Intel Image Classification

March 21, 2020

Importing all the necessary libraries

[1]:
```
import tensorflow.keras.layers as Layers
import tensorflow.keras.activations as Activations
import tensorflow.keras.models as Models
import tensorflow.keras.optimizers as Optimizer
import tensorflow.keras.metrics as Metrics
import tensorflow.keras.utils as Utils
import keras
from keras.preprocessing.image import ImageDataGenerator
import os
import matplotlib.pyplot as plt
import cv2
import numpy as np
import pandas as pd
from sklearn.utils import shuffle
from IPython.display import SVG
import seaborn as sns
```

```
Using TensorFlow backend.
```

Getting Images from the directory

[2]:
```
def get_images(directory):
    Images = []
    Labels = []

    for labels in os.listdir(directory):
        if labels == 'glacier':
            label = 2
        elif labels == 'sea':
            label = 4
        elif labels == 'buildings':
            label = 0
        elif labels == 'forest':
            label = 1
        elif labels == 'street':
            label = 5
        elif labels == 'mountain':
```

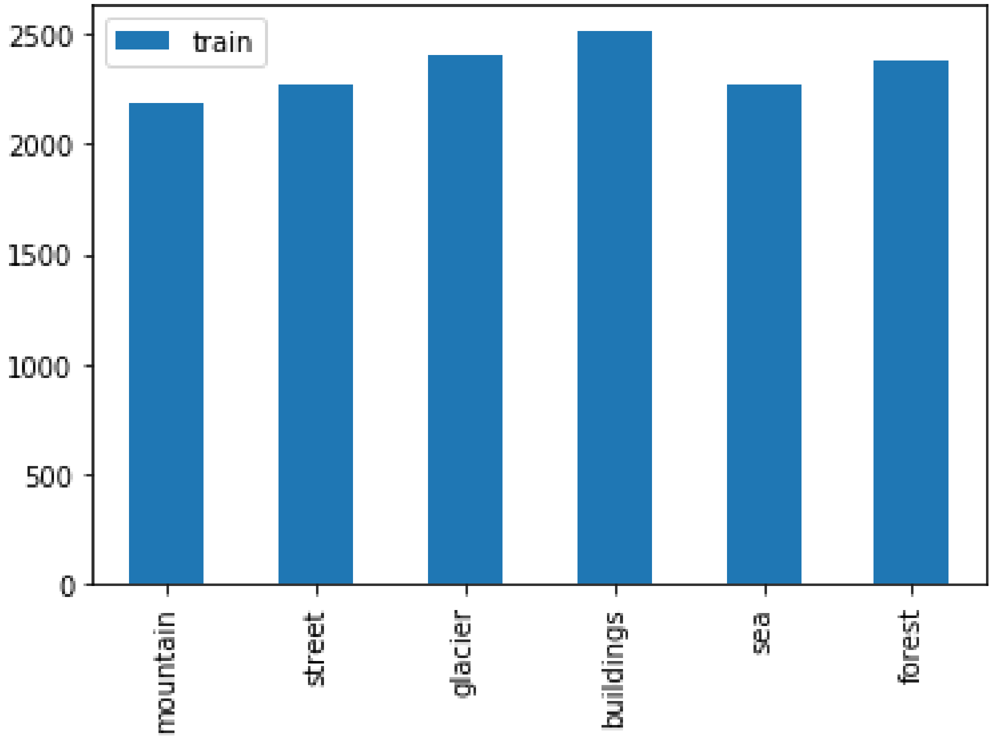
```
            label = 3

        for image_file in os.listdir(directory+'/'+labels):
            image = cv2.imread(directory+ '/'+labels+'/'+image_file)
            image = cv2.resize(image,(150,150))
            Images.append(image)
            Labels.append(label)

    return shuffle(Images,Labels,random_state=1000)
```

[3]:
```
def get_category(x):
    labels = {2:'glacier', 4:'sea', 0:'buildings', 1:'forest', 5:'street', 3:
 ↪'mountain'}
    return labels[x]
```

