# Image Classifier for Satellite Images Using Non Deep Learning and Deep Learning Methods

**Author**: Ruoyang ZHANG

This notebook demonstrates how we construct an image classifier using non deep learning methods.

More specifically, it will cover the following topics in order:

## Agenda

#### 1. Data Preparation: converting image data into vector form

#### 2. Vanilla Random Forest as a benchmark

#### 3. Data Augmentation to deal with class inbalance

#### 4. Random Forest with augmented data

```
4.1 Strategy 1
4.2 Strategy 2
4.3 Strategy 3
4.4 Discussion
```

#### 5. Performance comparison with CNN using pretrained InceptionV3

#### 6. Conclusions

#### 7. Appendix - all functions and classes contained in seperate .py files

```
7.1 image_augmentation.py (Random Forest)
7.2 custom_dset_new_alt.py (Random Forest & CNN)
7.3 pretrained_inceptionv3_alt.py (CNN)
7.4 train_alt.py (CNN)
7.5 test_alt.py (CNN)
7.6 execute_training_alt.py (CNN)
```

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## 1. Data Preparation: converting image data into vector form

1. We conver the image files into single dimension vectors of 28 *28* 3 dimensions
2. We will also convert the image classes into integers using the following scheme:

   {'water':0, 'trees':1, 'road':2, 'barren_land': 3, 'building': 4, 'grassland':5}

In [1]:
```
import cv2
import os
from custom_dset_new import train_val_test_split
import numpy as np
from tqdm import tqdm
```

In [ ]:
```
# set the directory to the image data
data_dir = '/Users/ruoyangzhang/Documents/PythonWorkingDirectory/Assignment_dat
a/images'
```

In [3]:
```
# split the dataset into train and test
# we use the function that we created for the Convolution Neural Net
# Since there is barely any hyper parameters for with the Random Forest Algorit
hm, we set val_proportion = 0
train_data, val_data, test_data = train_val_test_split(data_dir, train_split=0.
8, val_split=0.0, test_split = 0.2)
```

In [4]:
```
# additional step to remove unwanted sys files
ordered_train_dirs = [dir for dir in sorted(list(train_data.keys())) if os.path
.split(dir)[-1] != '.DS_Store']
```

In [5]:
```
# function to convert the images to a vector
def convert_to_vector(img_dir):
    img = cv2.imread(img_dir)
    b, g, r = cv2.split(img)
    rgb_img = cv2.merge([r, g, b])
    rgb_img.shape = (1, 28*28*3)
    return(rgb_img)
```

In [6]:
```
# convert training images to input data
input_images = np.array([convert_to_vector(dir) for dir in tqdm(ordered_train_d
irs)])
```

```
100%|██████████| 259200/259200 [02:10<00:00, 1982.67it/s]
```

In [7]:
```
# reshape training input data
input_images.shape = (input_images.shape[0], input_images.shape[2])
```

In [31]:
```
# construct training input labels
train_labels = np.array([train_data[dir] for dir in ordered_train_dirs])
```

Now we make test data into np.arrays

In [9]:
```
# additional step to remove unwanted sys files
ordered_test_dirs = [testdir for testdir in sorted(list(test_data.keys())) if o
s.path.split(testdir)[-1] != '.DS_Store']
```

In [10]:
```
# convert testing images to input data
test_images = np.array([convert_to_vector(dir) for dir in tqdm(ordered_test_dir
s)])
```

```
100%|██████████| 64800/64800 [00:36<00:00, 1792.34it/s]
```

In [11]:
```
# reshape test input data
test_images.shape = (test_images.shape[0], test_images.shape[2])
```

In [29]:
```
# construct test input labels
test_labels = np.array([test_data[testdir] for testdir in ordered_test_dirs])
```

## 2. Vanilla Random Forest as a benchmark

We opt to use the Random Forest algorithm for the particular mission for the following reasons:

```
1. Its robust performance

2. Its lack of hyper parameter tuning, this is vital since the image dataset is lar
ge (> 300k images), the training time can be significant and hyperparameter tuning
should be minimised given the time constraints

3. It's quick to train

4. Excellent free open source implementation (Sklearn)

5. Simplicity
```

We note also the disadvantage of the Random Forest algorithm:

```
1. Its model size can easily get quite large and evaluation can be relatively slow

2. The lack of interpretability. While decision trees are easy to interpret, a fore
st is not so much. Random Forest is regarded by some as a blackbox due to the weigh
ting mechanism behind its decisions
```

In [13]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn import metrics
from collections import Counter
```

In [14]:
```
# instantiate the classifier
clf = RandomForestClassifier(n_estimators=100, n_jobs = 5)
```

In [15]:
```
# fit the model to the data
clf.fit(input_images,train_labels)
```

Out[15]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=5,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [16]:
```
# make predictions
preds = clf.predict(test_images)
```

In [17]:
```
# evaluate the accuracy
print("Accuracy:",metrics.accuracy_score(test_labels, preds))
```

