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DriverdistractionML

January 11, 2022

1 Detection of distracted driver using Convolutional Neural Networks

1.0.1 Introduction

In this project, the detection of distracted driver with Machine Learning using Convolutional Neural Networks was analysed and predicted.

1.0.2 Dataset description

The dataset had set of training and test images. The training data splitted into ten classes from c0 to c9. The 10 classes to predict are:

```
c0: normal driving
c1: texting - right
c2: talking on the phone - right
c3: texting - left
c4: talking on the phone - left
c5: operating the radio
c6: drinking
c7: reaching behind
c8: hair and makeup
c9: talking to passenger
```

Along with the set of images, two csv files were presented to assist our project. One with the details about the name of the images along with the class and another sample csv to show the submission format of the project.

1.0.3 Libraries

The libraries were imported to support our project. The assistance of tensorflow and keras is vital to proceed ahead. With matplot to plot charts and pandas to perform csv read and write operations.

[1]:
```
import os
from os.path import join
import tensorflow as tf
import keras_preprocessing
from keras_preprocessing import image
from keras_preprocessing.image import ImageDataGenerator
```

```
import matplotlib.pyplot as plt
import pandas as pd
```

1.0.4 Model

The Convolutional Neural Network was constructed with input size of (100,100) with the '3' represents 'rgb' format of the image. With Batch normalization, we can standardize the data in between convolutional layers. Maxpooling is to find out the maximum value from the region covered by filter and the data will be converted to one dimensional array using flatten and dropout will help us to prevent overfitting. The dense layers were added to improve efficiency and with the final dense layer represents output with 10 classes. The optimizer 'adam' was used to compile the model.

[2]:
```
cnnmodel = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(100, 100,␣
 ↪3)),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu', padding = 'same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu', padding = 'same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu', padding = 'same'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1024, activation='relu'),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
    ])
cnnmodel.compile(loss = 'categorical_crossentropy', optimizer = 'adam', metrics␣
 ↪= ['accuracy'])
cnnmodel.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 98, 98, 32)        896
_________________________________________________________________
batch_normalization (BatchNo (None, 98, 98, 32)        128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 49, 49, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 49, 49, 64)        18496
_________________________________________________________________
batch_normalization_1 (Batch (None, 49, 49, 64)        256
```

```
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 49, 49, 64)        36928
_________________________________________________________________
batch_normalization_2 (Batch (None, 49, 49, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 24, 24, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 24, 24, 128)       73856
_________________________________________________________________
batch_normalization_3 (Batch (None, 24, 24, 128)       512
_________________________________________________________________
flatten (Flatten)            (None, 73728)             0
_________________________________________________________________
dropout (Dropout)            (None, 73728)             0
_________________________________________________________________
dense (Dense)                (None, 1024)              75498496
_________________________________________________________________
dense_1 (Dense)              (None, 512)               524800
_________________________________________________________________
dense_2 (Dense)              (None, 10)                5130
=================================================================
Total params: 76,159,754
Trainable params: 76,159,178
Non-trainable params: 576
_________________________________________________________________
```

1.0.5 Data preprocessing

The working directory was set to acccess the folder contains training images.

[3]:
```
workingdir = os.path.abspath('')
trainingdirectory = os.path.join(workingdir + '/
↪state-farm-distracted-driver-detection/imgs/train/')
```

1.0.6 Train and validation dataset split

Image generator was built to get access of images from the training folder. The data augumentation was used to generalize the model with horizontal flip, width and heigth shift range and rotation range. To improve the model, the training data were splitted into training and validation data in the ratio of 80:20. From the generator, the training and validation set can be accessed in the batch size of 64.

[4]:
```
trainingdataimage = ImageDataGenerator(rescale = 1./255, rotation_range = 40,␣
↪width_shift_range = 0.2,
                                       height_shift_range = 0.2, shear_range =␣
↪0.2, zoom_range = 0.2,
                                       horizontal_flip = True, fill_mode =␣
↪'nearest', validation_split = 0.2)
trainingset = trainingdataimage.flow_from_directory(trainingdirectory,
```

```
                                                            target_size = (100,␣
 ↪100), batch_size = 64,
                                                            class_mode =␣
 ↪'categorical', subset = 'training', shuffle = True)
validationset = trainingdataimage.flow_from_directory(trainingdirectory,
                                                            target_size = (100,␣
 ↪100), batch_size = 64,
                                                            class_mode =␣
 ↪'categorical', subset = 'validation', shuffle = True)
```

```
Found 17943 images belonging to 10 classes.
Found 4481 images belonging to 10 classes.
```

1.0.7 Model fit

The training and validation images made to fit with the CNN model on 60 iterations with steps per iteration will be length of the image generator of training set and length of image generator of validation set was denoted as validation steps.

