

# Detection of distracted driver using Convolutional Neural Networks

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## Introduction

Machine learning is the study of computer algorithms that may improve themselves over time by gaining experience and using data. Machine learning algorithms create a model based on training data to make predictions or judgments without having to be explicitly programmed to do so. Like the description, we will build a model to detect the distracted driver with Machine Learning using Convolutional Neural Networks and train the model with the training and validation set before predict them with the test images given.

## 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.

## Libraries

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

In [43]:

```
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
```

## 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 hidden 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.

In [3]:

```
cnmodel = 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')
])
cnmodel.compile(loss = 'categorical_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
cnmodel.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		

## Data preprocessing

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

In [4]:

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

## 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 heighth 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.

In [5]:

```
trainingdataimage = ImageDataGenerator(rescale = 1./255, height_shift_range = 0.2,
                                       width_shift_range = 0.2, shear_range = 0.2, rotation_range = 40, zoom_r
ange = 0.2,
                                       fill_mode = 'nearest', horizontal_flip = True, validation_split = 0.2)
trainingset = trainingdataimage.flow_from_directory(trainingdirectory,
                                                    target_size = (100, 100), batch_size = 64,
                                                    class_mode = 'categorical', subset = 'training', sh
uffle = 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.

## 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.

In [6]:

```
history = cnnmodel.fit(trainingset, epochs = 100, steps_per_epoch = len(trainingset),
                      validation_data = validationset, verbose = 1, validation_steps = len(validationset))
```

```
Epoch 1/100
281/281 [=====] - 148s 488ms/step - loss: 2.4414 - accuracy: 0.1635 - val_l
oss: 4.3076 - val_accuracy: 0.1029
Epoch 2/100
281/281 [=====] - 122s 435ms/step - loss: 1.8286 - accuracy: 0.3173 - val_l
oss: 1.9818 - val_accuracy: 0.2584
Epoch 3/100
281/281 [=====] - 130s 464ms/step - loss: 1.4419 - accuracy: 0.4667 - val_l
oss: 1.4742 - val_accuracy: 0.4720
Epoch 4/100
281/281 [=====] - 138s 491ms/step - loss: 1.1670 - accuracy: 0.5744 - val_l
oss: 1.1714 - val_accuracy: 0.5775
Epoch 5/100
281/281 [=====] - 138s 490ms/step - loss: 0.9647 - accuracy: 0.6579 - val_l
oss: 1.0323 - val_accuracy: 0.6523
Epoch 6/100
281/281 [=====] - 141s 502ms/step - loss: 0.7974 - accuracy: 0.7266 - val_l
oss: 1.0666 - val_accuracy: 0.6746
Epoch 7/100
281/281 [=====] - 139s 493ms/step - loss: 0.6497 - accuracy: 0.7790 - val_l
oss: 1.3936 - val_accuracy: 0.5791
Epoch 8/100
281/281 [=====] - 137s 486ms/step - loss: 0.5769 - accuracy: 0.8069 - val_l
oss: 0.9682 - val_accuracy: 0.6954
Epoch 9/100
281/281 [=====] - 151s 538ms/step - loss: 0.5109 - accuracy: 0.8285 - val_l
oss: 0.9519 - val_accuracy: 0.7148
Epoch 10/100
281/281 [=====] - 137s 487ms/step - loss: 0.4517 - accuracy: 0.8492 - val_l
oss: 0.8535 - val_accuracy: 0.7626
Epoch 11/100
281/281 [=====] - 133s 473ms/step - loss: 0.4151 - accuracy: 0.8638 - val_l
oss: 0.5685 - val_accuracy: 0.8228
Epoch 12/100
281/281 [=====] - 131s 467ms/step - loss: 0.3923 - accuracy: 0.8735 - val_l
oss: 0.9384 - val_accuracy: 0.7340
Epoch 13/100
281/281 [=====] - 133s 474ms/step - loss: 0.3725 - accuracy: 0.8794 - val_l
oss: 0.4266 - val_accuracy: 0.8592
Epoch 14/100
281/281 [=====] - 133s 474ms/step - loss: 0.3609 - accuracy: 0.8825 - val_l
oss: 0.4366 - val_accuracy: 0.8576
Epoch 15/100
281/281 [=====] - 134s 477ms/step - loss: 0.3286 - accuracy: 0.8933 - val_l
oss: 0.8717 - val_accuracy: 0.7393
Epoch 16/100
281/281 [=====] - 136s 484ms/step - loss: 0.3130 - accuracy: 0.9001 - val_l
oss: 0.7410 - val_accuracy: 0.7967
Epoch 17/100
281/281 [=====] - 132s 469ms/step - loss: 0.3092 - accuracy: 0.8998 - val_l
oss: 0.3593 - val_accuracy: 0.8806
Epoch 18/100
281/281 [=====] - 134s 477ms/step - loss: 0.2896 - accuracy: 0.9070 - val_l
```

