dat300-ca02

December 1, 2021

1 DAT300 - Compulsory assignment 2

2 Introduction

We were provided with a dataset of images of trees that were taken from above. The training dataset had a lenth of 4000. The task was to train Unet model and a transfer learning that will classify each pixel in the image as birch tree or not. If the pixel is a birch tree pixel the model will provide a result of 1 otherwise 0. Furthermore, we submitted a job to Orion i.e NMBU's distributed system.

3 Data handling and visualisation

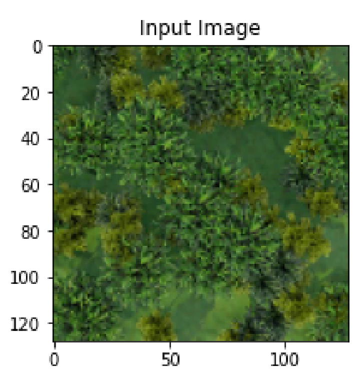
[1]:
```
# Import and extraction of data.
import numpy as np # linear algebra
import pandas as pd


import h5py
import matplotlib.pyplot as plt
import cv2
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Dense, Flatten, Conv2D
from tensorflow.keras.losses import binary_crossentropy
from tensorflow.keras.optimizers import Adam, RMSprop, SGD
from tensorflow.keras.layers import Input, Conv2D, BatchNormalization,␣
↪Activation, MaxPooling2D, Dropout, Conv2DTranspose, concatenate
from tensorflow.keras.models import Model
from tensorflow.keras.applications import VGG16

import os
for dirname, _, filenames in os.walk('../input/dat300ca2'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Extract train data
train_data_path = "../input/dat300ca2/tree_train.h5/tree_train.h5"
train_data = h5py.File(train_data_path, 'r')
```

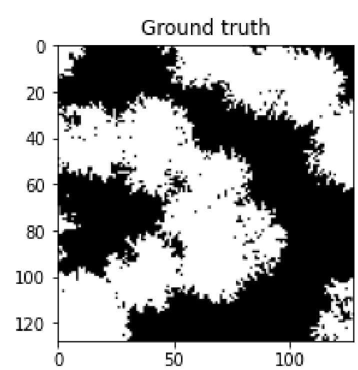
```python
print(train_data.keys())
X = train_data['X'][:]
y = train_data['y'][:]

print(X.shape)
print(y.shape)
```