```
Accuracy: 0.966358024691358
```

In [18]:
```
# the confusion matrix
metrics.confusion_matrix(test_labels, preds)
```

Out[18]:
```
array([[24137,     0,     0,     0,     0,     0],
       [   10, 11285,     0,     5,     0,    62],
       [   83,    30,  1282,    26,   134,    44],
       [    1,    44,     0, 14050,    31,   480],
       [   18,     0,    39,     2,  2943,     0],
       [   35,   650,     3,   483,     0,  8923]])
```

In [19]:
```
# its precision, recall and fscore in relation to the proportion of each class
in the training data

bookmark = {0: 'precision', 1: 'recall   ', 2: 'fscore   ', 3: 'support'}
class_dict = {0: 'water', 1: 'trees', 2: 'road', 3: 'barren_land', 4: 'building
', 5: 'grassland'}
train_class_count = Counter(test_data.values())
train_class_balance = {k:round(v/sum(train_class_count.values()),4) for k,v in
train_class_count.items()}

print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4
f}'\
              .format('balance  ',
                      class_dict[0], train_class_balance[0],
                      class_dict[1], train_class_balance[1],
                      class_dict[2], train_class_balance[2],
                      class_dict[3], train_class_balance[3],
                      class_dict[4], train_class_balance[4],
                      class_dict[5], train_class_balance[5]))

print('---------------')

for i, scores in enumerate(metrics.precision_recall_fscore_support(test_labels,
preds)):
    if i < 3:
        print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f},
{}: {:.4f}'\
              .format(bookmark[i],
                      class_dict[0], scores[0],
                      class_dict[1], scores[1],
                      class_dict[2], scores[2],
                      class_dict[3], scores[3],
                      class_dict[4], scores[4],
                      class_dict[5], scores[5]))
        print('---------------')
```

```
balance  , water: 0.3725, trees: 0.1753, road: 0.0247, barren_land: 0.2254, bu
ilding: 0.0463, grassland: 0.1558
---------------
precision, water: 0.9939, trees: 0.9397, road: 0.9683, barren_land: 0.9646, bu
ilding: 0.9469, grassland: 0.9384
---------------
recall   , water: 1.0000, trees: 0.9932, road: 0.8018, barren_land: 0.9619, bu
ilding: 0.9803, grassland: 0.8840
---------------
fscore   , water: 0.9970, trees: 0.9657, road: 0.8772, barren_land: 0.9633, bu
ilding: 0.9633, grassland: 0.9104
---------------
```

As we can tell, we have some evidence to suspect that the class inbalance is costing us performance. We note the following observations:

```
1. the class 'road' is grossly underrepresented in the training set, potentially le
ading to a low recall score and low overal performance (fscore: 0.8772)

2. curiously, the class 'building', despite being underrepresented in the training
set, obtained an acceptable prediction performance, possibly due to its visual dist
inctiveness

3. on the contrary, the class 'grassland', despite having a relatively fair represe
ntation (15.58%), its recall score is below overal performance (fscore: 0.9104), le
ading us to believe that the class is harder to distinguish from other classes, esp
ecially from 'trees' and 'barren_land'
```

### Going forward:

The vanilla Random Forest's performance reached a respectable 96.5% accuracy with not excellent but acceptable class-wise performance, notably with minimum engineering.

Going forward, we keep its performance as our baseline benchmark.

We aim to improve the prediction performance of the model by artifitially balancing out the classes a bit by data augmentation of the 2 worst performing classes:

```
1. road: 2
2. grassland: 5
```

## 3. Data Augmentation to deal with class inbalance

We have written data augmentation functions (image_augmentation.py) which provides the following image transformations:

```
1. random rotation between -25 and 25 degrees
2. random rotation between 26 and 75 degrees
3. random rotation either -90 or 90 degrees
4. adding random noise to the data
5. horizontal flip
6. vertical flip
7. transpose
8. zoom (maximum 1.4x)
```

With the 8 options, we can increase the representation of a particular class by 8 fold maximum without going into composite transformations

We will try 3 strategies in order to evaluate which data augmentation gives us the most desired result:

```
1. strategy 1
    a. to increase 2 fold the volume of the class 'road'
    b. to increase 2 fold the volume of the class 'grassland'
2. Strategy 2
    a. to increase 4 fold the volume of the class 'road'
    b. to increase 2 fold the volume of the class 'grassland'
3. Strategy 3
    a. to increase 3 fold the volume of the class 'road'
    b. to increase 2 fold the volume of the class 'grassland'
```

### Strategy 1

In [108]:
```
from image_augmentation import *

# set fold variables for the 2 classes
class_2_fold = 2
class_5_fold = 2
```

We first prep the augmented training data and the respective labels for class 2 and 5

In [109]:
```
# we first extract the image_dirs for class 2 & 5
class_2_dirs = [ordered_train_dirs[i] for i, cls in enumerate(train_labels) if
cls == 2]
class_2_labels = np.array([2] * len(class_2_dirs) * class_2_fold)
class_5_dirs = [ordered_train_dirs[i] for i, cls in enumerate(train_labels) if
cls == 5]
class_5_labels = np.array([5] * len(class_5_dirs) * class_5_fold)
```

In [110]:
```
# we then augment the data for class 2
augmented_class_2 = image_augmentation(class_2_dirs, class_2_fold)
```