[5]:
```
history =  cnnmodel.fit(trainingset, epochs = 60, steps_per_epoch =␣
 ↪len(trainingset),
                              validation_data = validationset, verbose = 1,␣
 ↪validation_steps = len(validationset))
```

```
Epoch 1/60
281/281 [==============================] - 114s 391ms/step - loss: 2.3757 -
accuracy: 0.1876 - val_loss: 9.6513 - val_accuracy: 0.1033
Epoch 2/60
281/281 [==============================] - 110s 389ms/step - loss: 1.7734 -
accuracy: 0.3377 - val_loss: 2.3622 - val_accuracy: 0.2540
Epoch 3/60
281/281 [==============================] - 110s 391ms/step - loss: 1.4419 -
accuracy: 0.4602 - val_loss: 1.5239 - val_accuracy: 0.4300
Epoch 4/60
281/281 [==============================] - 109s 389ms/step - loss: 1.1783 -
accuracy: 0.5696 - val_loss: 1.1394 - val_accuracy: 0.5876
Epoch 5/60
281/281 [==============================] - 110s 390ms/step - loss: 0.9663 -
accuracy: 0.6582 - val_loss: 1.4248 - val_accuracy: 0.5242
Epoch 6/60
281/281 [==============================] - 110s 392ms/step - loss: 0.7862 -
accuracy: 0.7288 - val_loss: 0.9391 - val_accuracy: 0.6800
Epoch 7/60
281/281 [==============================] - 110s 390ms/step - loss: 0.6675 -
accuracy: 0.7702 - val_loss: 1.0366 - val_accuracy: 0.6637
Epoch 8/60
281/281 [==============================] - 110s 392ms/step - loss: 0.5899 -
accuracy: 0.8018 - val_loss: 0.7342 - val_accuracy: 0.7581
```

```
Epoch 9/60
281/281 [==============================] - 110s 391ms/step - loss: 0.5231 -
accuracy: 0.8212 - val_loss: 0.9168 - val_accuracy: 0.7304
Epoch 10/60
281/281 [==============================] - 110s 390ms/step - loss: 0.4707 -
accuracy: 0.8436 - val_loss: 0.9220 - val_accuracy: 0.7364
Epoch 11/60
281/281 [==============================] - 110s 391ms/step - loss: 0.4250 -
accuracy: 0.8570 - val_loss: 0.6162 - val_accuracy: 0.8045
Epoch 12/60
281/281 [==============================] - 110s 391ms/step - loss: 0.4047 -
accuracy: 0.8667 - val_loss: 0.8444 - val_accuracy: 0.7193
Epoch 13/60
281/281 [==============================] - 110s 391ms/step - loss: 0.3838 -
accuracy: 0.8721 - val_loss: 0.7112 - val_accuracy: 0.7706
Epoch 14/60
281/281 [==============================] - 110s 393ms/step - loss: 0.3554 -
accuracy: 0.8835 - val_loss: 0.3851 - val_accuracy: 0.8764
Epoch 15/60
281/281 [==============================] - 111s 393ms/step - loss: 0.3435 -
accuracy: 0.8886 - val_loss: 0.3924 - val_accuracy: 0.8744
Epoch 16/60
281/281 [==============================] - 111s 392ms/step - loss: 0.3276 -
accuracy: 0.8963 - val_loss: 0.5650 - val_accuracy: 0.8201
Epoch 17/60
281/281 [==============================] - 110s 390ms/step - loss: 0.3142 -
accuracy: 0.8964 - val_loss: 0.4193 - val_accuracy: 0.8592
Epoch 18/60
281/281 [==============================] - 126s 449ms/step - loss: 0.3005 -
accuracy: 0.9049 - val_loss: 0.9475 - val_accuracy: 0.7242
Epoch 19/60
281/281 [==============================] - 113s 401ms/step - loss: 0.2899 -
accuracy: 0.9072 - val_loss: 0.4327 - val_accuracy: 0.8596
Epoch 20/60