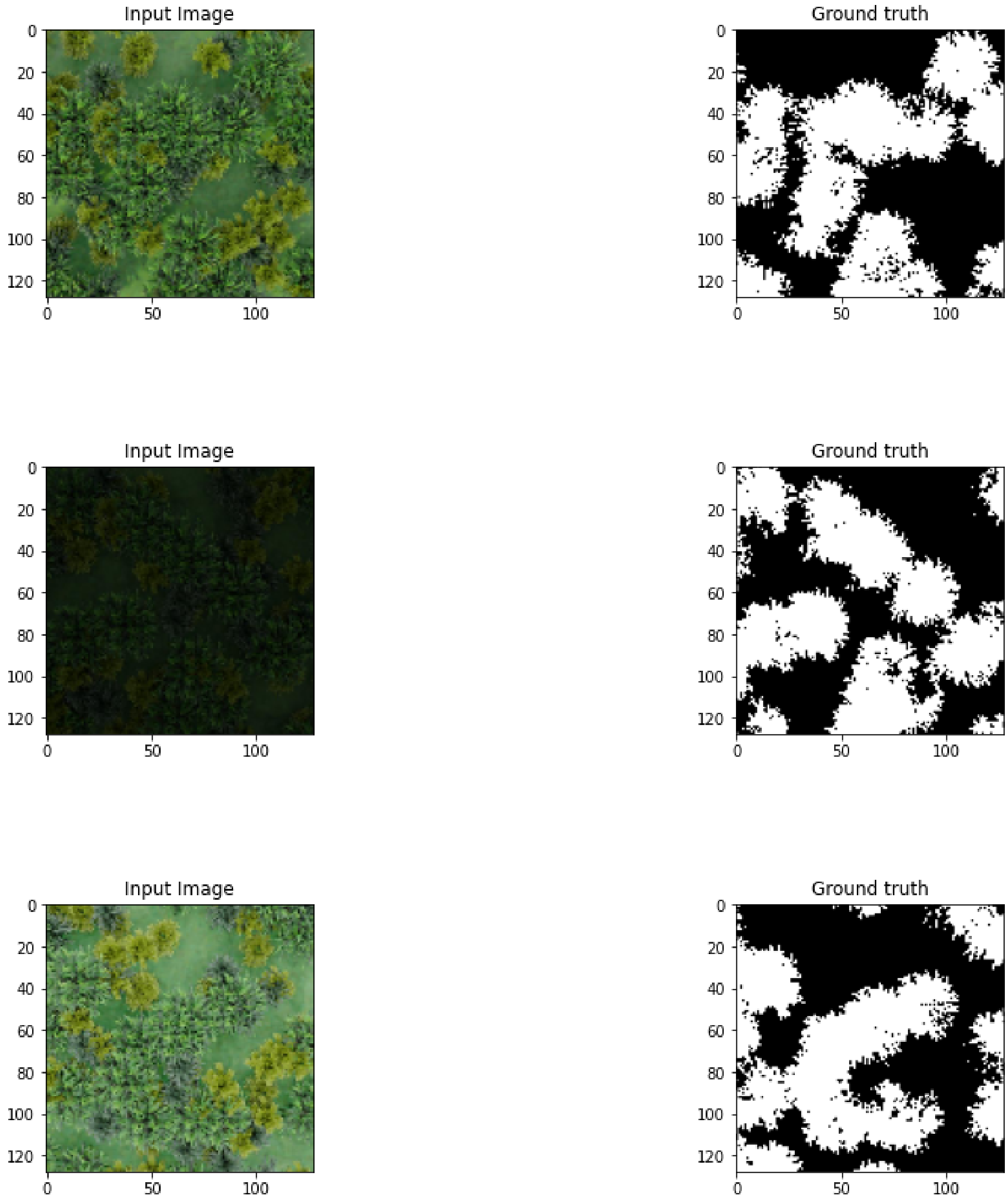
```
../input/dat300ca2/tree_train.h5/tree_train.h5
../input/dat300ca2/tree_test.h5/tree_test.h5
<KeysViewHDF5 ['X', 'y']>
(4000, 128, 128, 3)
(4000, 128, 128, 1)
```

The training dataset has a total of 4000 birch tree images, each of these has a dimension of (128x128) pixels and has 3 channel. The ground truth (y) has the same dimensions but just 1 channel.

[2]:
```python
# Short exploration and visualisation of dataset (point 1 in Canvas).
i=1
for num in range(4):
    plt.figure(figsize = (15,15))
    plt.subplot(420+i) # Shorthand for size 3x3, position i
    i+=1
    image = cv2.cvtColor(X[i], cv2.COLOR_BGR2RGB)
    plt.title('Input Image')
    plt.imshow(image)
    plt.subplot(420+i)
    image = y[i]
    plt.title('Ground truth')
    plt.imshow(image, cmap = 'gray')
    i+=1
plt.show()
```







In the ground truths, birch trees are segmented in white while everything else is masked with black. Apart from ground, there´re other trees in the images as well, so it would be challenging for any classifier to distinguish between them. The edges could be another challenge as they´re hard to distinguish.

4 Methods

For modeling we have used 90% of the train data for training while have used the rest for validation at the later stage. We have trained UNet and a VGG-16 models separately using different combinations of parameters randomly, which includes batch size, epochs, learning rate, number of filters and dropouts and manually tuned them to get optimised results. The plan was to use random grid search to auto tune parameters but due to shortage of time we could not acheive that. We also tried models with different convolutional layers and chose the best performing one.

