23 (Conv2D)	(None, 64, 64, 128)	295040	dropout_10[0][0]
batch_normalization_22 (Batch Normalization)	(None, 64, 64, 128)	512	conv2d_23[0][0]
activation_22 (Activation)	(None, 64, 64, 128)	0	batch_normalization_22[0][0]
conv2d_24 (Conv2D)	(None, 64, 64, 128)	147584	activation_22[0][0]
batch_normalization_23 (Batch Normalization)	(None, 64, 64, 128)	512	conv2d_24[0][0]
activation_23 (Activation)	(None, 64, 64, 128)	0	batch_normalization_23[0][0]
conv2d_transpose_7 (Conv2DTranspose)	(None, 128, 128, 64)	73792	activation_23[0][0]
concatenate_7 (Concatenate)	(None, 128, 128, 128)	0	conv2d_transpose_7[0][0] block1_conv2[0][0]
dropout_11 (Dropout)	(None, 128, 128, 128)	0	concatenate_7[0][0]
conv2d_25 (Conv2D)	(None, 128, 128, 64)	73792	dropout_11[0][0]
batch_normalization_24 (Batch Normalization)	(None, 128, 128, 64)	256	conv2d_25[0][0]
activation_24 (Activation)	(None, 128, 128, 64)	0	batch_normalization_24[0][0]
conv2d_26 (Conv2D)	(None, 128, 128, 64)	36928	activation_24[0][0]
batch_normalization_25 (Batch Normalization)	(None, 128, 128, 64)	256	conv2d_26[0][0]
activation_25 (Activation)	(None, 128, 128, 64)	0	batch_normalization_25[0][0]

conv2d\_27 (Conv2D)

(None, 128, 128, 1) 65

activation\_25[0][0]

```
=====
=====
Total params: 28,033,217
Trainable params: 13,314,689
Non-trainable params: 14,718,528
```

---

In [19]:

```
inputs = Input((128,128,3))
model_vg.compile(optimizer = Adam(learning_rate = 0.001), loss = "binary_crossentropy", me
# Fit data to model

history = model_vg.fit(X_train, y_train,
                        epochs=50,
                        batch_size=42,
                        # shuffle=True,
                        validation_data=(X_test, y_test),
                        callbacks= callback
                        )
```

2022-11-09 12:18:12.148071: W tensorflow/core/framework/cpu\_allocator\_impl.cc:80] Allocation of 491913216 exceeds 10% of free system memory.

Epoch 1/50

60/60 [=====] - 57s 732ms/step - loss: 0.2168 - acc: 0.9089 - f1\_m: 0.9308 - val\_loss: 1.1796 - val\_acc: 0.9323 - val\_f1\_m: 0.9485

Epoch 2/50

60/60 [=====] - 32s 528ms/step - loss: 0.1299 - acc: 0.9483 - f1\_m: 0.9617 - val\_loss: 0.2013 - val\_acc: 0.9489 - val\_f1\_m: 0.9615

Epoch 3/50

60/60 [=====] - 32s 530ms/step - loss: 0.1127 - acc: 0.9552 - f1\_m: 0.9669 - val\_loss: 0.1433 - val\_acc: 0.9525 - val\_f1\_m: 0.9641

Epoch 4/50

60/60 [=====] - 32s 531ms/step - loss: 0.1032 - acc: 0.9593 - f1\_m: 0.9700 - val\_loss: 0.1274 - val\_acc: 0.9591 - val\_f1\_m: 0.9695

Epoch 5/50

60/60 [=====] - 32s 530ms/step - loss: 0.0925 - acc: 0.9634 - f1\_m: 0.9729 - val\_loss: 0.1229 - val\_acc: 0.9582 - val\_f1\_m: 0.9692

Epoch 6/50

60/60 [=====] - 32s 529ms/step - loss: 0.0836 - acc: 0.9667 - f1\_m: 0.9755 - val\_loss: 0.0883 - val\_acc: 0.9664 - val\_f1\_m: 0.9751

Epoch 7/50

60/60 [=====] - 32s 529ms/step - loss: 0.0746 - acc: 0.9703 - f1\_m: 0.9781 - val\_loss: 0.1229 - val\_acc: 0.9529 - val\_f1\_m: 0.9656

Epoch 8/50

60/60 [=====] - 32s 529ms/step - loss: 0.0666 - acc: 0.9737 - f1\_m: 0.9806 - val\_loss: 0.0846 - val\_acc: 0.9678 - val\_f1\_m: 0.9761

Epoch 9/50

60/60 [=====] - 32s 528ms/step - loss: 0.0643 - acc: 0.9748 - f1\_m: 0.9814 - val\_loss: 0.0906 - val\_acc: 0.9671 - val\_f1\_m: 0.9757