281/281 [==============================] - 111s 395ms/step - loss: 0.2800 -
accuracy: 0.9116 - val_loss: 0.4845 - val_accuracy: 0.8453
Epoch 21/60
281/281 [==============================] - 112s 397ms/step - loss: 0.2797 -
accuracy: 0.9104 - val_loss: 0.3755 - val_accuracy: 0.8842
Epoch 22/60
281/281 [==============================] - 110s 392ms/step - loss: 0.2530 -
accuracy: 0.9185 - val_loss: 1.1566 - val_accuracy: 0.6987
Epoch 23/60
281/281 [==============================] - 111s 394ms/step - loss: 0.2626 -
accuracy: 0.9151 - val_loss: 0.6235 - val_accuracy: 0.8286
Epoch 24/60
281/281 [==============================] - 110s 392ms/step - loss: 0.2279 -
accuracy: 0.9265 - val_loss: 0.4207 - val_accuracy: 0.8723
```

```
Epoch 25/60
281/281 [==============================] - 111s 394ms/step - loss: 0.2392 -
accuracy: 0.9253 - val_loss: 0.3143 - val_accuracy: 0.9005
Epoch 26/60
281/281 [==============================] - 111s 393ms/step - loss: 0.2376 -
accuracy: 0.9278 - val_loss: 0.5371 - val_accuracy: 0.8561
Epoch 27/60
281/281 [==============================] - 111s 394ms/step - loss: 0.2296 -
accuracy: 0.9249 - val_loss: 0.4364 - val_accuracy: 0.8788
Epoch 28/60
281/281 [==============================] - 112s 399ms/step - loss: 0.2225 -
accuracy: 0.9289 - val_loss: 0.7858 - val_accuracy: 0.7884
Epoch 29/60
281/281 [==============================] - 112s 397ms/step - loss: 0.2192 -
accuracy: 0.9294 - val_loss: 0.3663 - val_accuracy: 0.8909
Epoch 30/60
281/281 [==============================] - 111s 395ms/step - loss: 0.2199 -
accuracy: 0.9308 - val_loss: 0.3474 - val_accuracy: 0.8971
Epoch 31/60
281/281 [==============================] - 111s 393ms/step - loss: 0.1921 -
accuracy: 0.9390 - val_loss: 0.5469 - val_accuracy: 0.8422
Epoch 32/60
281/281 [==============================] - 111s 393ms/step - loss: 0.2081 -
accuracy: 0.9347 - val_loss: 0.5347 - val_accuracy: 0.8514
Epoch 33/60
281/281 [==============================] - 111s 394ms/step - loss: 0.1980 -
accuracy: 0.9399 - val_loss: 0.3975 - val_accuracy: 0.8802
Epoch 34/60
281/281 [==============================] - 111s 393ms/step - loss: 0.1897 -
accuracy: 0.9445 - val_loss: 0.3922 - val_accuracy: 0.8875
Epoch 35/60
281/281 [==============================] - 111s 393ms/step - loss: 0.1963 -
accuracy: 0.9390 - val_loss: 0.3592 - val_accuracy: 0.8947
Epoch 36/60
281/281 [==============================] - 111s 394ms/step - loss: 0.1797 -
accuracy: 0.9461 - val_loss: 0.4619 - val_accuracy: 0.8657
Epoch 37/60
281/281 [==============================] - 110s 390ms/step - loss: 0.1861 -
accuracy: 0.9432 - val_loss: 0.2377 - val_accuracy: 0.9264
Epoch 38/60
281/281 [==============================] - 111s 395ms/step - loss: 0.1728 -
accuracy: 0.9461 - val_loss: 0.2581 - val_accuracy: 0.9252
Epoch 39/60
281/281 [==============================] - 111s 396ms/step - loss: 0.1836 -
accuracy: 0.9458 - val_loss: 0.2636 - val_accuracy: 0.9154
Epoch 40/60
281/281 [==============================] - 110s 392ms/step - loss: 0.1711 -
accuracy: 0.9468 - val_loss: 0.6902 - val_accuracy: 0.8137
```