```
  2%|▏         | 146/6593 [00:00<00:08, 723.97it/s]

the functions to be used for augmentation are:
1 random_rotation_75
2 random_rotation_90

100%|██████████| 6593/6593 [00:08<00:00, 807.71it/s]
```

In [111]:
```
# we then augment the data for class 5
augmented_class_5 = image_augmentation(class_5_dirs, class_5_fold)
```

```
  0%|          | 195/40253 [00:00<00:41, 970.79it/s]

the functions to be used for augmentation are:
1 random_rotation_75
2 horizontal_flip

100%|██████████| 40253/40253 [00:39<00:00, 1024.45it/s]
```

In [112]:
```
# new input data and labels
input_images_aug = np.concatenate((input_images,augmented_class_2,augmented_cla
ss_5), axis = 0)
train_labels_aug = np.concatenate((train_labels, class_2_labels, class_5_labels
))
```

### Strategy 2

In [120]:
```
# set fold variables for the 2 classes
class_2_fold_2 = 4
class_5_fold_2 = 2
```

In [121]:
```
# we make the labels for the augmented data for class 2
class_2_labels_2 = np.array([2] * len(class_2_dirs) * class_2_fold_2)
```

In [123]:
```
# we then augment the data for class 2
augmented_class_2_2 = image_augmentation(class_2_dirs, class_2_fold_2)
```

```
  0%|          | 0/6593 [00:00<?, ?it/s]/Users/ruoyangzhang/anaconda3/lib/pyth
on3.6/site-packages/skimage/transform/_warps.py:84: UserWarning: The default m
ode, 'constant', will be changed to 'reflect' in skimage 0.15.
  warn("The default mode, 'constant', will be changed to 'reflect' in "
  2%|▏         | 145/6593 [00:00<00:08, 721.27it/s]

the functions to be used for augmentation are:
1 vertical_flip
2 horizontal_flip
3 random_rotation_90
4 zoom

100%|██████████| 6593/6593 [00:09<00:00, 694.62it/s]
```

In [126]:
```
# new input data and labels
input_images_aug_2 = np.concatenate((input_images,augmented_class_2_2,augmented
_class_5), axis = 0)
train_labels_aug_2 = np.concatenate((train_labels, class_2_labels_2, class_5_la
bels))
```

### Strategy 3

In [144]:
```
# set fold variables for the 2 classes
class_2_fold_3 = 3
class_5_fold_3 = 2
```

In [145]:
```
# we make the labels for the augmented data for class 2
class_2_labels_3 = np.array([2] * len(class_2_dirs) * class_2_fold_3)
```

In [146]:
```
# we then augment the data for class 2
augmented_class_2_3 = image_augmentation(class_2_dirs, class_2_fold_3)
```

```
  1%|          | 40/6593 [00:00<00:16, 399.73it/s]

the functions to be used for augmentation are:
1 random_rotation_90
2 random_rotation_75
3 horizontal_flip

100%|██████████| 6593/6593 [00:08<00:00, 800.33it/s]
```

In [149]:
```
# new input data and labels
input_images_aug_3 = np.concatenate((input_images,augmented_class_2_3,augmented
_class_5), axis = 0)
train_labels_aug_3 = np.concatenate((train_labels, class_2_labels_3, class_5_la
bels))
```

## 4. Random Forest with augmented data

### 4.1 Strategy 1

In [113]:
```
# instantiate the classifier
clf_aug = RandomForestClassifier(n_estimators=100, n_jobs = 5)
```

In [129]:
```
# fit the model to the data
clf_aug.fit(input_images_aug,train_labels_aug)
```

Out[129]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=5,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [130]:
```
# make predictions
preds_new = clf_aug.predict(test_images)
```

In [131]:
```
# evaluate the accuracy
print("Accuracy:",metrics.accuracy_score(test_labels, preds_new))
```

```
Accuracy: 0.9700308641975308
```

In [132]:
```
# the confusion matrix
metrics.confusion_matrix(test_labels, preds_new)
```

Out[132]:
```
array([[24137,     0,     0,     0,     0,     0],
       [   10, 11285,     0,     5,     0,    62],
       [   83,    30,  1282,    26,   134,    44],
       [    1,    44,     0, 14050,    31,   480],
       [   18,     0,    39,     2,  2943,     0],
       [   35,   650,     3,   483,     0,  8923]])
```

In [136]:
```
# its precision, recall and fscore in relation to the proportion of each class
in the training data

bookmark = {0: 'precision', 1: 'recall   ', 2: 'fscore   ', 3: 'support'}
class_dict = {0: 'water', 1: 'trees', 2: 'road', 3: 'barren_land', 4: 'building
', 5: 'grassland'}
train_class_count_aug = Counter(train_labels_aug)
train_class_balance_aug = {k:round(v/sum(train_class_count_aug.values()),4) for
k,v in train_class_count_aug.items()}