4.1 Data split and Normalization

[3]:
```
# Split train data reserving 10% for testing
X_train,X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1,␣
↪random_state = 42)
shape = X_train[0].shape
```

[4]:
```
X_train = X_train/255.
X_test = X_test/255.
```

4.2 UNet

[5]:
```
"""
Version of U-Net with dropout and size preservation (padding= 'same')
"""
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 = 1):
    # 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
```

[6]:
```
input_img = Input(shape=(128,128,3))
model = get_unet(input_img, n_filters = 64, dropout = 0.01, batchnorm = False,␣
↪n_classes = 1)

model.compile(optimizer = Adam(learning_rate= 0.001), loss =␣
↪binary_crossentropy, metrics = ['accuracy'])
```

```
2021-11-29 17:58:56.474492: 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
2021-11-29 17:58:56.570612: 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
2021-11-29 17:58:56.571377: 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
2021-11-29 17:58:56.572485: 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.
2021-11-29 17:58:56.573248: 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
2021-11-29 17:58:56.573935: 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
2021-11-29 17:58:56.574603: 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
2021-11-29 17:58:58.402295: 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
2021-11-29 17:58:58.403433: 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
2021-11-29 17:58:58.404383: 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
2021-11-29 17:58:58.405237: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1510] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 15403 MB memory:  -> device:
0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04.0, compute capability: 6.0
```