oss: 0.4192 - val\_accuracy: 0.8688  
Epoch 19/100  
281/281 [=====] - 133s 472ms/step - loss: 0.2694 - accuracy: 0.9137 - val\_l  
oss: 0.3361 - val\_accuracy: 0.8998  
Epoch 20/100  
281/281 [=====] - 129s 458ms/step - loss: 0.2699 - accuracy: 0.9161 - val\_l  
oss: 0.3338 - val\_accuracy: 0.8940  
Epoch 21/100  
281/281 [=====] - 129s 459ms/step - loss: 0.2624 - accuracy: 0.9152 - val\_l  
oss: 0.3663 - val\_accuracy: 0.8877  
Epoch 22/100  
281/281 [=====] - 131s 467ms/step - loss: 0.2501 - accuracy: 0.9185 - val\_l  
oss: 0.4382 - val\_accuracy: 0.8639  
Epoch 23/100  
281/281 [=====] - 130s 461ms/step - loss: 0.2519 - accuracy: 0.9197 - val\_l  
oss: 0.5820 - val\_accuracy: 0.8384  
Epoch 24/100  
281/281 [=====] - 139s 495ms/step - loss: 0.2426 - accuracy: 0.9240 - val\_l  
oss: 0.3229 - val\_accuracy: 0.9034  
Epoch 25/100  
281/281 [=====] - 143s 510ms/step - loss: 0.2282 - accuracy: 0.9280 - val\_l  
oss: 0.3494 - val\_accuracy: 0.8940  
Epoch 26/100  
281/281 [=====] - 138s 491ms/step - loss: 0.2282 - accuracy: 0.9289 - val\_l  
oss: 0.3791 - val\_accuracy: 0.8851  
Epoch 27/100  
281/281 [=====] - 132s 471ms/step - loss: 0.2201 - accuracy: 0.9288 - val\_l  
oss: 0.2320 - val\_accuracy: 0.9252  
Epoch 28/100  
281/281 [=====] - 135s 479ms/step - loss: 0.2207 - accuracy: 0.9312 - val\_l  
oss: 0.3931 - val\_accuracy: 0.8826  
Epoch 29/100  
281/281 [=====] - 135s 481ms/step - loss: 0.2179 - accuracy: 0.9318 - val\_l  
oss: 0.2930 - val\_accuracy: 0.9092  
Epoch 30/100  
281/281 [=====] - 131s 467ms/step - loss: 0.2057 - accuracy: 0.9370 - val\_l  
oss: 0.4461 - val\_accuracy: 0.8652  
Epoch 31/100  
281/281 [=====] - 138s 490ms/step - loss: 0.2061 - accuracy: 0.9357 - val\_l  
oss: 0.2509 - val\_accuracy: 0.9185  
Epoch 32/100  