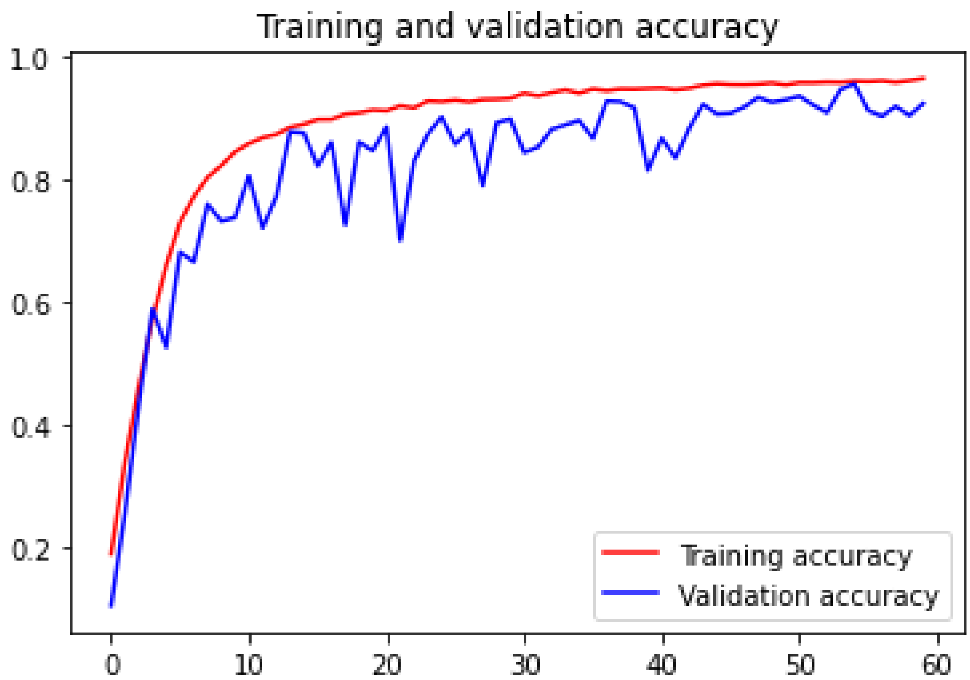
```
Epoch 41/60
281/281 [==============================] - 111s 394ms/step - loss: 0.1743 -
accuracy: 0.9476 - val_loss: 0.4437 - val_accuracy: 0.8661
Epoch 42/60
281/281 [==============================] - 111s 393ms/step - loss: 0.1788 -
accuracy: 0.9447 - val_loss: 0.5826 - val_accuracy: 0.8333
Epoch 43/60
281/281 [==============================] - 110s 391ms/step - loss: 0.1790 -
accuracy: 0.9473 - val_loss: 0.3731 - val_accuracy: 0.8822
Epoch 44/60
281/281 [==============================] - 111s 395ms/step - loss: 0.1613 -
accuracy: 0.9521 - val_loss: 0.2974 - val_accuracy: 0.9210
Epoch 45/60
281/281 [==============================] - 113s 403ms/step - loss: 0.1425 -
accuracy: 0.9546 - val_loss: 0.3171 - val_accuracy: 0.9052
Epoch 46/60
281/281 [==============================] - 118s 418ms/step - loss: 0.1465 -
accuracy: 0.9531 - val_loss: 0.3139 - val_accuracy: 0.9065
Epoch 47/60
281/281 [==============================] - 116s 413ms/step - loss: 0.1480 -
accuracy: 0.9529 - val_loss: 0.2613 - val_accuracy: 0.9165
Epoch 48/60
281/281 [==============================] - 114s 406ms/step - loss: 0.1512 -
accuracy: 0.9539 - val_loss: 0.2615 - val_accuracy: 0.9324
Epoch 49/60
281/281 [==============================] - 114s 406ms/step - loss: 0.1450 -
accuracy: 0.9558 - val_loss: 0.2617 - val_accuracy: 0.9243
Epoch 50/60
281/281 [==============================] - 117s 415ms/step - loss: 0.1535 -
accuracy: 0.9526 - val_loss: 0.2505 - val_accuracy: 0.9284
Epoch 51/60
281/281 [==============================] - 116s 411ms/step - loss: 0.1430 -
accuracy: 0.9564 - val_loss: 0.2140 - val_accuracy: 0.9344
Epoch 52/60
281/281 [==============================] - 114s 405ms/step - loss: 0.1474 -
accuracy: 0.9563 - val_loss: 0.2797 - val_accuracy: 0.9199
Epoch 53/60
281/281 [==============================] - 115s 410ms/step - loss: 0.1425 -
accuracy: 0.9572 - val_loss: 0.2915 - val_accuracy: 0.9074
Epoch 54/60
281/281 [==============================] - 115s 409ms/step - loss: 0.1470 -
accuracy: 0.9568 - val_loss: 0.1852 - val_accuracy: 0.9453
Epoch 55/60
281/281 [==============================] - 115s 409ms/step - loss: 0.1298 -
accuracy: 0.9589 - val_loss: 0.1680 - val_accuracy: 0.9543
Epoch 56/60
281/281 [==============================] - 115s 407ms/step - loss: 0.1350 -
accuracy: 0.9583 - val_loss: 0.2776 - val_accuracy: 0.9110
```

```
Epoch 57/60
281/281 [==============================] - 115s 409ms/step - loss: 0.1307 -
accuracy: 0.9595 - val_loss: 0.4642 - val_accuracy: 0.9016
Epoch 58/60
281/281 [==============================] - 115s 410ms/step - loss: 0.1422 -
accuracy: 0.9569 - val_loss: 0.2760 - val_accuracy: 0.9177
Epoch 59/60
281/281 [==============================] - 115s 408ms/step - loss: 0.1331 -
accuracy: 0.9596 - val_loss: 0.3813 - val_accuracy: 0.9027
Epoch 60/60
281/281 [==============================] - 115s 407ms/step - loss: 0.1243 -
accuracy: 0.9631 - val_loss: 0.2915 - val_accuracy: 0.9223
```