[7]:

```python
# Fit data to model
history = model.fit(X_train, y_train,
            batch_size=32,
            epochs=50,
            shuffle=True,
            verbose=1,
            validation_data=(X_test, y_test))
```

```
2021-11-29 17:58:59.386182: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 707788800
exceeds 10% of free system memory.
2021-11-29 17:59:00.297981: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 707788800
exceeds 10% of free system memory.
2021-11-29 17:59:00.837302: I
tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR
Optimization Passes are enabled (registered 2)

Epoch 1/50

2021-11-29 17:59:03.048316: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369]
Loaded cuDNN version 8005

113/113 [==============================] - 41s 257ms/step - loss: 0.4550 -
accuracy: 0.7811 - val_loss: 0.2583 - val_accuracy: 0.8976
Epoch 2/50
113/113 [==============================] - 26s 233ms/step - loss: 0.4632 -
accuracy: 0.8109 - val_loss: 0.2853 - val_accuracy: 0.8869
Epoch 3/50
113/113 [==============================] - 26s 233ms/step - loss: 0.2491 -
accuracy: 0.9025 - val_loss: 0.2452 - val_accuracy: 0.9026
Epoch 4/50
113/113 [==============================] - 26s 233ms/step - loss: 0.2106 -
accuracy: 0.9152 - val_loss: 0.1999 - val_accuracy: 0.9203
Epoch 5/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1910 -
accuracy: 0.9225 - val_loss: 0.1794 - val_accuracy: 0.9268
Epoch 6/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1749 -
```

```
accuracy: 0.9291 - val_loss: 0.1669 - val_accuracy: 0.9321
Epoch 7/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1634 -
accuracy: 0.9336 - val_loss: 0.1574 - val_accuracy: 0.9359
Epoch 8/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1553 -
accuracy: 0.9367 - val_loss: 0.1498 - val_accuracy: 0.9388
Epoch 9/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1492 -
accuracy: 0.9391 - val_loss: 0.1445 - val_accuracy: 0.9409
Epoch 10/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1434 -
accuracy: 0.9413 - val_loss: 0.1393 - val_accuracy: 0.9430
Epoch 11/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1393 -
accuracy: 0.9430 - val_loss: 0.1385 - val_accuracy: 0.9434
Epoch 12/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1348 -
accuracy: 0.9447 - val_loss: 0.1315 - val_accuracy: 0.9459
Epoch 13/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1305 -
accuracy: 0.9463 - val_loss: 0.1282 - val_accuracy: 0.9472
Epoch 14/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1272 -
accuracy: 0.9477 - val_loss: 0.1281 - val_accuracy: 0.9475
Epoch 15/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1242 -
accuracy: 0.9488 - val_loss: 0.1252 - val_accuracy: 0.9486
Epoch 16/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1213 -
accuracy: 0.9499 - val_loss: 0.1203 - val_accuracy: 0.9503
Epoch 17/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1191 -
accuracy: 0.9508 - val_loss: 0.1184 - val_accuracy: 0.9510
Epoch 18/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1170 -
accuracy: 0.9517 - val_loss: 0.1169 - val_accuracy: 0.9517
Epoch 19/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1151 -
accuracy: 0.9524 - val_loss: 0.1157 - val_accuracy: 0.9522
Epoch 20/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1136 -
accuracy: 0.9530 - val_loss: 0.1132 - val_accuracy: 0.9531
Epoch 21/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1117 -
accuracy: 0.9537 - val_loss: 0.1144 - val_accuracy: 0.9527
Epoch 22/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1108 -
```

```
accuracy: 0.9542 - val_loss: 0.1112 - val_accuracy: 0.9540
Epoch 23/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1091 -
accuracy: 0.9548 - val_loss: 0.1092 - val_accuracy: 0.9547
Epoch 24/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1078 -
accuracy: 0.9553 - val_loss: 0.1085 - val_accuracy: 0.9550
Epoch 25/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1069 -
accuracy: 0.9557 - val_loss: 0.1084 - val_accuracy: 0.9551
Epoch 26/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1055 -
accuracy: 0.9562 - val_loss: 0.1066 - val_accuracy: 0.9558
Epoch 27/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1047 -
accuracy: 0.9566 - val_loss: 0.1059 - val_accuracy: 0.9561
Epoch 28/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1039 -
accuracy: 0.9569 - val_loss: 0.1051 - val_accuracy: 0.9564
Epoch 29/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1028 -
accuracy: 0.9573 - val_loss: 0.1044 - val_accuracy: 0.9567
Epoch 30/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1020 -
accuracy: 0.9576 - val_loss: 0.1040 - val_accuracy: 0.9568
Epoch 31/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1009 -
accuracy: 0.9581 - val_loss: 0.1030 - val_accuracy: 0.9573
Epoch 32/50
113/113 [==============================] - 26s 233ms/step - loss: 0.1002 -
accuracy: 0.9583 - val_loss: 0.1036 - val_accuracy: 0.9570
Epoch 33/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0996 -
accuracy: 0.9586 - val_loss: 0.1035 - val_accuracy: 0.9572
Epoch 34/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0987 -
accuracy: 0.9589 - val_loss: 0.1017 - val_accuracy: 0.9578
Epoch 35/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0983 -
accuracy: 0.9591 - val_loss: 0.1031 - val_accuracy: 0.9574
Epoch 36/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0975 -
accuracy: 0.9594 - val_loss: 0.1007 - val_accuracy: 0.9582
Epoch 37/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0969 -
accuracy: 0.9597 - val_loss: 0.1000 - val_accuracy: 0.9585
Epoch 38/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0963 -
```

```
accuracy: 0.9599 - val_loss: 0.0997 - val_accuracy: 0.9586
Epoch 39/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0957 -
accuracy: 0.9601 - val_loss: 0.1026 - val_accuracy: 0.9576
Epoch 40/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0952 -
accuracy: 0.9603 - val_loss: 0.0992 - val_accuracy: 0.9588
Epoch 41/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0945 -
accuracy: 0.9606 - val_loss: 0.1004 - val_accuracy: 0.9585
Epoch 42/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0946 -
accuracy: 0.9606 - val_loss: 0.0978 - val_accuracy: 0.9594
Epoch 43/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0932 -
accuracy: 0.9611 - val_loss: 0.0977 - val_accuracy: 0.9594
Epoch 44/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0927 -
accuracy: 0.9613 - val_loss: 0.0989 - val_accuracy: 0.9589
Epoch 45/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0926 -
accuracy: 0.9614 - val_loss: 0.0971 - val_accuracy: 0.9598
Epoch 46/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0924 -
accuracy: 0.9615 - val_loss: 0.0971 - val_accuracy: 0.9597
Epoch 47/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0915 -
accuracy: 0.9618 - val_loss: 0.0965 - val_accuracy: 0.9599
Epoch 48/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0913 -
accuracy: 0.9619 - val_loss: 0.0963 - val_accuracy: 0.9600
Epoch 49/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0909 -
accuracy: 0.9620 - val_loss: 0.0962 - val_accuracy: 0.9600
Epoch 50/50
113/113 [==============================] - 26s 233ms/step - loss: 0.0904 -
accuracy: 0.9623 - val_loss: 0.0957 - val_accuracy: 0.9602
```