print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4
f}'\
              .format('balance  ',
                      class_dict[0], train_class_balance_aug[0],
                      class_dict[1], train_class_balance_aug[1],
                      class_dict[2], train_class_balance_aug[2],
                      class_dict[3], train_class_balance_aug[3],
                      class_dict[4], train_class_balance_aug[4],
                      class_dict[5], train_class_balance_aug[5]))

print('---------------')

for i, scores in enumerate(metrics.precision_recall_fscore_support(test_labels,
preds_new)):
    if i < 3:
        print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f},
{}: {:.4f}'\
              .format(bookmark[i],
                      class_dict[0], scores[0],
                      class_dict[1], scores[1],
                      class_dict[2], scores[2],
                      class_dict[3], scores[3],
                      class_dict[4], scores[4],
                      class_dict[5], scores[5]))
        print('---------------')
```

```
balance  , water: 0.2726, trees: 0.1288, road: 0.0560, barren_land: 0.1666, bu
ilding: 0.0338, grassland: 0.3422
---------------
precision, water: 0.9946, trees: 0.9669, road: 0.9709, barren_land: 0.9823, bu
ilding: 0.9463, grassland: 0.9072
---------------
recall   , water: 1.0000, trees: 0.9843, road: 0.7724, barren_land: 0.9460, bu
ilding: 0.9800, grassland: 0.9453
---------------
fscore   , water: 0.9973, trees: 0.9755, road: 0.8603, barren_land: 0.9638, bu
ilding: 0.9629, grassland: 0.9259
---------------
```

## 4.2 Strategy 2

In [137]:
```
# instantiate the classifier
clf_aug_2 = RandomForestClassifier(n_estimators=100, n_jobs = 5)
```

In [139]:
```
# fit the model to the data
clf_aug_2.fit(input_images_aug_2,train_labels_aug_2)
```

Out[139]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=5,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [140]:
```
# make predictions
preds_new_2 = clf_aug_2.predict(test_images)
```

In [141]:
```
# evaluate the accuracy
print("Accuracy:",metrics.accuracy_score(test_labels, preds_new_2))
```

```
Accuracy: 0.9695370370370371
```

In [142]:
```
# the confusion matrix
metrics.confusion_matrix(test_labels, preds_new_2)
```

Out[142]:
```
array([[24136,     0,     1,     0,     0,     0],
       [   14, 11182,     1,     2,     0,   163],
       [   42,    28,  1455,     8,    35,    31],
       [    1,    40,    13, 13828,    23,   701],
       [    5,     1,   291,     1,  2702,     2],
       [   18,   326,     6,   221,     0,  9523]])
```

In [143]:
```
# its precision, recall and fscore in relation to the proportion of each class
in the training data

bookmark = {0: 'precision', 1: 'recall   ', 2: 'fscore   ', 3: 'support'}
class_dict = {0: 'water', 1: 'trees', 2: 'road', 3: 'barren_land', 4: 'building
', 5: 'grassland'}
train_class_count_aug_2 = Counter(train_labels_aug_2)
train_class_balance_aug_2 = {k:round(v/sum(train_class_count_aug_2.values()),4)
for k,v in train_class_count_aug_2.items()}

print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4
f}'\
              .format('balance  ',
                      class_dict[0], train_class_balance_aug_2[0],
                      class_dict[1], train_class_balance_aug_2[1],
                      class_dict[2], train_class_balance_aug_2[2],
                      class_dict[3], train_class_balance_aug_2[3],
                      class_dict[4], train_class_balance_aug_2[4],
                      class_dict[5], train_class_balance_aug_2[5]))

print('---------------')

for i, scores in enumerate(metrics.precision_recall_fscore_support(test_labels,
preds_new_2)):
    if i < 3:
        print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f},
{}: {:.4f}'\
              .format(bookmark[i],
                      class_dict[0], scores[0],
                      class_dict[1], scores[1],
                      class_dict[2], scores[2],
                      class_dict[3], scores[3],
                      class_dict[4], scores[4],
                      class_dict[5], scores[5]))
        print('---------------')
```

```
balance  , water: 0.2628, trees: 0.1241, road: 0.0900, barren_land: 0.1606, bu
ilding: 0.0326, grassland: 0.3299
---------------
precision, water: 0.9967, trees: 0.9659, road: 0.8234, barren_land: 0.9835, bu
ilding: 0.9790, grassland: 0.9139
---------------
recall   , water: 1.0000, trees: 0.9842, road: 0.9099, barren_land: 0.9467, bu
ilding: 0.9001, grassland: 0.9434
---------------
fscore   , water: 0.9983, trees: 0.9749, road: 0.8645, barren_land: 0.9648, bu
ilding: 0.9379, grassland: 0.9284
---------------
```

### 4.3 Strategy 3

In [150]:
```
# instantiate the classifier
clf_aug_3 = RandomForestClassifier(n_estimators=100, n_jobs = 5)
```

In [152]:
```
# fit the model to the data
clf_aug_3.fit(input_images_aug_3,train_labels_aug_3)
```

Out[152]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=5,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [153]:
```
# make predictions
preds_new_3 = clf_aug_3.predict(test_images)
```

In [154]:
```
# evaluate the accuracy
print("Accuracy:",metrics.accuracy_score(test_labels, preds_new_3))
```