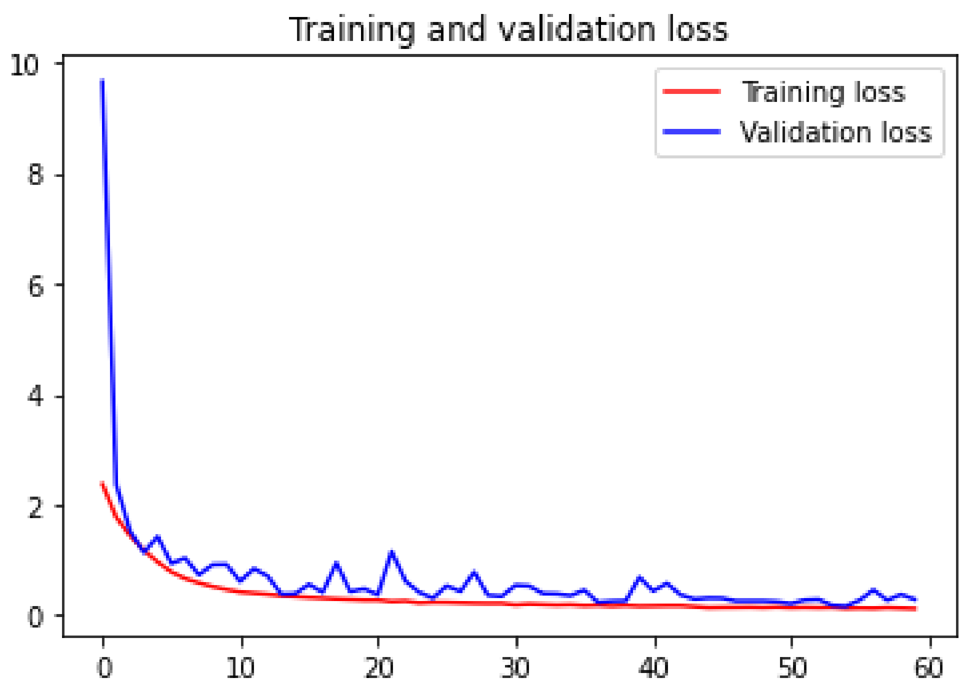
1.0.8 Plot to show training accuracy vs validation accuracy