4.3 Transfer learning model(VGG-16)

[8]:
```
inputs = Input((128,128,3))
vgg16 = VGG16(include_top=False, weights="imagenet", input_tensor=inputs)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 1s 0us/step
58900480/58889256 [==============================] - 1s 0us/step
```

```
[9]: 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 build_vgg(input_shape, n_filters=64, dropout = 0.01, batchnorm = True):
        vgg16 = VGG16(include_top=False, weights="imagenet", input_tensor=inputs)
        for layer in vgg16.layers:
            layer.trainable = False
        """ Encoder """
        s1 = vgg16.get_layer("block1_conv2").output         ## (128 x 128)
        s2 = vgg16.get_layer("block2_conv2").output         ## (64 x 64)
        s3 = vgg16.get_layer("block3_conv3").output         ## (132 x 32)
        s4 = vgg16.get_layer("block4_conv3").output         ## (16 x 16)
        """ Bridge """
        b1 = vgg16.get_layer("block5_conv3").output         ## (8 x 8)


        u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides = (2, 2), padding =␣
     ↪'same')(b1)
        u6 = concatenate([u6, s4])
        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, s3])
        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, s2])
```

```
    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, s1])
    u9 = Dropout(dropout)(u9)
    c9 = conv2d_block(u9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)




    """ Output """
    outputs = Conv2D(1, 1, padding="same", activation="sigmoid")(c9)

    model = Model(inputs, outputs, name="VGG16_U-Net")

    return model
```