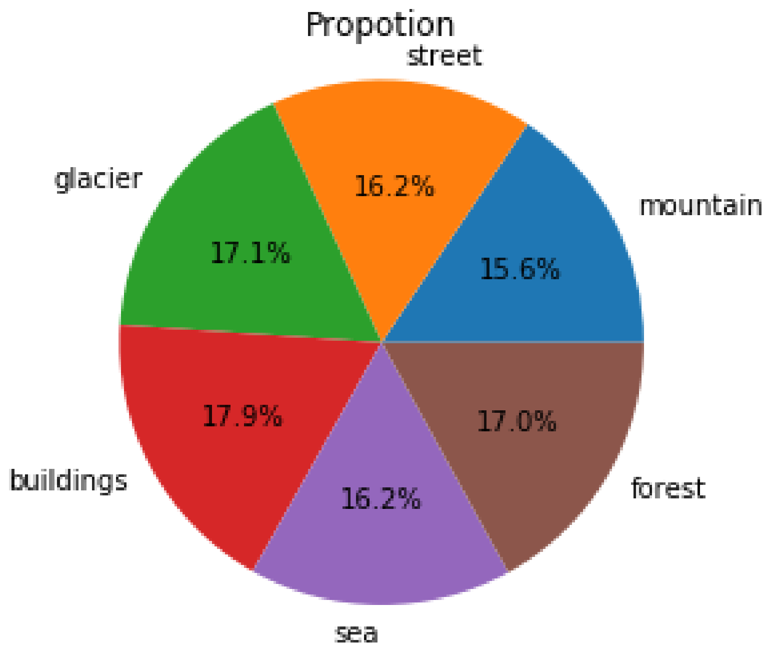
[4]:
```
Images,Labels = get_images('../input/intel-image-classification/seg_train/
 ↪seg_train')
Images = np.array(Images)
Labels = np.array(Labels)
```

Distribution of Images across each category

[5]:
```
category = ['mountain', 'street', 'glacier', 'buildings', 'sea', 'forest']
_,count = np.unique(Labels, return_counts = True)
pd.DataFrame({"train": count}, index = category).plot.bar()
plt.show()
```