The two plots were designed to visualize the learning curve of the model. One plot concentrated on Training and validation accuracy over 60 iterations and next one concentrated on training and validation loss.

[6]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()

plt.plot(epochs, loss, 'r', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend(loc=0)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```



```
<Figure size 432x288 with 0 Axes>
```

1.0.9 Test data prediction

Like training data, image generator were built for test data along with its directory. The important step of the project is the prediction of test images with the learning the CNN model has undergone with training and validation images.

[49]:
```
testparentdirectory = os.path.join(workingdir + '/
 ↪state-farm-distracted-driver-detection/imgs/')
testdataimage = ImageDataGenerator(rescale = 1./255)
testdata = testdataimage.flow_from_directory(testparentdirectory,␣
 ↪classes=['test'], target_size = (100,100))
testoutput = cnnmodel.predict(testdata, verbose = 1)
```

```
Found 79726 images belonging to 1 classes.
2492/2492 [==============================] - 247s 99ms/step
```

1.0.10 Preparing output dataframe

The sample submission csv was read by pandas to prepare the format of output. With image and images name taken from the csv, the prediction values was replaced with the original value of csv in the same format and convert it to a dataframe to export it easily into a csv file.

[50]:
```
specimencsv = pd.read_csv(os.path.join(workingdir + '/
 ↪state-farm-distracted-driver-detection/sample_submission.csv'))
result = {'img':list(specimencsv.values[:,0]),}
for value in range(0,10):
    result['c' + str(value)] = list(testoutput[:,value])
```

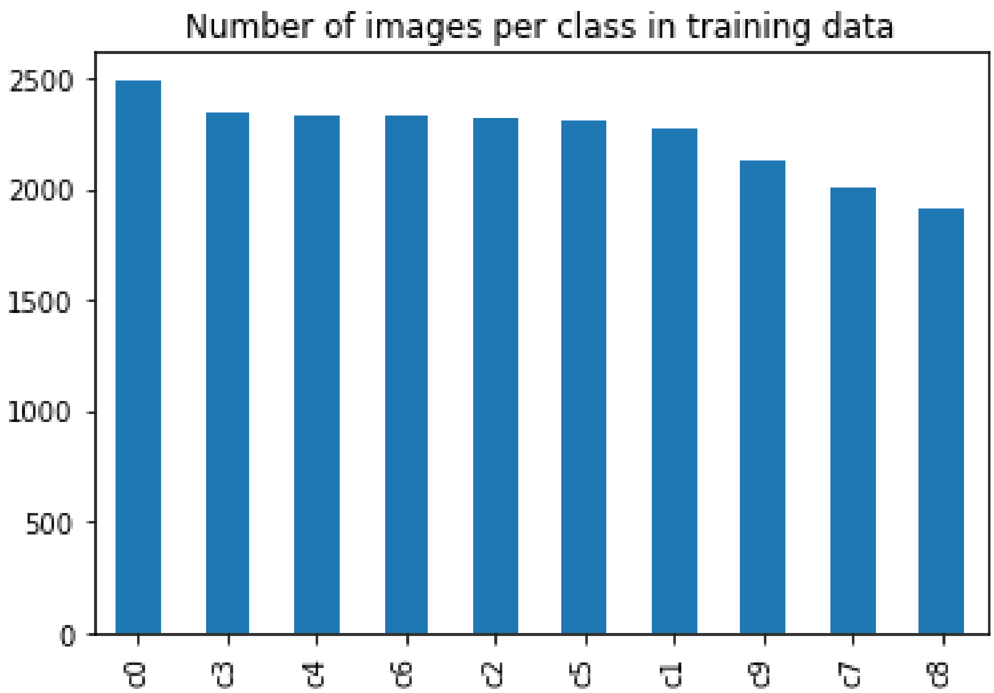
[53]:
```
testoutput = pd.DataFrame(result)
```

1.0.11 Exploratory data analysis

The number of images in each class were depicted with a bar plot.

[57]:
```
imagescsv = pd.read_csv(os.path.join(workingdir + '/
 ↪state-farm-distracted-driver-detection/driver_imgs_list.csv'))
imagescsv.classname.value_counts().plot(kind = 'bar', label = 'index')
plt.title('Number of images per class in training data')
```

[57]:
```
Text(0.5, 1.0, 'Number of images per class in training data')
```



1.0.12 Preparing output file

Then, the csv had been written from the ‘testoutput’ dataframe.

[60]:
```
testoutput.to_csv('Testoutput.csv', index = False, encoding='utf-8')
```

1.0.13 Conclusion

Thus, the prediction of test images from the model with the learning of training and validation images was successfully exported as a csv file with over 96% accuracy.