[10]:

```
vgg_unet = build_vgg(inputs,batchnorm = False)
vgg_unet.compile(optimizer = Adam(learning_rate = 0.001), loss =␣
↪binary_crossentropy, metrics = ['accuracy'])
# Fit data to model
history2 = vgg_unet.fit(X_train, y_train,
            batch_size=32,
            epochs=50,
            shuffle=True,
            verbose=1,
            validation_data=(X_test, y_test))
```

```
2021-11-29 18:21:26.556824: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 707788800
exceeds 10% of free system memory.
2021-11-29 18:21:27.444722: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation of 707788800
exceeds 10% of free system memory.

Epoch 1/50
113/113 [==============================] - 22s 184ms/step - loss: 0.4583 -
accuracy: 0.8327 - val_loss: 0.2251 - val_accuracy: 0.9079
Epoch 2/50
113/113 [==============================] - 20s 179ms/step - loss: 0.2076 -
accuracy: 0.9141 - val_loss: 0.1920 - val_accuracy: 0.9200
Epoch 3/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1860 -
accuracy: 0.9220 - val_loss: 0.1771 - val_accuracy: 0.9256
Epoch 4/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1750 -
```

```
accuracy: 0.9263 - val_loss: 0.1688 - val_accuracy: 0.9287
Epoch 5/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1673 -
accuracy: 0.9293 - val_loss: 0.1621 - val_accuracy: 0.9314
Epoch 6/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1591 -
accuracy: 0.9326 - val_loss: 0.1715 - val_accuracy: 0.9278
Epoch 7/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1553 -
accuracy: 0.9342 - val_loss: 0.1549 - val_accuracy: 0.9344
Epoch 8/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1493 -
accuracy: 0.9366 - val_loss: 0.1490 - val_accuracy: 0.9370
Epoch 9/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1454 -
accuracy: 0.9382 - val_loss: 0.1487 - val_accuracy: 0.9371
Epoch 10/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1426 -
accuracy: 0.9394 - val_loss: 0.1466 - val_accuracy: 0.9379
Epoch 11/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1396 -
accuracy: 0.9406 - val_loss: 0.1419 - val_accuracy: 0.9398
Epoch 12/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1366 -
accuracy: 0.9418 - val_loss: 0.1409 - val_accuracy: 0.9405
Epoch 13/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1333 -
accuracy: 0.9431 - val_loss: 0.1372 - val_accuracy: 0.9420
Epoch 14/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1318 -
accuracy: 0.9438 - val_loss: 0.1374 - val_accuracy: 0.9419
Epoch 15/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1307 -
accuracy: 0.9443 - val_loss: 0.1360 - val_accuracy: 0.9426
Epoch 16/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1275 -
accuracy: 0.9456 - val_loss: 0.1337 - val_accuracy: 0.9436
Epoch 17/50
113/113 [==============================] - 20s 178ms/step - loss: 0.1250 -
accuracy: 0.9466 - val_loss: 0.1331 - val_accuracy: 0.9441
Epoch 18/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1238 -
accuracy: 0.9471 - val_loss: 0.1322 - val_accuracy: 0.9443
Epoch 19/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1219 -
accuracy: 0.9479 - val_loss: 0.1327 - val_accuracy: 0.9445
Epoch 20/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1207 -
```

```
accuracy: 0.9484 - val_loss: 0.1307 - val_accuracy: 0.9452
Epoch 21/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1189 -
accuracy: 0.9491 - val_loss: 0.1300 - val_accuracy: 0.9453
Epoch 22/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1175 -
accuracy: 0.9498 - val_loss: 0.1287 - val_accuracy: 0.9459
Epoch 23/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1167 -
accuracy: 0.9501 - val_loss: 0.1283 - val_accuracy: 0.9461
Epoch 24/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1169 -
accuracy: 0.9501 - val_loss: 0.1288 - val_accuracy: 0.9465
Epoch 25/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1136 -
accuracy: 0.9514 - val_loss: 0.1270 - val_accuracy: 0.9469
Epoch 26/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1120 -
accuracy: 0.9521 - val_loss: 0.1272 - val_accuracy: 0.9471
Epoch 27/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1116 -
accuracy: 0.9523 - val_loss: 0.1263 - val_accuracy: 0.9473
Epoch 28/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1106 -
accuracy: 0.9527 - val_loss: 0.1267 - val_accuracy: 0.9473
Epoch 29/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1085 -
accuracy: 0.9536 - val_loss: 0.1252 - val_accuracy: 0.9477
Epoch 30/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1074 -
accuracy: 0.9541 - val_loss: 0.1270 - val_accuracy: 0.9475
Epoch 31/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1065 -
accuracy: 0.9544 - val_loss: 0.1253 - val_accuracy: 0.9482
Epoch 32/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1063 -
accuracy: 0.9546 - val_loss: 0.1252 - val_accuracy: 0.9482
Epoch 33/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1038 -
accuracy: 0.9556 - val_loss: 0.1252 - val_accuracy: 0.9485
Epoch 34/50
113/113 [==============================] - 20s 178ms/step - loss: 0.1036 -
accuracy: 0.9557 - val_loss: 0.1246 - val_accuracy: 0.9486
Epoch 35/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1025 -
accuracy: 0.9562 - val_loss: 0.1256 - val_accuracy: 0.9484
Epoch 36/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1062 -
```

```
accuracy: 0.9547 - val_loss: 0.1242 - val_accuracy: 0.9488
Epoch 37/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1000 -
accuracy: 0.9572 - val_loss: 0.1241 - val_accuracy: 0.9491
Epoch 38/50
113/113 [==============================] - 20s 179ms/step - loss: 0.1021 -
accuracy: 0.9565 - val_loss: 0.1247 - val_accuracy: 0.9483
Epoch 39/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0999 -
accuracy: 0.9573 - val_loss: 0.1238 - val_accuracy: 0.9490
Epoch 40/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0975 -
accuracy: 0.9583 - val_loss: 0.1253 - val_accuracy: 0.9490
Epoch 41/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0965 -
accuracy: 0.9587 - val_loss: 0.1253 - val_accuracy: 0.9492
Epoch 42/50
113/113 [==============================] - 20s 180ms/step - loss: 0.0952 -
accuracy: 0.9593 - val_loss: 0.1260 - val_accuracy: 0.9493
Epoch 43/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0945 -
accuracy: 0.9596 - val_loss: 0.1253 - val_accuracy: 0.9491
Epoch 44/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0941 -
accuracy: 0.9598 - val_loss: 0.1259 - val_accuracy: 0.9490
Epoch 45/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0932 -
accuracy: 0.9601 - val_loss: 0.1267 - val_accuracy: 0.9489
Epoch 46/50
113/113 [==============================] - 20s 178ms/step - loss: 0.0925 -
accuracy: 0.9604 - val_loss: 0.1263 - val_accuracy: 0.9493
Epoch 47/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0911 -
accuracy: 0.9611 - val_loss: 0.1267 - val_accuracy: 0.9481
Epoch 48/50
113/113 [==============================] - 20s 180ms/step - loss: 0.0912 -
accuracy: 0.9610 - val_loss: 0.1280 - val_accuracy: 0.9489
Epoch 49/50
113/113 [==============================] - 20s 178ms/step - loss: 0.0905 -
accuracy: 0.9614 - val_loss: 0.1329 - val_accuracy: 0.9482
Epoch 50/50
113/113 [==============================] - 20s 179ms/step - loss: 0.0897 -
accuracy: 0.9617 - val_loss: 0.1288 - val_accuracy: 0.9488
```