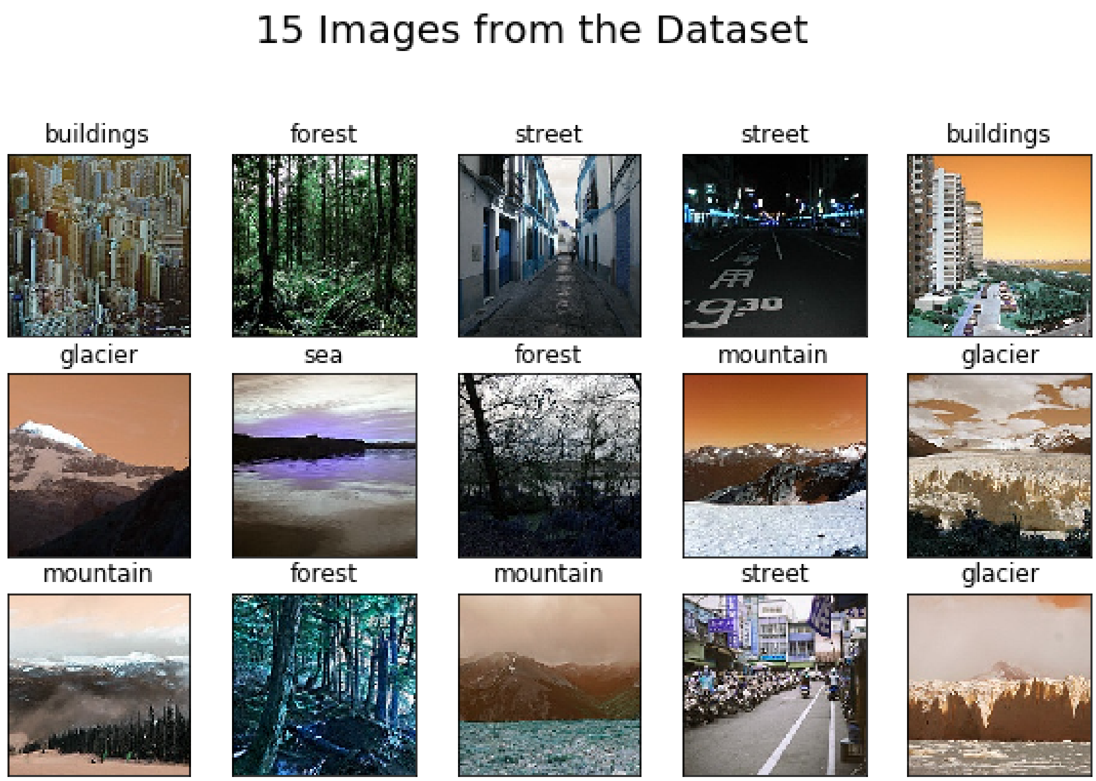


[6]:
```
plt.pie(count,explode=(0, 0, 0, 0, 0, 0),labels = category,autopct='%1.1f%%')
plt.axis('equal')
plt.title("Propotion")
plt.show()
```



[7]:
```
def display_image(image,label):
    fig = plt.figure(figsize = (10,10))
    fig.suptitle('15 Images from the Dataset', fontsize = 20)
    for i in range(15):
        index = np.random.randint(Images.shape[0])
        plt.subplot(5,5,i+1)
        plt.imshow(image[index])
        plt.xticks([]) #Scale doesn't appear
        plt.yticks([]) #Scale doesn't apper
        plt.title(get_category(label[index]))
        plt.grid(False)
    plt.show()
 #Maximum 25 images can only be displayed.
```

[8]:
```
display_image(Images, Labels)
```



[9]:
```
print(Images.shape)
print(Labels.shape)
```

```
(14034, 150, 150, 3)
(14034,)
```

Neural Network Architecture

[10]:
```
model = Models.Sequential()
model.add(Layers.
 ↪Conv2D(256,kernel_size=(3,3),activation='relu',input_shape=(150,150,3)))
model.add(Layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Conv2D(256,kernel_size=(3,3),activation='relu'))
model.add(Layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Conv2D(128,kernel_size=(3,3),activation='relu'))
model.add(Layers.Conv2D(64,kernel_size=(3,3),activation='relu'))
model.add(Layers.MaxPool2D(3,3))
model.add(Layers.Flatten())
model.add(Layers.Dense(180,activation='relu'))
model.add(Layers.Dense(128,activation='relu'))
model.add(Layers.Dense(64,activation='relu'))
```

```python
model.add(Layers.Dropout(rate=0.5))
model.add(Layers.Dense(6,activation='softmax'))
model.compile(optimizer=Optimizer.Adam(lr=0.
 ↪0001),loss='sparse_categorical_crossentropy',metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 256)     7168
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 146, 146, 128)     295040
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 48, 48, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 46, 46, 256)       295168
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 44, 44, 128)       295040
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 12, 12, 128)       147584
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 10, 10, 64)        73792
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 3, 3, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 576)               0
_________________________________________________________________
dense (Dense)                (None, 180)               103860
_________________________________________________________________
dense_1 (Dense)              (None, 128)               23168
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 390
=================================================================
Total params: 1,249,466
Trainable params: 1,249,466
Non-trainable params: 0

_________________________________________________________________
```

