Find a car Park using CNN

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In this project we propose to develop a model for identifying whether there is free space in theparking lot image, or whether the parking is full using CNN.

Code & Explanations:

Import all the necessary libraries:

We have used Python libraries:

- tensorflow v1
- sklearn

In [1]:
```
import tensorflow.compat.v1 as tf
# tf.disable_v2_behavior()
# import tensorflow as tf
import cv2
import os
from tqdm import tqdm
import numpy as np
import random as rn

from __future__ import division, print_function, absolute_import

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix
from sklearn import metrics


import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

rs = 42 # random seed
```

fix random seed:

In [2]:
```
np.random.seed(rs)
rn.seed(rs)
tf.set_random_seed(rs)
```

import the data:

In [3]:
```
X = []
Z = []
IMG_SIZE=160

FREE_DIR='/home/ido/Desktop/Find-a-Car-Park/data/Free'
FULL_DIR='/home/ido/Desktop/Find-a-Car-Park/data/Full'
```

In [4]:
```
def make_train_data(label,DIR):
    for img in tqdm(os.listdir(DIR)):
        path = os.path.join(DIR,img)
        img = plt.imread(path)
        img = cv2.resize(img, (IMG_SIZE, IMG_SIZE))
#         img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
        np_img=np.asarray(img)
        X.append(np_img)
        Z.append(str(label))
```

In [5]:
```
# make 'Full' data
make_train_data('Full',FULL_DIR)
print(len(X))
```

```
100%|██████████| 2195/2195 [00:20<00:00, 105.07it/s]
2195
```

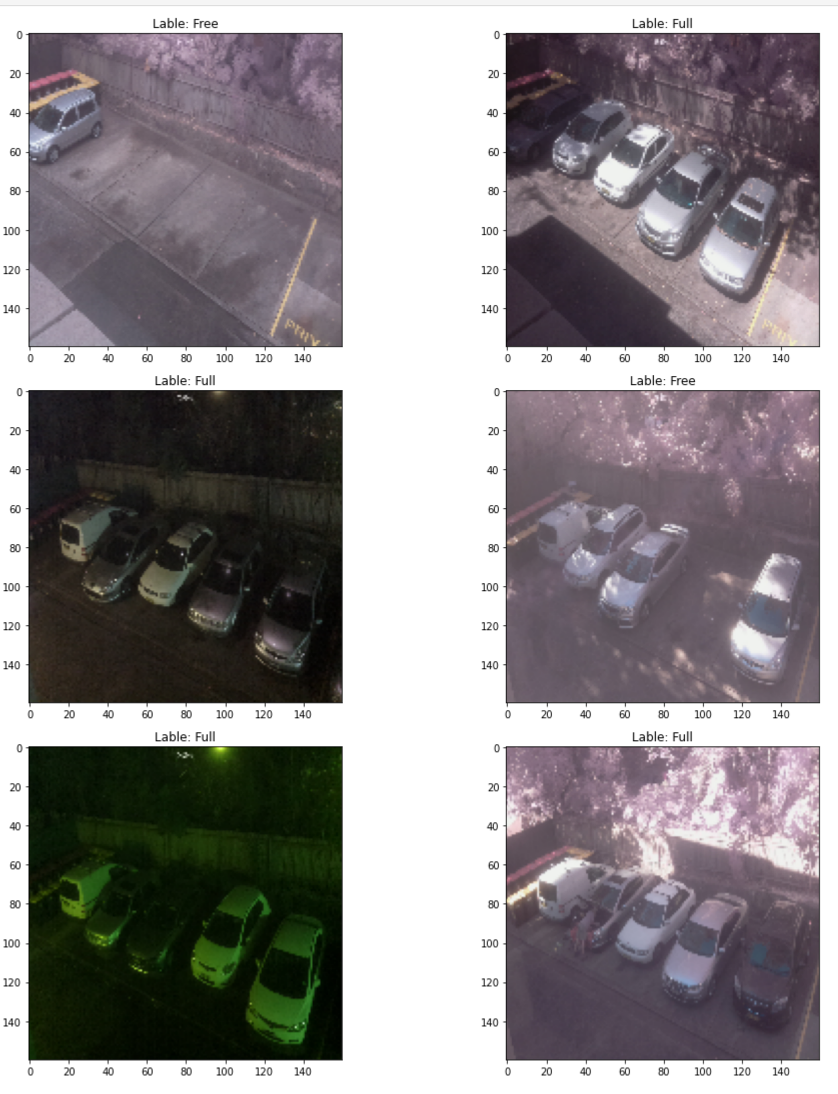
In [6]:
```
# make 'Free' data
make_train_data('Free',FREE_DIR)
print(len(X))
```

```
100%|██████████| 1067/1067 [00:09<00:00, 109.37it/s]
3262
```