5 Results

5.1 UNet

[11]:
```
# Test performance on validation data
score = model.evaluate(X_test, y_test, verbose=0)
print(f'Test loss: {score[0]} / Test accuracy: {score[1]}')
y_pred = model.predict(X_test)
```

```
Test loss: 0.09572907537221909 / Test accuracy: 0.9601858258247375
```

Results are discussed afterwards cumulatively.

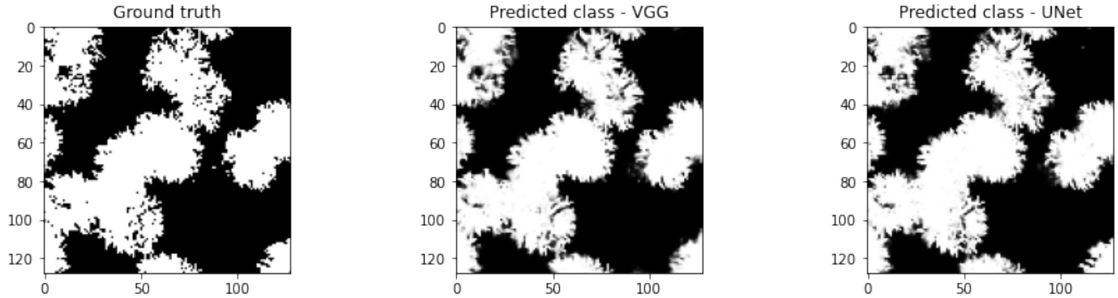
5.2 Transfer learning model

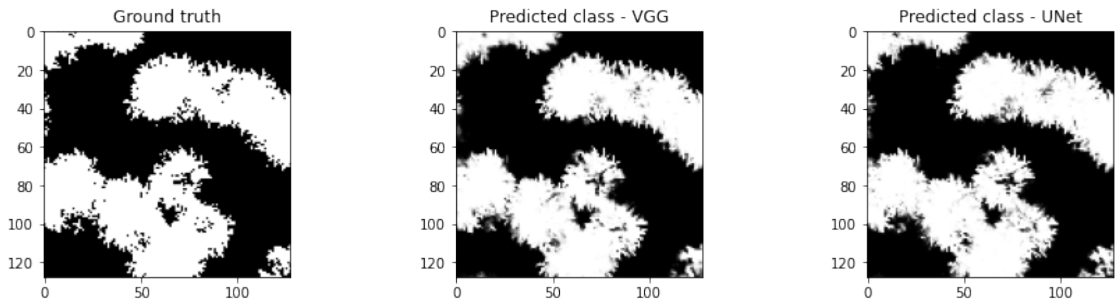
[12]:
```
# Test performance on validation data
score_vgg = vgg_unet.evaluate(X_test, y_test, verbose=0)
print(f'Test loss: {score_vgg[0]} / Test accuracy: {score_vgg[1]}')
y_pred_vgg = vgg_unet.predict(X_test)
```