Now we will fit the model

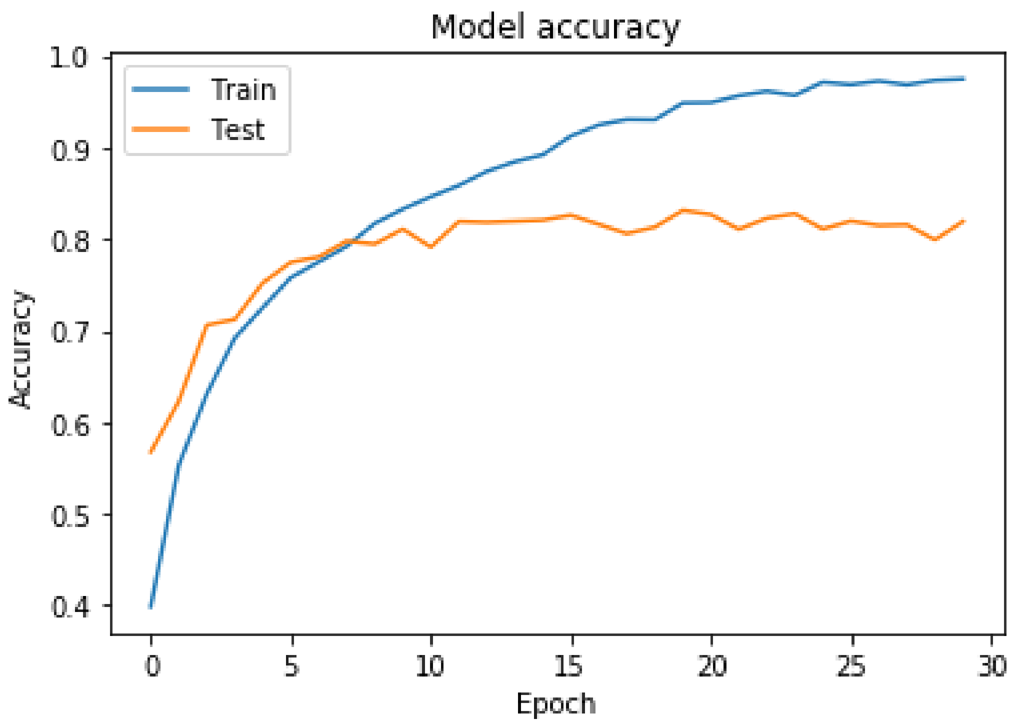
[11]:
```python
trained = model.fit(Images,Labels,epochs=30,validation_split=0.30)
```