```
Accuracy: 0.9702006172839506
```

In [155]:
```
# the confusion matrix
metrics.confusion_matrix(test_labels, preds_new_3)
```

Out[155]:
```
array([[24137,     0,     0,     0,     0,     0],
       [   16, 11183,     0,     1,     0,   162],
       [   50,    30,  1395,    10,    57,    57],
       [    1,    42,    10, 13817,    23,   713],
       [   15,     0,   170,     1,  2814,     2],
       [   17,   327,     4,   223,     0,  9523]])
```

In [156]:
```
# its precision, recall and fscore in relation to the proportion of each class
in the training data

bookmark = {0: 'precision', 1: 'recall   ', 2: 'fscore   ', 3: 'support'}
class_dict = {0: 'water', 1: 'trees', 2: 'road', 3: 'barren_land', 4: 'building
', 5: 'grassland'}
train_class_count_aug_3 = Counter(train_labels_aug_3)
train_class_balance_aug_3 = {k:round(v/sum(train_class_count_aug_3.values()),4)
for k,v in train_class_count_aug_3.items()}

print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4
f}'\
              .format('balance  ',
                      class_dict[0], train_class_balance_aug_3[0],
                      class_dict[1], train_class_balance_aug_3[1],
                      class_dict[2], train_class_balance_aug_3[2],
                      class_dict[3], train_class_balance_aug_3[3],
                      class_dict[4], train_class_balance_aug_3[4],
                      class_dict[5], train_class_balance_aug_3[5]))

print('---------------')

for i, scores in enumerate(metrics.precision_recall_fscore_support(test_labels,
preds_new_3)):
    if i < 3:
        print('{}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f}, {}: {:.4f},
{}: {:.4f}'\
              .format(bookmark[i],
                      class_dict[0], scores[0],
                      class_dict[1], scores[1],
                      class_dict[2], scores[2],
                      class_dict[3], scores[3],
                      class_dict[4], scores[4],
                      class_dict[5], scores[5]))
        print('---------------')
```

```
balance  , water: 0.2676, trees: 0.1264, road: 0.0734, barren_land: 0.1635, bu
ilding: 0.0332, grassland: 0.3359
---------------
precision, water: 0.9959, trees: 0.9655, road: 0.8835, barren_land: 0.9833, bu
ilding: 0.9724, grassland: 0.9107
---------------
recall   , water: 1.0000, trees: 0.9842, road: 0.8724, barren_land: 0.9460, bu
ilding: 0.9374, grassland: 0.9434
---------------
fscore   , water: 0.9980, trees: 0.9748, road: 0.8779, barren_land: 0.9643, bu
ilding: 0.9545, grassland: 0.9268
---------------
```

## 4.3 Discussion

In resume, we have trained 4 models with different data augmentations with the following accuracy performance:

Original Vanilla Model: 0.9664

Model of strategy 1 : 0.9700

Model of strategy 2 : 0.9695

Model of strategy 3 : 0.9702

We can see a minor increase in model accuracy after various degrees of data augmentation. From an accuracy's point of view, the data augmented models are generally superior.

However, we know that accuracy is not a very holistic metric in evaluating a model's performance. We have noted previously that :

1. the original model's performance was skewed towards classes with large sample sizes
2. the original model's precision/recall balance was weak for the aforementioned classes: 2 & 5

This is when the data augmented models performed quite differently:

1. model of strategy 1 performed poorly for class 2 and 5, with class 2's precision (0.9709) being largely superior than its recall (0.7724)
2. model of strategy 2 had a similar problem with the precision of class 2 (0.8234) being largely inferior to its recall (0.9099)
3. model of strategy 3's class-wise precision-recall balance is fairly well upheld

Overall, the original model not only lacked in accuracy, it also had class-wise performance inbalance (measured in fscore). The data augmented models performed better in that regard, but model 1 and 2 both had precision-recall balance issues for class 2, whereas model 3 achieved a relatively good level of balance, both in terms of class-wise performance and class-wise precision-recall balance.

# 5. Performance comparison with CNN using pretrained InceptionV3

## 5.1 The CNN Architecture

We applied the transfer learning technique to avoid retrainning the model from scratch. We used the pretrained InceptionV3 model provided by the PyTorch framework for the following reasons:

```
1. Its relative light weight for training in comparison with other popular architec
tures such as Resnet or VGG
2. Its availability in torch.vision (there are other light architectures such as mo
bilenet but they are not readily available in torch.vision)
3. Its rebust performance
```

We trained multiple models using this architecture:

Shared variables:

Optimisation: SGD

Loss Function: Cross Entropy

Batchsize: 32

Group 1, 8 training epochs:

```
1. fully connected layers unfrozen, decaying learning rate 1e-3, step size = 7, gam
ma = 0.1
2. layers after 'Conv2d_4a_3x3' unfrozen, decaying learning rate 1e-3, step size =
7, gamma = 0.1
```

Group 2, 5 training epochs:

```
1. fully connected layers unfrozen & decaying learning rate 1e-5, step size = 3, ga
mma = 0.2
2. layers after 'Conv2d_4a_3x3' unfrozen, decaying learning rate 1e-5, step size =
3, gamma = 0.2
```

Group 2 performed better on the validation set with considerably less training data:

Best alidation accuracy:

```
Group 1:
    1. 0.8789
    2. 0.8827
Group 2:
    1. 0.9043
    2. 0.9156
```

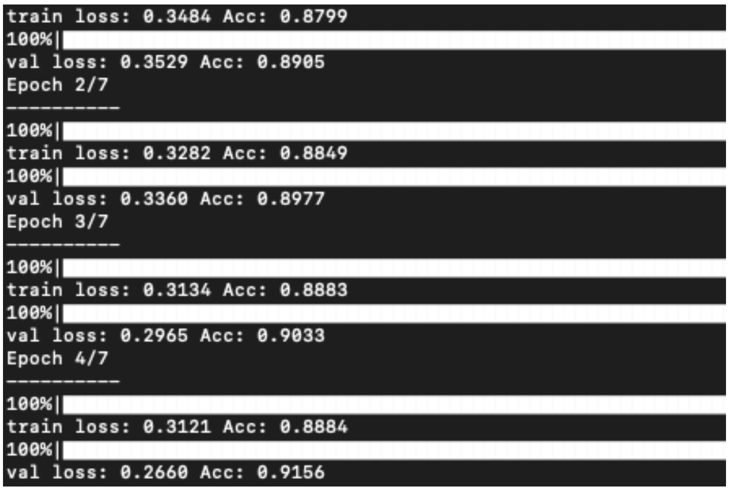
We finally kept the 2nd model from group 2.

We chose not to further tune the hyper parameter or run any more epochs since the Random Forest algorithm provides a much superior performance in terms of accuracy.

**Due to training being interrupted half way, the model not the testing data was not succesfully saved, please find below a proof of the best performing model (group 2 model 2)'s validation performing during training**

In [10]:
```
from IPython.display import Image
Image(filename="Screenshot.png")
```

Out[10]:



```
train loss: 0.3484 Acc: 0.8799
100%|
val loss: 0.3529 Acc: 0.8905
Epoch 2/7
----------
100%|
train loss: 0.3282 Acc: 0.8849
100%|
val loss: 0.3360 Acc: 0.8977
Epoch 3/7
----------
100%|
train loss: 0.3134 Acc: 0.8883
100%|
val loss: 0.2965 Acc: 0.9033
Epoch 4/7
----------
100%|
train loss: 0.3121 Acc: 0.8884
100%|
val loss: 0.2660 Acc: 0.9156
```

## 6. Conclusions

**In conclusion, model from strategy 3 is the most desirable model**

Model description:

Algorithm: Random Forest (SkLearn implementation)

Number of estimators: 100

Data Augmentation: 3 fold data augmentation of class 2 (road):

1. random_rotation_90
2. random_rotation_75
3. horizontal_flip

2 fold data augmentation of class 5 (grassland):

1. random_rotation_75
2. horizontal_flip

---

The model performed well with an **accuray of 0.9702** with minimum class-wise performance inbalance.

Class-wise precision, recall and fscore:

**precision**, *water*: 0.9959, *trees*: 0.9655, *road*: 0.8835, _barren*land*: 0.9833, *building*: 0.9724, *grassland*: 0.9107

**recall** , *water*: 1.0000, *trees*: 0.9842, *road*: 0.8724, _barren*land*: 0.9460, *building*: 0.9374, *grassland*: 0.9434

**fscore** , *water*: 0.9980, *trees*: 0.9748, *road*: 0.8779, _barren*land*: 0.9643, *building*: 0.9545, *grassland*: 0.9268

## 7. Appendix - all functions and classes contained in seperate .py files

### 7.1 image_augmentation.py

function used in the code above to perform image data augmentation

In [11]:
```
import random
from scipy import ndarray
import skimage as sk
from skimage import util
from math import floor
import cv2
from tqdm import tqdm
import numpy as np


def random_rotation_25(image_array: ndarray):
    # pick a random degree of rotation between 25 on the left and 25 degrees on
the right
    random_degree = random.uniform(-25, 25)
    return(sk.transform.rotate(image_array, random_degree))

def random_rotation_75(image_array: ndarray):
    # pick a random degree of rotation between 26 on the right and 75 degrees o
n the right
    random_degree = random.uniform(26, 75)
    return(sk.transform.rotate(image_array, random_degree))

def random_rotation_90(image_array: ndarray):
    # randomly rotate image of 90 degrees either to the left or to the right
    random_degree = random.choice([-90, 90])
    return(sk.transform.rotate(image_array, random_degree))