Epoch 10/50

60/60 [=====] - 32s 528ms/step - loss: 0.0585 - acc: 0.9769 - f1\_m: 0.9829 - val\_loss: 0.0961 - val\_acc: 0.9679 - val\_f1\_m: 0.9760

Epoch 11/50

60/60 [=====] - 32s 529ms/step - loss: 0.0553 - acc: 0.9781 - f1\_m: 0.9839 - val\_loss: 0.1050 - val\_acc: 0.9657 - val\_f1\_m: 0.9741

Epoch 12/50

60/60 [=====] - 32s 530ms/step - loss: 0.0498 - acc: 0.9806 - f1\_m: 0.9857 - val\_loss: 0.0908 - val\_acc: 0.9698 - val\_f1\_m: 0.9774

Epoch 13/50

60/60 [=====] - 32s 532ms/step - loss: 0.0456 - acc: 0.9823 - f1\_m: 0.9869 - val\_loss: 0.0857 - val\_acc: 0.9696 - val\_f1\_m: 0.9774

Epoch 14/50

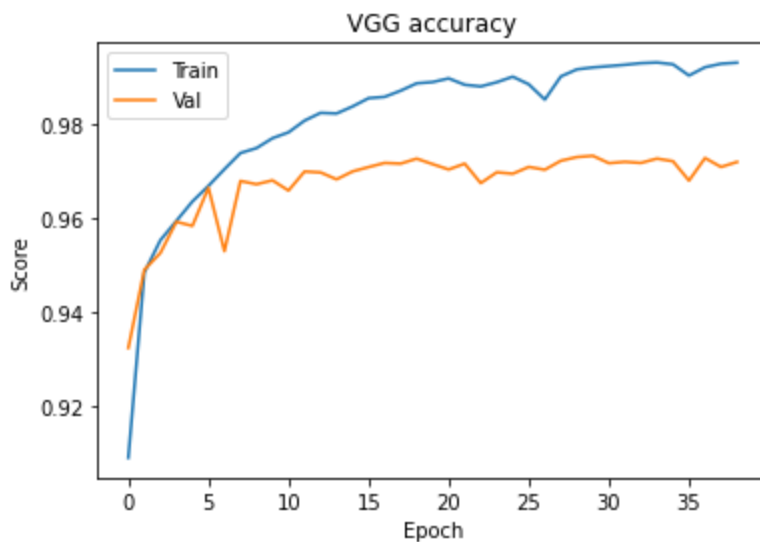
60/60 [=====] - 32s 530ms/step - loss: 0.0459 - acc: 0.9821 - f1\_m:

m: 0.9868 - val\_loss: 0.0990 - val\_acc: 0.9681 - val\_f1\_m: 0.9763  
Epoch 15/50  
60/60 [=====] - 32s 531ms/step - loss: 0.0419 - acc: 0.9836 - f1\_m: 0.9879 - val\_loss: 0.0892 - val\_acc: 0.9698 - val\_f1\_m: 0.9775  
Epoch 16/50  
60/60 [=====] - 32s 531ms/step - loss: 0.0374 - acc: 0.9854 - f1\_m: 0.9892 - val\_loss: 0.0842 - val\_acc: 0.9707 - val\_f1\_m: 0.9784  
Epoch 17/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0367 - acc: 0.9857 - f1\_m: 0.9894 - val\_loss: 0.0863 - val\_acc: 0.9716 - val\_f1\_m: 0.9790  
Epoch 18/50  
60/60 [=====] - 32s 530ms/step - loss: 0.0332 - acc: 0.9870 - f1\_m: 0.9904 - val\_loss: 0.0877 - val\_acc: 0.9715 - val\_f1\_m: 0.9787  
Epoch 19/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0291 - acc: 0.9885 - f1\_m: 0.9915 - val\_loss: 0.0815 - val\_acc: 0.9725 - val\_f1\_m: 0.9796  
Epoch 20/50  
60/60 [=====] - 32s 528ms/step - loss: 0.0285 - acc: 0.9888 - f1\_m: 0.9918 - val\_loss: 0.0968 - val\_acc: 0.9714 - val\_f1\_m: 0.9787  
Epoch 21/50  
60/60 [=====] - 32s 528ms/step - loss: 0.0264 - acc: 0.9896 - f1\_m: 0.9923 - val\_loss: 0.1042 - val\_acc: 0.9702 - val\_f1\_m: 0.9779  
Epoch 22/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0300 - acc: 0.9882 - f1\_m: 0.9913 - val\_loss: 0.1100 - val\_acc: 0.9715 - val\_f1\_m: 0.9788  
Epoch 23/50  
60/60 [=====] - 32s 528ms/step - loss: 0.0306 - acc: 0.9879 - f1\_m: 0.9911 - val\_loss: 0.1187 - val\_acc: 0.9673 - val\_f1\_m: 0.9757  
Epoch 24/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0284 - acc: 0.9888 - f1\_m: 0.9917 - val\_loss: 0.1055 - val\_acc: 0.9696 - val\_f1\_m: 0.9774  
Epoch 25/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0253 - acc: 0.9900 - f1\_m: 0.9926 - val\_loss: 0.1012 - val\_acc: 0.9693 - val\_f1\_m: 0.9773  
Epoch 26/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0298 - acc: 0.9883 - f1\_m: 0.9914 - val\_loss: 0.1057 - val\_acc: 0.9708 - val\_f1\_m: 0.9783  
Epoch 27/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0376 - acc: 0.9851 - f1\_m: 0.9890 - val\_loss: 0.1142 - val\_acc: 0.9702 - val\_f1\_m: 0.9777  
Epoch 28/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0251 - acc: 0.9900 - f1\_m: 0.9926 - val\_loss: 0.0974 - val\_acc: 0.9721 - val\_f1\_m: 0.9792  
Epoch 29/50  
60/60 [=====] - 32s 528ms/step - loss: 0.0213 - acc: 0.9915 - f1\_m: 0.9937 - val\_loss: 0.0930 - val\_acc: 0.9729 - val\_f1\_m: 0.9798  
Epoch 30/50  
60/60 [=====] - 32s 528ms/step - loss: 0.0201 - acc: 0.9919 - f1\_m: 0.9940 - val\_loss: 0.0983 - val\_acc: 0.9731 - val\_f1\_m: 0.9800  
Epoch 31/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0193 - acc: 0.9922 - f1\_m: 0.9942 - val\_loss: 0.1072 - val\_acc: 0.9716 - val\_f1\_m: 0.9789  
Epoch 32/50  
60/60 [=====] - 32s 530ms/step - loss: 0.0186 - acc: 0.9925 - f1\_m: 0.9945 - val\_loss: 0.1109 - val\_acc: 0.9719 - val\_f1\_m: 0.9790  
Epoch 33/50  
60/60 [=====] - 32s 529ms/step - loss: 0.0177 - acc: 0.9928 - f1\_m: 0.9947 - val\_loss: 0.1053 - val\_acc: 0.9716 - val\_f1\_m: 0.9790  
Epoch 34/50  
60/60 [=====] - 32s 531ms/step - loss: 0.0173 - acc: 0.9930 - f1\_m: 0.9948 - val\_loss: 0.1088 - val\_acc: 0.9725 - val\_f1\_m: 0.9796  
Epoch 35/50  
60/60 [=====] - 32s 530ms/step - loss: 0.0184 - acc: 0.9926 - f1\_m: 0.9945 - val\_loss: 0.1357 - val\_acc: 0.9720 - val\_f1\_m: 0.9794  
Epoch 36/50  
60/60 [=====] - 32s 532ms/step - loss: 0.0247 - acc: 0.9902 - f1\_m:

```
m: 0.9928 - val_loss: 0.1557 - val_acc: 0.9679 - val_f1_m: 0.9763
Epoch 37/50
60/60 [=====] - 32s 530ms/step - loss: 0.0199 - acc: 0.9920 - f1_
m: 0.9941 - val_loss: 0.1132 - val_acc: 0.9727 - val_f1_m: 0.9797
Epoch 38/50
60/60 [=====] - 32s 529ms/step - loss: 0.0181 - acc: 0.9927 - f1_
m: 0.9946 - val_loss: 0.1253 - val_acc: 0.9708 - val_f1_m: 0.9785
Epoch 39/50
60/60 [=====] - 32s 529ms/step - loss: 0.0175 - acc: 0.9929 - f1_
m: 0.9948 - val_loss: 0.1184 - val_acc: 0.9718 - val_f1_m: 0.9791
```

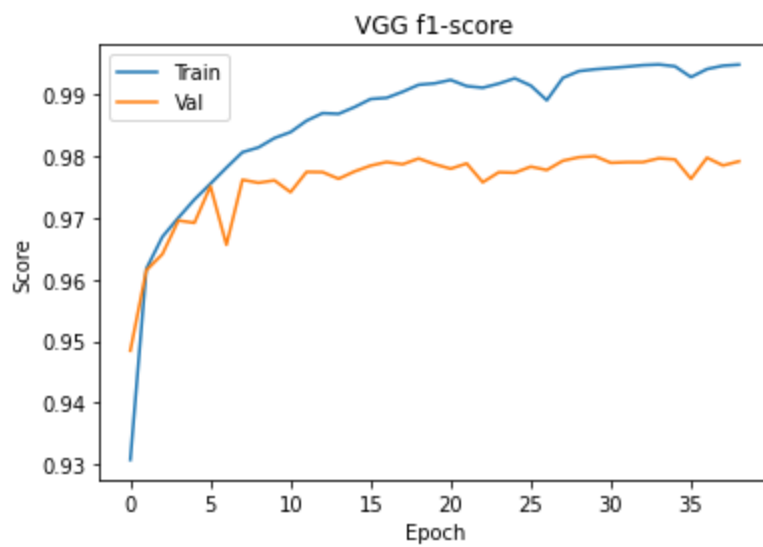
In [20]: *# Plot of the accuracy of the VGG model over each epoch*

```
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('VGG accuracy')
plt.ylabel('Score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
```