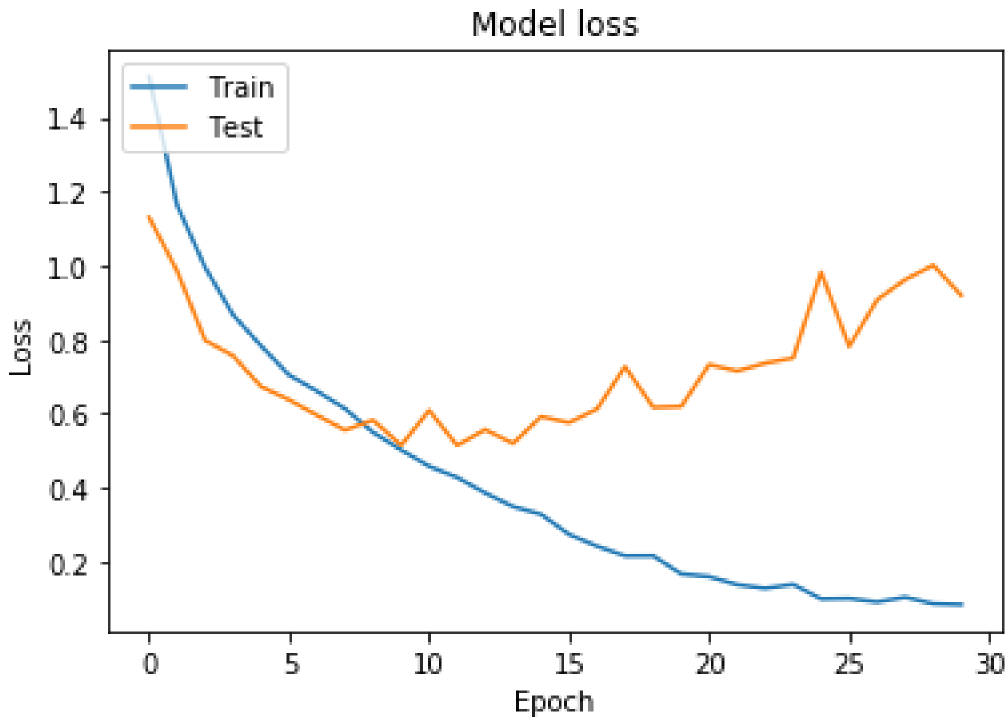
```
Train on 9823 samples, validate on 4211 samples
Epoch 1/30
9823/9823 [==============================] - 48s 5ms/sample - loss: 1.5101 -
accuracy: 0.3988 - val_loss: 1.1299 - val_accuracy: 0.5676
Epoch 2/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 1.1626 -
accuracy: 0.5532 - val_loss: 0.9854 - val_accuracy: 0.6229
Epoch 3/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.9953 -
accuracy: 0.6309 - val_loss: 0.7979 - val_accuracy: 0.7062
Epoch 4/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.8666 -
accuracy: 0.6920 - val_loss: 0.7561 - val_accuracy: 0.7124
Epoch 5/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.7828 -
accuracy: 0.7252 - val_loss: 0.6732 - val_accuracy: 0.7523
Epoch 6/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.7043 -
accuracy: 0.7580 - val_loss: 0.6374 - val_accuracy: 0.7746
Epoch 7/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.6607 -
accuracy: 0.7751 - val_loss: 0.5956 - val_accuracy: 0.7806
Epoch 8/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.6133 -
accuracy: 0.7920 - val_loss: 0.5553 - val_accuracy: 0.7979
Epoch 9/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.5493 -
accuracy: 0.8171 - val_loss: 0.5825 - val_accuracy: 0.7946
Epoch 10/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.5017 -
accuracy: 0.8328 - val_loss: 0.5142 - val_accuracy: 0.8110
Epoch 11/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.4576 -
accuracy: 0.8463 - val_loss: 0.6088 - val_accuracy: 0.7913
Epoch 12/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.4279 -
accuracy: 0.8586 - val_loss: 0.5138 - val_accuracy: 0.8193
Epoch 13/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.3859 -
accuracy: 0.8740 - val_loss: 0.5567 - val_accuracy: 0.8183
Epoch 14/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.3488 -
accuracy: 0.8846 - val_loss: 0.5194 - val_accuracy: 0.8195
Epoch 15/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.3281 -
accuracy: 0.8921 - val_loss: 0.5918 - val_accuracy: 0.8207
Epoch 16/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.2736 -
```

```
accuracy: 0.9126 - val_loss: 0.5755 - val_accuracy: 0.8262
Epoch 17/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.2417 -
accuracy: 0.9248 - val_loss: 0.6126 - val_accuracy: 0.8162
Epoch 18/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.2155 -
accuracy: 0.9307 - val_loss: 0.7270 - val_accuracy: 0.8060
Epoch 19/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.2157 -
accuracy: 0.9304 - val_loss: 0.6171 - val_accuracy: 0.8131
Epoch 20/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1668 -
accuracy: 0.9488 - val_loss: 0.6193 - val_accuracy: 0.8314
Epoch 21/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1598 -
accuracy: 0.9492 - val_loss: 0.7325 - val_accuracy: 0.8269
Epoch 22/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1381 -
accuracy: 0.9567 - val_loss: 0.7151 - val_accuracy: 0.8107
Epoch 23/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1283 -
accuracy: 0.9615 - val_loss: 0.7361 - val_accuracy: 0.8228
Epoch 24/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1389 -
accuracy: 0.9571 - val_loss: 0.7498 - val_accuracy: 0.8278
Epoch 25/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.0996 -
accuracy: 0.9713 - val_loss: 0.9821 - val_accuracy: 0.8110
Epoch 26/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1008 -
accuracy: 0.9686 - val_loss: 0.7813 - val_accuracy: 0.8198
Epoch 27/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.0914 -
accuracy: 0.9725 - val_loss: 0.9073 - val_accuracy: 0.8150
Epoch 28/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.1041 -
accuracy: 0.9684 - val_loss: 0.9621 - val_accuracy: 0.8157
Epoch 29/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.0867 -
accuracy: 0.9733 - val_loss: 1.0009 - val_accuracy: 0.7991
Epoch 30/30
9823/9823 [==============================] - 41s 4ms/sample - loss: 0.0842 -
accuracy: 0.9748 - val_loss: 0.9196 - val_accuracy: 0.8193
```