281/281 [=====] - 136s 483ms/step - loss: 0.2046 - accuracy: 0.9359 - val\_l  
oss: 0.3411 - val\_accuracy: 0.8969  
Epoch 33/100  
281/281 [=====] - 132s 470ms/step - loss: 0.1978 - accuracy: 0.9385 - val\_l  
oss: 0.4390 - val\_accuracy: 0.8788  
Epoch 34/100  
281/281 [=====] - 132s 469ms/step - loss: 0.1877 - accuracy: 0.9420 - val\_l  
oss: 0.4584 - val\_accuracy: 0.8630  
Epoch 35/100  
281/281 [=====] - 137s 489ms/step - loss: 0.1880 - accuracy: 0.9418 - val\_l  
oss: 0.2382 - val\_accuracy: 0.9255  
Epoch 36/100  
281/281 [=====] - 134s 477ms/step - loss: 0.1781 - accuracy: 0.9434 - val\_l  
oss: 0.3078 - val\_accuracy: 0.9114  
Epoch 37/100  
281/281 [=====] - 133s 471ms/step - loss: 0.1858 - accuracy: 0.9437 - val\_l  
oss: 0.3713 - val\_accuracy: 0.8873  
Epoch 38/100  
281/281 [=====] - 134s 476ms/step - loss: 0.1820 - accuracy: 0.9449 - val\_l  
oss: 0.2263 - val\_accuracy: 0.9250  
Epoch 39/100  
281/281 [=====] - 134s 477ms/step - loss: 0.1809 - accuracy: 0.9453 - val\_l  
oss: 0.4650 - val\_accuracy: 0.8726  
Epoch 40/100  
281/281 [=====] - 138s 489ms/step - loss: 0.1663 - accuracy: 0.9474 - val\_l  
oss: 0.1690 - val\_accuracy: 0.9489  
Epoch 41/100  
281/281 [=====] - 134s 475ms/step - loss: 0.1723 - accuracy: 0.9473 - val\_l  
oss: 0.3327 - val\_accuracy: 0.9005  
Epoch 42/100  
281/281 [=====] - 135s 480ms/step - loss: 0.1550 - accuracy: 0.9540 - val\_l  
oss: 0.3882 - val\_accuracy: 0.8846  
Epoch 43/100  
281/281 [=====] - 132s 469ms/step - loss: 0.1609 - accuracy: 0.9493 - val\_l  
oss: 0.3929 - val\_accuracy: 0.8922  
Epoch 44/100  
281/281 [=====] - 136s 485ms/step - loss: 0.1642 - accuracy: 0.9512 - val\_l  
oss: 0.2316 - val\_accuracy: 0.9284  
Epoch 45/100  
281/281 [=====] - 134s 476ms/step - loss: 0.1565 - accuracy: 0.9503 - val\_l  
oss: 0.2183 - val\_accuracy: 0.9366  
Epoch 46/100