def random_noise(image_array: ndarray):
    # add random noise to the image
    return(sk.util.random_noise(image_array))

def horizontal_flip(image_array: ndarray):
    # horizontal flip
    return(image_array[:, ::-1])

def vertical_flip(image_array: ndarray):
    # vertical flip
    return(image_array[::-1, :])

def transpose(image_array: ndarray):
        # transpose the image
        return(image_array[::-1, ::-1])

def zoom(image_array: ndarray):
        # zoom in on the image, maximum zoom: 1.4
        dim = image_array.shape[0]
        zoom_factor = random.uniform(1.01, 1.4)
        zoomed_image = sk.transform.rescale(image_array, zoom_factor)
        crop_border = floor((zoomed_image.shape[0] - dim)/2)
        cropped_image = zoomed_image[crop_border : crop_border + dim, crop_bord
er : crop_border + dim]
        return(cropped_image)

def image_augmentation(image_dirs, fold):
        """
        this function will augment selected images and return it as a vector
        -----
        image_dirs: list of dirs to the images to transform
        fold: the number of times the data is augmented, max = 8
        """

        # check if fold limits are respected
        if fold > 8 or fold < 1:
                return('fold has to be between 1 and 8')

        # convert it to an integer in case where a float was received
        fold = int(fold)
```

### 7.2 custom_dset_alt.py

contains custom dataset class as well as a function to split our image dataset into train, validation and test subsets

In [ ]:
```
import os
import torch
import pandas as pd
from skimage import io, transform
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
import torch.nn as nn
from torchvision import models, transforms, utils
from PIL import Image
from tqdm import tqdm
from torch.optim import Adam
import math


def train_val_test_split(data_dir, train_split, val_split, test_split):
    """
    Split data set into training, validation, and test sets.
    data_dir : path to images folder
    train_split : proportion of the data to be used for training
    val_split : proportion of the data to be used for validation
    test_split : proportion of the data to be used for testing
    """

    # getting the sub folders and getting rid off irrelevant readings
    sub_paths = [os.path.join(data_dir, file_dir) for file_dir in os.listdir(da
ta_dir)]
    sub_paths = [path for path in sub_paths if os.path.isdir(path)]

    # creating a dict to convert string classes into integers that can be conve
rted to tensors
    class_dict = {'water':0, 'trees':1, 'road':2, 'barren_land': 3, 'building':
4, 'grassland':5}

    # creating a dict for all files stored in the different class specific fold
ers
    # the dict contains key-value pairs of the form: full_file_dir: class
    all_files_dict = {}
    for path in sub_paths:
        all_files_dict = {**all_files_dict, **{os.path.join(path, file_name):cl
ass_dict[os.path.split(path)[1]] for file_name in os.listdir(path)}}

    # now sample according to the proportions
    # Size of data set
    N = len(all_files_dict)

    # Size of train set
    train_size = math.floor(train_split * N)

    # Size of validation set
    val_size = math.floor(val_split * N)

    # List of all data indices
    indices = list(range(N))

    # Random selection of indices for train set
    train_ids = np.random.choice(indices, size=train_size, replace=False)
    train_ids = list(train_ids)

    # Deletion of indices used for train set
    indices = list(set(indices) - set(train_ids))

    # Random selection of indices for validation set
    val_ids = np.random.choice(indices, size=val_size, replace=False)
    val_ids = list(val_ids)

    # Selecting remaining indices for test set
    test_ids = list(set(indices) - set(val_ids))
```

### 7.3 pretrain_inceptionv3_alt.py

class for the pretrained torch.vision inception_v3 model

In [ ]:
```
import os
import torch
import pandas as pd
from skimage import io, transform
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
import torch.nn as nn
from torchvision import models, transforms, utils
from PIL import Image
from tqdm import tqdm
from torch.optim import Adam
import math


#-----------------------------------------------------
# the pretrained inception v3 model class
#-----------------------------------------------------

class pretrained_inception_v3(nn.Module):

        def __init__(self, num_class, use_cuda):
                super(pretrained_inception_v3, self).__init__()
                """
                num_class : the total number of classes to predict
                use_cude : if we're using the GPU to compute and optimise
                """

                # setting variables for if we're using the GPU, the number of o
utput classes as well as the tensor dtype
                self.use_cuda = use_cuda
                self.num_class = num_class
                self.dtype = torch.cuda.FloatTensor if self.use_cuda else torch
.FloatTensor

                # we're using the pretrained inceptionv3 model provided by torc
hvision
                model = models.inception_v3(pretrained=True)
                self.model = model.cuda() if self.use_cuda else model

                # freeze all layer weights
                for param in self.model.parameters():
                        param.requires_grad = False

                # modifying the classifier layer
                num_features = self.model.fc.in_features
                self.model.fc = nn.Linear(num_features, num_class)