[12]:
```python
plt.plot(trained.history['accuracy'])
plt.plot(trained.history['val_accuracy'])
plt.title('Model accuracy')
```

```
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

plt.plot(trained.history['loss'])
plt.plot(trained.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```





Overfitting is clearly visible

Using Image Augmentation

[13]:
```
train_generator = ImageDataGenerator(rescale = 1/255, zoom_range = 0.3,␣
 ↪horizontal_flip = True, rotation_range = 30)
train_generator = train_generator.flow(Images, Labels, batch_size = 64, shuffle␣
 ↪= False)
```

[19]:
```
history = model.fit_generator(train_generator, epochs = 30, shuffle = False)
```

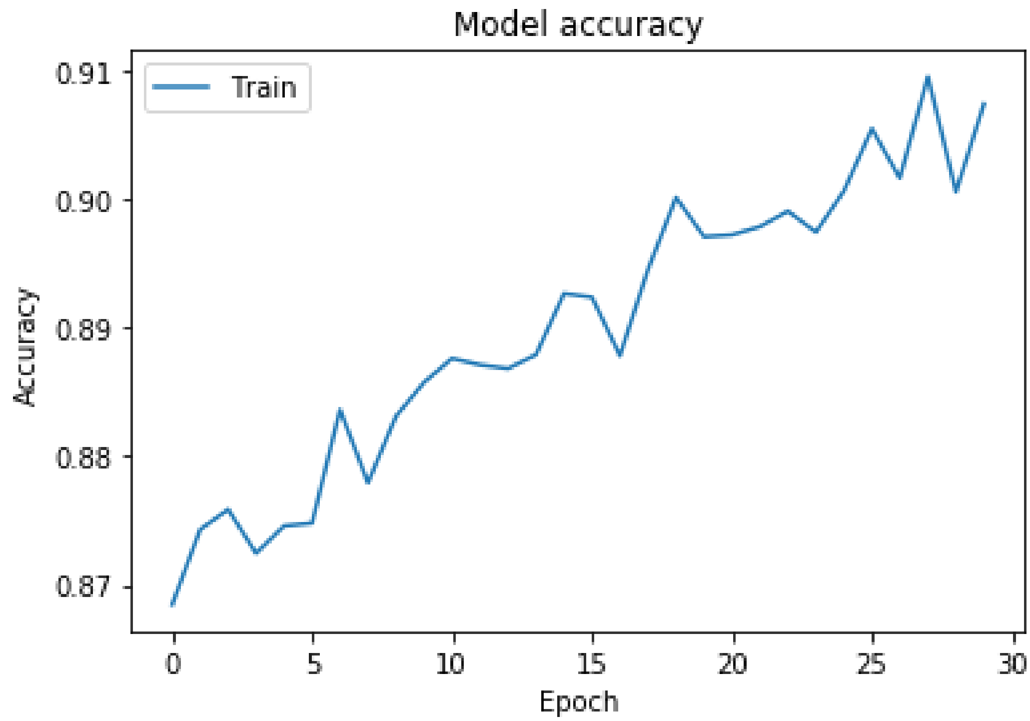
```
Train for 220 steps
Epoch 1/30
220/220 [==============================] - 90s 408ms/step - loss: 0.3852 -
accuracy: 0.8685
Epoch 2/30
220/220 [==============================] - 90s 411ms/step - loss: 0.3757 -
accuracy: 0.8743
Epoch 3/30
220/220 [==============================] - 90s 408ms/step - loss: 0.3744 -
accuracy: 0.8759
Epoch 4/30
220/220 [==============================] - 90s 410ms/step - loss: 0.3869 -
accuracy: 0.8725
Epoch 5/30
```

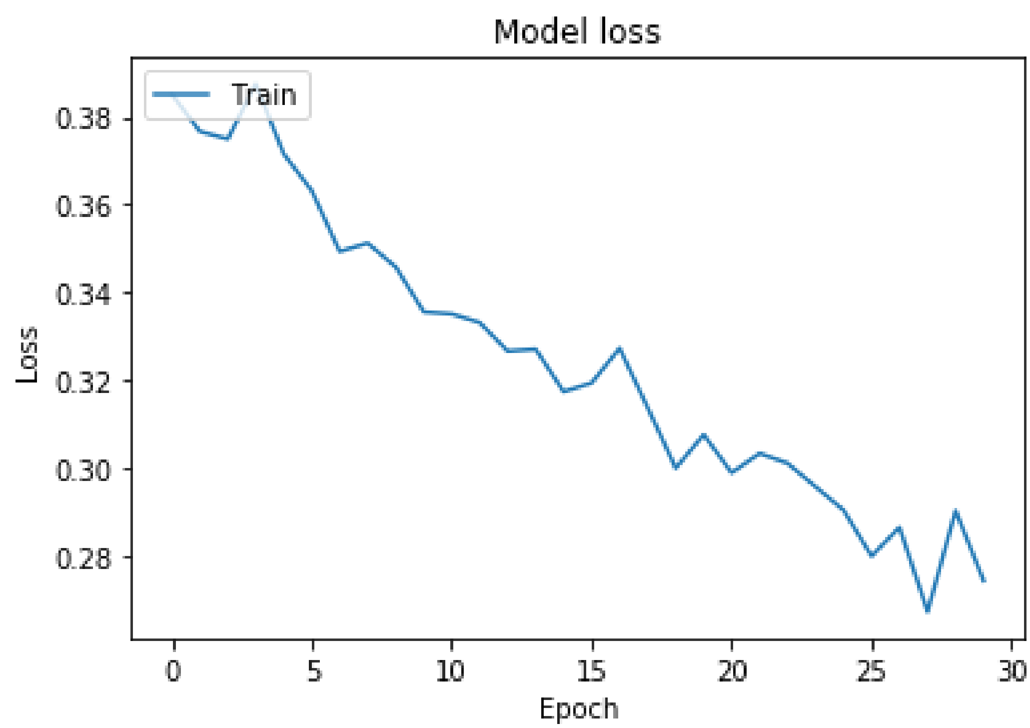
```
220/220 [==============================] - 90s 408ms/step - loss: 0.3709 -
accuracy: 0.8746
Epoch 6/30
220/220 [==============================] - 90s 409ms/step - loss: 0.3626 -
accuracy: 0.8748
Epoch 7/30