281/281 [=====] - 135s 481ms/step - loss: 0.1549 - accuracy: 0.9537 - val\_loss: 0.2164 - val\_accuracy: 0.9299  
Epoch 47/100  
281/281 [=====] - 134s 476ms/step - loss: 0.1645 - accuracy: 0.9500 - val\_loss: 0.2303 - val\_accuracy: 0.9331  
Epoch 48/100  
281/281 [=====] - 134s 477ms/step - loss: 0.1439 - accuracy: 0.9574 - val\_loss: 0.7071 - val\_accuracy: 0.8511  
Epoch 49/100  
281/281 [=====] - 135s 480ms/step - loss: 0.1481 - accuracy: 0.9561 - val\_loss: 0.1810 - val\_accuracy: 0.9440  
Epoch 50/100  
281/281 [=====] - 134s 477ms/step - loss: 0.1380 - accuracy: 0.9586 - val\_loss: 0.2181 - val\_accuracy: 0.9355  
Epoch 51/100  
281/281 [=====] - 133s 471ms/step - loss: 0.1419 - accuracy: 0.9570 - val\_loss: 0.1824 - val\_accuracy: 0.9460  
Epoch 52/100  
281/281 [=====] - 134s 476ms/step - loss: 0.1348 - accuracy: 0.9591 - val\_loss: 0.3641 - val\_accuracy: 0.9016  
Epoch 53/100  
281/281 [=====] - 130s 463ms/step - loss: 0.1455 - accuracy: 0.9556 - val\_loss: 0.1847 - val\_accuracy: 0.9453  
Epoch 54/100  
281/281 [=====] - 130s 461ms/step - loss: 0.1391 - accuracy: 0.9585 - val\_loss: 0.2141 - val\_accuracy: 0.9384  
Epoch 55/100  
281/281 [=====] - 128s 455ms/step - loss: 0.1330 - accuracy: 0.9585 - val\_loss: 0.1290 - val\_accuracy: 0.9621  
Epoch 56/100  
281/281 [=====] - 125s 446ms/step - loss: 0.1398 - accuracy: 0.9593 - val\_loss: 0.4562 - val\_accuracy: 0.8753  
Epoch 57/100  
281/281 [=====] - 126s 449ms/step - loss: 0.1296 - accuracy: 0.9607 - val\_loss: 0.3413 - val\_accuracy: 0.9141  
Epoch 58/100  
281/281 [=====] - 127s 453ms/step - loss: 0.1247 - accuracy: 0.9628 - val\_loss: 0.2970 - val\_accuracy: 0.9125  
Epoch 59/100  
281/281 [=====] - 125s 445ms/step - loss: 0.1313 - accuracy: 0.9622 - val\_loss: 0.4540 - val\_accuracy: 0.8732  
Epoch 60/100  
281/281 [=====] - 128s 454ms/step - loss: 0.1260 - accuracy: 0.9628 - val\_loss: 0.3031 - val\_accuracy: 0.9217  
Epoch 61/100  
281/281 [=====] - 128s 454ms/step - loss: 0.1252 - accuracy: 0.9628 - val\_loss: 0.1651 - val\_accuracy: 0.9514  
Epoch 62/100  
281/281 [=====] - 126s 449ms/step - loss: 0.1312 - accuracy: 0.9608 - val\_loss: 0.2239 - val\_accuracy: 0.9322  
Epoch 63/100  
281/281 [=====] - 128s 457ms/step - loss: 0.1216 - accuracy: 0.9637 - val\_loss: 0.1756 - val\_accuracy: 0.9536  
Epoch 64/100  
281/281 [=====] - 129s 460ms/step - loss: 0.1215 - accuracy: 0.9653 - val\_loss: 0.2039 - val\_accuracy: 0.9386  
Epoch 65/100  
281/281 [=====] - 128s 456ms/step - loss: 0.1260 - accuracy: 0.9619 - val\_loss: 0.3576 - val\_accuracy: 0.8996  
Epoch 66/100  
281/281 [=====] - 128s 454ms/step - loss: 0.1215 - accuracy: 0.9624 - val\_loss: 0.1782 - val\_accuracy: 0.9509  
Epoch 67/100  
281/281 [=====] - 131s 467ms/step - loss: 0.1115 - accuracy: 0.9659 - val\_loss: 0.2101 - val\_accuracy: 0.9384  
Epoch 68/100  
281/281 [=====] - 143s 508ms/step - loss: 0.1031 - accuracy: 0.9671 - val\_loss: 0.1660 - val\_accuracy: 0.9527  
Epoch 69/100  
281/281 [=====] - 140s 498ms/step - loss: 0.1147 - accuracy: 0.9671 - val\_loss: 0.1323 - val\_accuracy: 0.9621  
Epoch 70/100  
281/281 [=====] - 136s 483ms/step - loss: 0.1102 - accuracy: 0.9682 - val\_loss: 0.1676 - val\_accuracy: 0.9484  
Epoch 71/100  
281/281 [=====] - 140s 497ms/step - loss: 0.1079 - accuracy: 0.9662 - val\_loss: 0.2142 - val\_accuracy: 0.9391  
Epoch 72/100  
281/281 [=====] - 142s 506ms/step - loss: 0.1108 - accuracy: 0.9666 - val\_loss: 0.4616 - val\_accuracy: 0.9063  
Epoch 73/100  
281/281 [=====] - 145s 515ms/step - loss: 0.1196 - accuracy: 0.9643 - val\_loss: 0.3285 - val\_accuracy: 0.9221