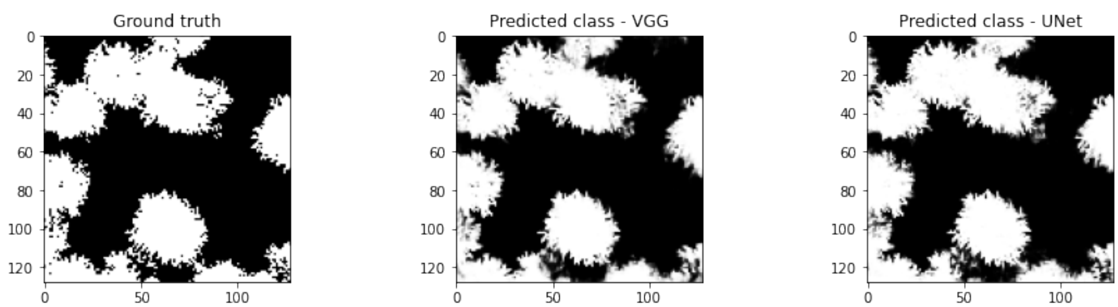
```
Test loss: 0.12883175909519196 / Test accuracy: 0.9487770199775696
```

5.3 Output comparision

[13]:
```
# Visualize model performance on validaton data for both models
i=1
tst = np.round(y_pred_vgg,0)
for num in range(3):
    plt.figure(figsize = (15,15))
    plt.subplot(430+i) # Shorthand for size 3x3, position i
    i+=1
    image = y_test[num]*255
    plt.title('Ground truth')
    plt.imshow(image, cmap = 'gray')
    plt.subplot(430+i)
    i+=1
    image = y_pred_vgg[num]*255
    plt.title('Predicted class - VGG')
    plt.imshow(image, cmap = 'gray')
    plt.subplot(430+i)
    image = y_pred[num]*255
    plt.title('Predicted class - UNet')
    plt.imshow(image, cmap = 'gray')
    i+=1
plt.show()
```







We achieved accuracies between 94-96 % using different parameters on UNet and between 93 – 95% using VGG, which in itself is a high number. We can see from the resulting segmented images above that both models were able to segment birch trees from the others pretty accurately, however VGG missed the small details at some points and the predictions are more inaccurate around the edges. While UNet was able to classify more accurately.

[14]:
```
#!/bin/bash
#SBATCH --ntasks=1                                    # 1 core (CPU)
#SBATCH --nodes=1                                    # Use 1 node
#SBATCH --job-name=g12_run_01           # Name of job
#SBATCH --mem=3G                                     # Default memory per CPU is 3GB
```

```
#SBATCH --partition=gpu                         # Use the GPU partition
#SBATCH --gres=gpu:1                                   # Use only one GPU core
#SBATCH --mail-user=goran.sildnes.gedde-dahl@nmbu.no                    # Your␣
↪email
#SBATCH --mail-type=ALL                     # Get notifications recarding your␣
↪job
#SBATCH --output=outputs.out   # Output stored in this file

#===============================================================================
# This is a template for a slurm script. You need to modify this according to
# your own experiments. You also need to choose appropriate
# sbatch parameters above (how much memory you need is especially important).
#===============================================================================

## Script commands
module load singularity


## Define paths to relevant folders
DATADIR="$HOME/dat300/$1"
SIFFILE="$HOME/dat300/keras.sif"


## Temporary results should be saved in $TMPDIR. Here is an example:

## RUN THE PYTHON SCRIPT
# Runs a python script named run.py which takes one input argument (the data␣
↪folder)
# Using a singularity container named keras.sif
singularity exec --nv $SIFFILE python dat300-ca2.py $DATADIR
```

```
  File "/tmp/ipykernel_26/1052967558.py", line 19
    module load singularity
           ^
SyntaxError: invalid syntax
```

6 Discussion / conclusion

The training process was really exhausting as training the models required a lot of time. Testing different combinations of hyper parameters to find the best set of paramters for this assignment was a difficult process.

The model performed really well and showed excellent results with validation accuracies scores varying between 94 and 96 approximately. Unet performs really well for the given data.

If we had more time and resources we would have done the hyper parameter tuning by using techniques like grid search and random search CV to identify the best set of parameters that provides the best score instead of the hit and try approach we used.

For this task, I think Unet should be used instead of transfer learning VGG technique. Transfer learning should be used when we have huge amounts of data and not much computational power. For this task the data set was large but we had the necessary computational power to perform the analysis. We can see in our analysis that training the VGG network took almost the same time as training the the Unet model. There was only a difference of 6 seconds which is ignorable. Unet also shows slighlty better results which was predictable because Unet is trained on this particular problem and the weights are set according to this data while for VGG this was not the case.