                # we choose to unfreeze the weights of parameters following(but
not including) the Conv2d_4a_3x3 layer
                # act as a testing mechanism
                ct = []
                # loop through through the layers
                for name, child in self.model.named_children():
                        if "Conv2d_4a_3x3" in ct:
                                for params in child.parameters():
                                        params.requires_grad = True


        def forward(self, inputs):
                return(self.model(inputs))
```

### 7.4 train_alt.py

function for training the CNN

In [ ]:
```
import os
import torch
import pandas as pd
from skimage import io, transform
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
import torch.nn as nn
from torchvision import models, transforms, utils
from PIL import Image
from tqdm import tqdm
from torch.optim import Adam, SGD, lr_scheduler
import math
from torch.utils.data import WeightedRandomSampler
from collections import Counter
import time
from pretrained_inceptionv3_alt import pretrained_inception_v3
from custom_dset_new_alt import custom_dset, train_val_test_split
import pickle


def train(data_dir, save_dir, num_class, num_epoch = 20,\
        bs = 4, lr = 1e-3, use_cuda = False, num_workers = 1,\
        name = 'model', train_prop = 0.7, val_prop = 0.2,
        step_size = 4, gamma = 0.1):
        """
        params:
        data_dir: where the image folder is stored
        save_dir: where the model should be saved after/during training
        number_class: the number of classes to predict
        num_epoch (20 by default): the number of epochs to train
        bs (4 by default): the batch size
        lr (0.001 by default): the starting learning rate
        use_cude(false by default): boolean, wether to use the GPU
        num_workers (1 by dfault): the number of workers to use for the computa
tion,
                                        note that if use_cude = True, it should be set
to equal 1
        name ('model' by default): name of the model when it is saved
        train_prop (0.7 by default): the propotion of the data used for trainni
ng
        val_prop (0.2 by default): the propotion of the data used for validatio
n
        step_size (4 by default): the frequency for learning rate decay
        gamma (0.1 by default): the factor by which the learning rate decays
        """

        # checkpoint beginning time
        begin = time.time()

        # instantiate the vgg model
        model = pretrained_inception_v3(num_class, use_cuda)

        # we check if the save_dir exists, if not, we create it
        if not os.path.isdir(save_dir):
                os.mkdir(save_dir)

        # define the model path
        modelpath = os.path.join(save_dir, '{}.pt'.format(name))

        # in the case of paused training, do we wish to continue training?
        if use_cuda:
                model = model.cuda()

        # setting up the loss and accuracy variables
        loss_record = {'train': np.zeros(num_epoch), 'val': np.zeros(num_epoch)
}
        acc_record = {'train': np.zeros(num_epoch), 'val': np.zeros(num_epoch)}
```

### 7.5 test_alt.py

function for testing model performance

In [ ]:
```
import os
import torch
import pandas as pd
from skimage import io, transform
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
import torch.nn as nn
from torchvision import models, transforms, utils
from PIL import Image
from tqdm import tqdm
from torch.optim import Adam, SGD, lr_scheduler
import math
from torch.utils.data import WeightedRandomSampler
from collections import Counter
import time
from pretrained_inceptionv3_alt import pretrained_inception_v3
from custom_dset_new_alt import custom_dset, train_val_test_split
import pickle


def test(model, test_files, bs):
        """
        model : the model to be tested
        test_files : the directories to the test images, output of the train_va
l_test_split function
        bs : batch size

        """

        # set model to eval mode
        model.eval()

        # cudafy model if specified
        if use_cuda:
                model = model.cuda()

        # recording the running performance and the dataset size
        running_loss = 0.0
        running_corrects = 0
        size = 0

        # set up the loss function
        loss_fun = torch.nn.CrossEntropyLoss(reduction = 'sum')

        # set up the datasets
        dset = custom_dset(data_files = test_files, transform = 'val')

        # set up the dataloader
        dataloader = DataLoader(dset, batch_size = bs, shuffle = True, num_work
ers = 1, pin_memory = False)

        # now iterate over the images to make predictions
        for inputs, labels in tqdm(dataloader):
                # cudafy inputs and labels if specified
                if use_cuda:
                        inputs = inputs.cuda()
                        labels = labels.cuda()
                # counting how many images is contained in this batch
                batch_count = labels.size(0)
                # Forward pass
                output = model(inputs)

                # calculate the loss and prediction performance statistics
                if type(output) == tuple:
                        output, _ = output
                        _, preds = torch.max(output.data, 1)
                        loss = loss_fun(output, labels)
```

### 7.6 execute_train_alt.py

python script used for training the CNN in linux terminal with GPU

In [ ]:
```
from train_alt import train
from custom_dset_new_alt import train_val_test_split, custom_dset
from pretrained_inceptionv3_alt import pretrained_inception_v3


# setting up variables
data_dir = '../../data/images/'
save_dir = '../../data/CNN_model_landtype_alt/'
num_class = 6
bs = 32
name = 'model_alt'
num_epoch = 8
lr = 1e-5
step_size = 4
gamma = 0.2


# run
loss_record, acc_record, model, test_data = train(data_dir = data_dir, save_dir
= save_dir, num_class = 6,

                        num_epoch = num_epoch, bs = bs, lr = lr, step_size = st
ep_size,

                        gamma = gamma, use_cuda = True)
```