220/220 [==============================] - 90s 409ms/step - loss: 0.3487 -
accuracy: 0.8836
Epoch 8/30
220/220 [==============================] - 90s 407ms/step - loss: 0.3509 -
accuracy: 0.8779
Epoch 9/30
220/220 [==============================] - 89s 405ms/step - loss: 0.3451 -
accuracy: 0.8831
Epoch 10/30
220/220 [==============================] - 89s 404ms/step - loss: 0.3348 -
accuracy: 0.8858
Epoch 11/30
220/220 [==============================] - 89s 406ms/step - loss: 0.3343 -
accuracy: 0.8876
Epoch 12/30
220/220 [==============================] - 89s 405ms/step - loss: 0.3327 -
accuracy: 0.8871
Epoch 13/30
220/220 [==============================] - 90s 407ms/step - loss: 0.3258 -
accuracy: 0.8868
Epoch 14/30
220/220 [==============================] - 89s 406ms/step - loss: 0.3263 -
accuracy: 0.8879
Epoch 15/30
220/220 [==============================] - 90s 410ms/step - loss: 0.3170 -
accuracy: 0.8927
Epoch 16/30
220/220 [==============================] - 89s 405ms/step - loss: 0.3188 -
accuracy: 0.8924
Epoch 17/30
220/220 [==============================] - 90s 408ms/step - loss: 0.3265 -
accuracy: 0.8878
Epoch 18/30
220/220 [==============================] - 90s 408ms/step - loss: 0.3129 -
accuracy: 0.8945
Epoch 19/30
220/220 [==============================] - 90s 411ms/step - loss: 0.2991 -
accuracy: 0.9002
Epoch 20/30
220/220 [==============================] - 89s 407ms/step - loss: 0.3069 -
accuracy: 0.8971
Epoch 21/30
```