The description of the data:

1. Number of instances: 722
2. Number of attributes: 150 *150* 3 = 67500

In [7]:
```
# check some image
fig,ax=plt.subplots(3,2)
fig.set_size_inches(15,15)
for i in range(3):
    for j in range (2):
        l=rn.randint(0,len(Z))
        ax[i,j].imshow(X[l])
        ax[i,j].set_title('Lable: '+Z[l])

plt.tight_layout()
```



Label encoding of the target:

'Full' = 0

'Free' = 1

In [8]:
```
Y = np.array(Z)
Y = np.where(Y=='Full', 0, Y)
Y = np.where(Y=='Free', 1, Y)
Y = Y.astype('int32')
```

normalization and flatten the images:

In [9]:
```
X = np.array([cv2.normalize(X[i], None, 0, 255, cv2.NORM_MINMAX) for i in range(len(X))]) # normalization
X=np.array(X)/255
X = X.flatten().reshape(len(X), (IMG_SIZE ** 2) * 3) # 3 is because it is RGB image
# X = X.flatten().reshape(len(X), (IMG_SIZE ** 2))
```

our dataset:

In [10]:
```
df = pd.DataFrame(data=X)
df
```

Out[10]:

	0	1	2	3	4	5	6	7	8	9	...	76790	76791	76792	76793	76794	76795	76796	76797	76798	76799
0	0.298039	0.168627	0.243137	0.270588	0.164706	0.219608	0.266667	0.160784	0.203922	0.270588	...	0.952941	0.917647	0.933333	0.960784	0.219608	0.203922	0.282353	0.160784	0.141176	0.207843
1	0.466667	0.337255	0.368627	0.501961	0.368627	0.400000	0.494118	0.337255	0.384314	0.478431	...	0.219608	0.372549	0.243137	0.215686	0.341176	0.207843	0.196078	0.321569	0.192157	0.184314
2	0.313725	0.200000	0.258824	0.309804	0.219608	0.247059	0.266667	0.156863	0.207843	0.262745	...	0.360784	0.290196	0.247059	0.152941	0.215686	0.172549	0.086275	0.333333	0.266667	0.215686
3	0.560784	0.360784	0.454902	0.635294	0.419608	0.525490	0.698039	0.458824	0.588235	0.596078	...	0.243137	0.215686	0.149020	0.196078	0.164706	0.094118	0.149020	0.247059	0.168627	0.207843
4	0.227451	0.184314	0.239216	0.207843	0.164706	0.239216	0.223529	0.188235	0.239216	0.215686	...	0.172549	0.454902	0.533333	0.537255	0.623529	0.796078	0.796078	0.772549	0.945098	0.933333
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3257	0.541176	0.384314	0.482353	0.568627	0.400000	0.490196	0.533333	0.376471	0.470588	0.541176	...	0.368627	0.368627	0.301961	0.356863	0.372549	0.301961	0.352941	0.368627	0.282353	0.317647
3258	0.278431	0.168627	0.207843	0.274510	0.168627	0.192157	0.419608	0.313725	0.329412	0.258824	...	0.180392	0.192157	0.192157	0.243137	0.223529	0.223529	0.278431	0.254902	0.243137	0.309804
3259	0.541176	0.403922	0.450980	0.552941	0.407843	0.462745	0.517647	0.368627	0.423529	0.513725	...	0.290196	0.294118	0.215686	0.266667	0.258824	0.172549	0.235294	0.203922	0.109804	0.160784
3260	0.388235	0.274510	0.356863	0.466667	0.333333	0.403922	0.458824	0.329412	0.403922	0.466667	...	0.333333	0.345098	0.290196	0.309804	0.298039	0.254902	0.266667	0.266667	0.219608	0.223529
3261	0.109804	0.027451	0.082353	0.133333	0.050980	0.109804	0.180392	0.121569	0.168627	0.160784	...	0.368627	0.372549	0.341176	0.352941	0.364706	0.321569	0.345098	0.349020	0.305882	0.325490

3262 rows × 76800 columns

We can see that the size of an image is 150 * 150 * 3 = 67500 that later it would be our featrues in our models.