In [21]: *# Plot of the f1-score of the VGG model over each epoch*

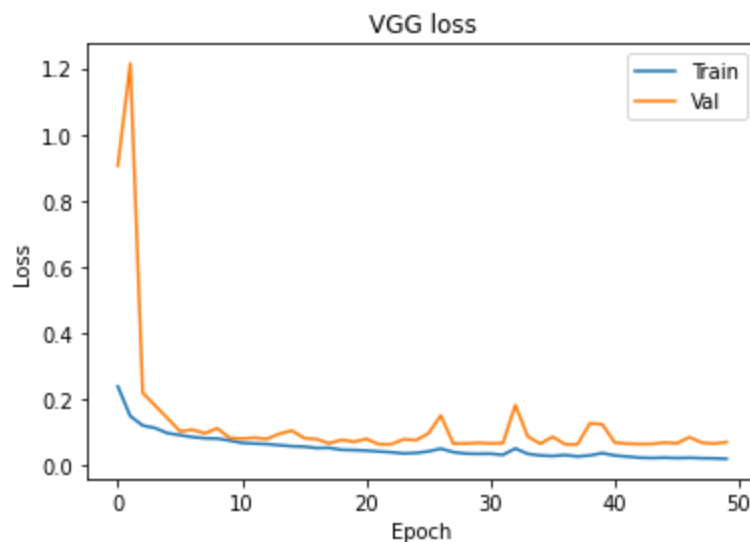
```
plt.plot(history.history['f1_m'])
plt.plot(history.history['val_f1_m'])
plt.title('VGG f1-score')
plt.ylabel('Score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
```



In [22]:

```
#Plot of the loss of the VGG model over each epoch
```

```
plt.plot(var.history['loss'])
plt.plot(var.history['val_loss'])
plt.title('VGG loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



One can see that the VGG model overfits much more than the manual U-net model

Orion related code, i.e. slurm-script, username, code to access data on Orion and time usage for your modelling (point 5)

Slurm script: singularity exec --nv --bind /mnt/courses/DAT300-22:/mnt/courses/DAT300-22 \$SIFFILE python Unet-CA2-Orion.py

From what we see, Orion was a little bit faster at training the models and predicting

In [23]:

```
# Optional: Code and model training for multiclass segmentation with U-net (Point 5 in Car
```

Describe the results you are observing.

In [24]:

```
unet_predictions = model.predict(X_test_final) # U-net predicting
```

```
pred_1 = unet_predictions.flatten()
pred_1

vg_predictions = model_vg.predict(X_test_final) # VGG16 predicting
pred_2 = vg_predictions.flatten()
pred_2
```

```
Out[24]: array([0.9989022 , 0.9969715 , 0.9989262 , ..., 0.9999335 , 0.99993956,
        0.9996289 ], dtype=float32)
```

```
In [ ]: submission_df = pd.DataFrame(data=list(range(len(pred))),
                                     columns=["Id"])

submission_df["Predicted"] = pred
submission_df = submission_df.round(0).astype("int")

submission_df['Predicted'] = np.where(submission_df['Predicted'] == 0,
                                     False, True)

submission_df.to_csv("CA2_goofy_submission.csv", index=False)
submission_df
```

## Discussion / conclusion

When we started modelling, we didn't change the output activation from softmax to sigmoid, which gave us an accuracy of around 60%. After changing this to sigmoid, our accuracy got much better on around 80%, but didn't really excel around 98% until we changed our preprocessing method. By using sklearn's train-test-split, we managed to get above beat me. We also had some problems with Orion, because it did not have sklearn and had a steep learning curve, because of the linux commands.

Our best model was the manual U-net, which was a little bit better than VGG, since it didn't overfit as much. Anyway, when running the models in Orion, each epoch for both of the models took less time to run, but the overall accuracy stayed the same. Given that Orion did not work for us for quite a long time, this increase in speed did not help us much.

In other words, we did not have a pleasant experience with Orion. Anyway, given more time we would commit to complete the optional task of multiclass segmentation. We did manage to make the function work, but we did not understand how to fit that to the model. We have therefore concluded with not including it in this compulsory assignment.