```
220/220 [==============================] - 90s 408ms/step - loss: 0.2991 -
accuracy: 0.8972
Epoch 22/30
220/220 [==============================] - 89s 406ms/step - loss: 0.3025 -
accuracy: 0.8979
Epoch 23/30
220/220 [==============================] - 90s 408ms/step - loss: 0.3004 -
accuracy: 0.8991
Epoch 24/30
220/220 [==============================] - 89s 403ms/step - loss: 0.2952 -
accuracy: 0.8975
Epoch 25/30
220/220 [==============================] - 90s 408ms/step - loss: 0.2896 -
accuracy: 0.9007
Epoch 26/30
220/220 [==============================] - 89s 405ms/step - loss: 0.2790 -
accuracy: 0.9055
Epoch 27/30
220/220 [==============================] - 90s 408ms/step - loss: 0.2858 -
accuracy: 0.9017
Epoch 28/30
220/220 [==============================] - 89s 404ms/step - loss: 0.2668 -
accuracy: 0.9096
Epoch 29/30
220/220 [==============================] - 90s 408ms/step - loss: 0.2897 -
accuracy: 0.9006
Epoch 30/30
220/220 [==============================] - 89s 405ms/step - loss: 0.2735 -
accuracy: 0.9074
```

[20]:

```
plt.plot(history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train'], loc='upper left')
plt.show()
```


Model accuracy
Train
0.91
0.90
0.89
0.88
0.87
Accuracy
0
5
10
15
20
25
30
Epoch


Model loss
Train
0.38
0.36
0.34
0.32
0.30
0.28
Loss
0
5
10
15
20
25
30
Epoch

[21]:
```
test_Images,test_Labels = get_images('../input/intel-image-classification/
 ↪seg_test/seg_test')
test_Images = np.array(test_Images)
test_Labels = np.array(test_Labels)
```

[22]:
```
test_generator = ImageDataGenerator(rescale = 1/255)
test_generator = test_generator.flow(test_Images, test_Labels, batch_size = 64,␣
 ↪shuffle = False)
```

[23]:
```
evaluate = model.evaluate(test_Images, test_Labels, verbose = 1)
```

```
3000/3000 [==============================] - 4s 1ms/sample - loss: 78.3051 -
accuracy: 0.6893
```

[24]:
```
print( "Accuracy: "  + str(evaluate[1] * 100) + "%")
```

```
Accuracy: 68.93333196640015%
```

[25]:
```
evaluate2 = model.evaluate_generator(test_generator, verbose = 1)
```

```
47/47 [==============================] - 4s 95ms/step - loss: 0.3805 - accuracy:
0.8807
```

[26]:
```
print("Accuracy:" + str(evaluate2[1] * 100) + "%")
```

```
Accuracy:88.06666731834412%
```

[27]:
```
def get_pred(directory):
    Images = []
    Labels = []
    label = 0

    for image_file in os.listdir(directory):
        image = cv2.imread(directory+ '/' +image_file)
        image = cv2.resize(image,(150,150))
        Images.append(image)
        Labels.append(label)

    return shuffle(Images,Labels,random_state=1000)
```

[28]:
```
pred_Images,pred_Labels = get_pred("../input/intel-image-classification/
 ↪seg_pred/seg_pred")
pred_Images = np.array(pred_Images)
```

[29]:
```
print(pred_Images.shape)
```

```
(7301, 150, 150, 3)
```

[30]:
```
pred_generator = ImageDataGenerator(rescale = 1/255)
pred_generator = pred_generator.flow(pred_Images, batch_size = 64, shuffle =␣
↪False)
```

[31]:
```
prediction = model.predict_generator(pred_generator, verbose=1)
```

```
115/115 [==============================] - 10s 86ms/step
```

[32]:
```
prediction.shape
```

[32]:
```
(7301, 6)
```