In [11]:
```
X.shape
```

Out[11]:
```
(3262, 76800)
```

Train-Test Split:

In [12]:
```
# separate data
X_train,X_test,y_train,y_test=train_test_split(X,Y,test_size=0.20,random_state=rs, shuffle=True)

freqs = pd.DataFrame({"Training dataset": [(y_train == 1).sum(),(y_train == 0).sum()],
                      "Test dataset": [(y_test == 1).sum(),(y_test == 0).sum()],
                      "Total": [(y_train == 1).sum()+(y_test == 1).sum(),(y_train == 0).sum()+(y_test == 0).sum()]},
                     index=["Free", "Full"])
freqs[["Training dataset", "Test dataset", "Total"]]
```

Out[12]:

	Training dataset	Test dataset	Total
Free	863	204	1067
Full	1746	449	2195

We'll build a classifier with two classes: "full", so we create the according labels.

In [13]:
```
labels_train = (np.arange(2) == y_train[:,None]).astype(np.float32)
labels_test = (np.arange(2) == y_test[:,None]).astype(np.float32)
```

In [14]:
```
def statistics(confusion):
    TP = sess.run(confusion[1, 1])
    TN = sess.run(confusion[0, 0])
    FP = sess.run(confusion[0, 1])
    FN = sess.run(confusion[1, 0])
    print('True Positives (TP):',TP)
    print('True Negatives (TN):',TN)
    print('False Positives (FP):',FP)
    print('False Negarives (FN):',FN)
    print('Classification Accuracy:',(TP + TN) / float(TP + TN + FP + FN))
    precision = TP / float(TP + FP)
    print('Precision:',precision)
    recall = TP / float(TP + FN)
    print('Recall:', recall)
    print('f-score:', 2 * precision * recall / (precision + recall))
```

Begin building the CNN model using tensorflow:

1. Define the requires training parameters:
   - learning rate
   - batch_size
   - number of iteration

In [83]:
```
learning_rate = 0.001
num_steps = 440
batch_size = 128
display_step = 10
channels = 3 # RGB
```

1. Define the requires network parameters
   - input size
   - classes number
   - dropout

In [84]:
```
num_input = IMG_SIZE * IMG_SIZE * channels
num_classes = 2
dropout = 0.8 # Dropout, probability to keep units
```

1. Define placeholders

In [85]:
```
tf.compat.v1.disable_eager_execution()

X = tf.placeholder(tf.float32, [None, num_input])
Y = tf.placeholder(tf.float32, [None, num_classes])
keep_prob = tf.placeholder(tf.float32) # dropout (keep probability)
```

1. Define the structure of the net.

In [86]:
```
weights = {
    # 5x5 conv, 1 input, 32 outputs
    'wc1': tf.Variable(tf.random_normal([5, 5, channels, 32])),
    # 3x3 conv, 32 inputs, 64 outputs
    'wc2': tf.Variable(tf.random_normal([3, 3, 32 , 64])),
    # 3x3 conv, 32 inputs, 64 outputs
    #'wc3': tf.Variable(tf.random_normal([3, 3, 64 , 96])),
    # fully connected, 10*10*96 inputs, 512 outputs
    'wd1': tf.Variable(tf.random_normal([40*40*64 , 1024])),
    # 1024 inputs, 2 outputs (class prediction)
    'out': tf.Variable(tf.random_normal([1024, num_classes]))
}

biases = {
    'bc1': tf.Variable(tf.random_normal([32])),
    'bc2': tf.Variable(tf.random_normal([64])),
    #'bc3': tf.Variable(tf.random_normal([96])),
    'bd1': tf.Variable(tf.random_normal([1024])),
    'out': tf.Variable(tf.random_normal([num_classes]))
}
```

1. Create some wrappers for simplicity and the CNN model

In [87]:
```
def conv2d(x, W, b, strides=1):
    # Conv2D wrapper, with bias and relu activation
    x = tf.nn.conv2d(x, W, strides=[1, strides, strides, 1], padding='SAME')
    x = tf.nn.bias_add(x, b)
    return tf.nn.relu(x)


def maxpool2d(x, k=2):
    # MaxPool2D wrapper
    return tf.nn.max_pool(x, ksize=[1, k, k, 1], strides=[1, k, k, 1], padding='SAME')
```

- Create model:

In [88]:
```
def conv_net(x, weights, biases, dropout):
    # Reshape to match picture format [Height x Width x Channel]
    # Tensor input become 4-D: [Batch Size, Height, Width, Channel]
    x = tf.reshape(x, shape=[-1, IMG_SIZE, IMG_SIZE, channels])

    # Convolution Layer
    conv1 = conv2d(x, weights['wc1'], biases['bc1'])
    # Max Pooling (sub-sampling)
    conv1 = maxpool2d(conv1, k=2)

    # Convolution Layer
    conv2 = conv2d(conv1, weights['wc2'], biases['bc2'])
    # Max Pooling (sub-sampling)
    conv2 = maxpool2d(conv2, k=2)

#     # Convolution Layer
#     conv3 = conv2d(conv2, weights['wc3'], biases['bc3'])
#     # Max Pooling (sub-sampling)
#     conv3 = maxpool2d(conv3, k=2)

    # Fully connected layer
    # Reshape conv2 output to fit fully connected layer input
    fc1 = tf.reshape(conv2, [-1, weights['wd1'].get_shape().as_list()[0]])
    fc1 = tf.add(tf.matmul(fc1, weights['wd1']), biases['bd1'])
    fc1 = tf.nn.relu(fc1)
    # Apply Dropout
    fc1 = tf.nn.dropout(fc1, dropout)

    # Output, class prediction
    out = tf.add(tf.matmul(fc1, weights['out']), biases['out'])
    return out
```

Construct model

In [89]:
```
logits = conv_net(X, weights, biases, keep_prob)
prediction = tf.nn.softmax(logits)
```

1. Loss function and optimizer (Back Propagation):

In [90]:
```
# loss = tf.reduce_mean(tf.nn.weighted_cross_entropy_with_logits(logits=logits, labels=Y, pos_weight=3))
loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(logits=logits, labels=Y))
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate).minimize(loss)
```

1. Evaluate model

In [91]:
```
predict = tf.argmax(logits, axis=1)
correct_pred = tf.equal(tf.argmax(prediction, 1), tf.argmax(Y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
```

1. Open session and initialize the variables

In [92]:
```
sess = tf.InteractiveSession()
init = tf.global_variables_initializer()
sess.run(init)
```

End of the definition of the model framework

In [93]:
```
# Define the variable that saves the result
loss_trace = []
train_acc = []
test_acc = []
```

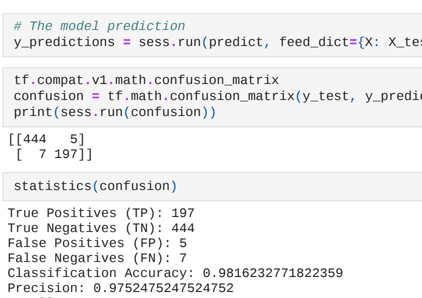
Start training the CNN model:

In [94]:
```
for step in range(1, num_steps+1):
    # Generate random batch index
    batch_index = np.random.choice(len(X_train), size=batch_size)
    batch_x = X_train[batch_index]
    batch_y = labels_train[batch_index]

    # Run optimization op (backprop)
    sess.run(optimizer, feed_dict={X: batch_x, Y: batch_y, keep_prob: dropout})

    # Calculate batch loss and accuracy
    loss_temp, temp_train_acc = sess.run([loss, accuracy], feed_dict={X: batch_x, Y: batch_y, keep_prob: 1.0})
    temp_test_acc = sess.run(accuracy, feed_dict={X: X_test, Y: labels_test, keep_prob: 1.0})
    if step % display_step == 0 or step == 1:
        print("Step " + str(step) + ", Loss= " + \
              "{:.4f}".format(loss_temp) + ", Training Accuracy= " + \
              "{:.3f}".format(temp_train_acc) + ", Test Accuracy= " + \
             "{:.3f}".format(temp_test_acc))

    # recode the result
    loss_trace.append(loss_temp)
    train_acc.append(temp_train_acc)
    test_acc.append(temp_test_acc)


print("Optimization Finished!")

# Calculate accuracy
print("Testing Accuracy:", \
    sess.run(accuracy, feed_dict={X: X_test,
                                  Y: labels_test,
                                  keep_prob: 1.0}))
```

```
Step 1, Loss= 143368.7656, Training Accuracy= 0.438, Test Accuracy= 0.312
Step 10, Loss= 35572.5352, Training Accuracy= 0.719, Test Accuracy= 0.732
Step 20, Loss= 20809.5234, Training Accuracy= 0.773, Test Accuracy= 0.783
Step 30, Loss= 14389.7031, Training Accuracy= 0.773, Test Accuracy= 0.824
Step 40, Loss= 7380.9180, Training Accuracy= 0.867, Test Accuracy= 0.839
Step 50, Loss= 4785.9756, Training Accuracy= 0.906, Test Accuracy= 0.809
Step 60, Loss= 5141.4932, Training Accuracy= 0.883, Test Accuracy= 0.881
Step 70, Loss= 6839.3911, Training Accuracy= 0.883, Test Accuracy= 0.873
Step 80, Loss= 1514.0216, Training Accuracy= 0.945, Test Accuracy= 0.891
Step 90, Loss= 1821.5341, Training Accuracy= 0.930, Test Accuracy= 0.894
Step 100, Loss= 1871.1790, Training Accuracy= 0.953, Test Accuracy= 0.911
Step 110, Loss= 1744.6630, Training Accuracy= 0.969, Test Accuracy= 0.923
Step 120, Loss= 1121.2007, Training Accuracy= 0.984, Test Accuracy= 0.936
Step 130, Loss= 1762.5992, Training Accuracy= 0.953, Test Accuracy= 0.934
Step 140, Loss= 1002.4485, Training Accuracy= 0.969, Test Accuracy= 0.943
Step 150, Loss= 214.4030, Training Accuracy= 0.984, Test Accuracy= 0.948
Step 160, Loss= 923.7325, Training Accuracy= 0.953, Test Accuracy= 0.923
Step 170, Loss= 703.9041, Training Accuracy= 0.977, Test Accuracy= 0.945
Step 180, Loss= 436.4450, Training Accuracy= 0.969, Test Accuracy= 0.936
Step 190, Loss= 372.4407, Training Accuracy= 0.984, Test Accuracy= 0.959
Step 200, Loss= 495.5238, Training Accuracy= 0.984, Test Accuracy= 0.957
Step 210, Loss= 134.1483, Training Accuracy= 0.992, Test Accuracy= 0.942
Step 220, Loss= 252.8299, Training Accuracy= 0.984, Test Accuracy= 0.969
Step 230, Loss= 232.1905, Training Accuracy= 0.984, Test Accuracy= 0.974
Step 240, Loss= 270.1645, Training Accuracy= 0.984, Test Accuracy= 0.979
Step 250, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.975
Step 260, Loss= 210.2519, Training Accuracy= 0.992, Test Accuracy= 0.971
Step 270, Loss= 15.4675, Training Accuracy= 0.992, Test Accuracy= 0.972
Step 280, Loss= 124.6720, Training Accuracy= 0.992, Test Accuracy= 0.972
Step 290, Loss= 124.5172, Training Accuracy= 0.984, Test Accuracy= 0.972
Step 300, Loss= 110.0144, Training Accuracy= 0.992, Test Accuracy= 0.977
Step 310, Loss= 341.0543, Training Accuracy= 0.984, Test Accuracy= 0.953
Step 320, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.979
Step 330, Loss= 186.5920, Training Accuracy= 1.000, Test Accuracy= 0.971
Step 340, Loss= 55.2260, Training Accuracy= 0.992, Test Accuracy= 0.979
Step 350, Loss= 28.3722, Training Accuracy= 1.000, Test Accuracy= 0.977
Step 360, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.979
Step 370, Loss= 115.1279, Training Accuracy= 0.992, Test Accuracy= 0.974
Step 380, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.971
Step 390, Loss= 43.8276, Training Accuracy= 0.992, Test Accuracy= 0.971
Step 400, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.982
Step 410, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.979
Step 420, Loss= 12.0338, Training Accuracy= 1.000, Test Accuracy= 0.979
Step 430, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.982
Step 440, Loss= 0.0000, Training Accuracy= 1.000, Test Accuracy= 0.982
Optimization Finished!
Testing Accuracy: 0.9816233
```

Visualization of the loss function results:

In [95]:
```
plt.plot(loss_trace)
plt.title('Cross Entropy Loss')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.show()
```



We can see that the loss value reduce during the train, there's a graph that shows that.

In [96]:
```
# The model prediction
y_predictions = sess.run(predict, feed_dict={X: X_test, Y: labels_test, keep_prob: 1.0})
```

In [97]:
```
tf.compat.v1.math.confusion_matrix
confusion = tf.math.confusion_matrix(y_test, y_predictions, num_classes=2, dtype=tf.int32)
print(sess.run(confusion))
```

```
[[444   5]
 [  7 197]]
```

In [98]:
```
statistics(confusion)
```

```
True Positives (TP): 197
True Negatives (TN): 444
False Positives (FP): 5
False Negarives (FN): 7
Classification Accuracy: 0.9816232771822359
Precision: 0.9752475247524752
Recall: 0.9656862745098039
f-score: 0.9704433497536946
```

The results indicate that the model could not recognize a lot of free parking spot because of the recall but when it did the precision was high.

In [99]:
```
sess.close()
```