Epoch 74/100  
281/281 [=====] - 147s 524ms/step - loss: 0.1172 - accuracy: 0.9652 - val\_loss: 0.1829 - val\_accuracy: 0.9531  
Epoch 75/100  
281/281 [=====] - 140s 498ms/step - loss: 0.1041 - accuracy: 0.9691 - val\_loss: 0.1952 - val\_accuracy: 0.9429  
Epoch 76/100  
281/281 [=====] - 137s 488ms/step - loss: 0.1039 - accuracy: 0.9691 - val\_loss: 0.1683 - val\_accuracy: 0.9498  
Epoch 77/100  
281/281 [=====] - 138s 490ms/step - loss: 0.1089 - accuracy: 0.9675 - val\_loss: 0.2088 - val\_accuracy: 0.9397  
Epoch 78/100  
281/281 [=====] - 133s 472ms/step - loss: 0.0998 - accuracy: 0.9690 - val\_loss: 0.2884 - val\_accuracy: 0.9197  
Epoch 79/100  
281/281 [=====] - 125s 444ms/step - loss: 0.1076 - accuracy: 0.9695 - val\_loss: 0.2008 - val\_accuracy: 0.9411  
Epoch 80/100  
281/281 [=====] - 128s 455ms/step - loss: 0.0975 - accuracy: 0.9696 - val\_loss: 0.1886 - val\_accuracy: 0.9473  
Epoch 81/100  
281/281 [=====] - 129s 458ms/step - loss: 0.1060 - accuracy: 0.9691 - val\_loss: 0.1043 - val\_accuracy: 0.9659  
Epoch 82/100  
281/281 [=====] - 128s 454ms/step - loss: 0.1043 - accuracy: 0.9690 - val\_loss: 0.1850 - val\_accuracy: 0.9418  
Epoch 83/100  
281/281 [=====] - 132s 468ms/step - loss: 0.0996 - accuracy: 0.9695 - val\_loss: 0.2020 - val\_accuracy: 0.9368  
Epoch 84/100  
281/281 [=====] - 137s 487ms/step - loss: 0.0953 - accuracy: 0.9707 - val\_loss: 0.4018 - val\_accuracy: 0.9081  
Epoch 85/100  
281/281 [=====] - 129s 460ms/step - loss: 0.1078 - accuracy: 0.9683 - val\_loss: 0.1658 - val\_accuracy: 0.9469  
Epoch 86/100  
281/281 [=====] - 130s 464ms/step - loss: 0.0933 - accuracy: 0.9722 - val\_loss: 0.1341 - val\_accuracy: 0.9605  
Epoch 87/100  
281/281 [=====] - 128s 456ms/step - loss: 0.0908 - accuracy: 0.9737 - val\_loss: 0.1350 - val\_accuracy: 0.9614  
Epoch 88/100  
281/281 [=====] - 128s 454ms/step - loss: 0.0997 - accuracy: 0.9693 - val\_loss: 0.1343 - val\_accuracy: 0.9612  
Epoch 89/100  
281/281 [=====] - 127s 453ms/step - loss: 0.0946 - accuracy: 0.9720 - val\_loss: 0.1742 - val\_accuracy: 0.9531  
Epoch 90/100  
281/281 [=====] - 127s 453ms/step - loss: 0.0882 - accuracy: 0.9743 - val\_loss: 0.1188 - val\_accuracy: 0.9656  
Epoch 91/100  
281/281 [=====] - 127s 453ms/step - loss: 0.0970 - accuracy: 0.9712 - val\_loss: 0.1561 - val\_accuracy: 0.9529  
Epoch 92/100  
281/281 [=====] - 127s 453ms/step - loss: 0.0937 - accuracy: 0.9716 - val\_loss: 0.1481 - val\_accuracy: 0.9540  
Epoch 93/100  
281/281 [=====] - 127s 450ms/step - loss: 0.0831 - accuracy: 0.9756 - val\_loss: 0.1140 - val\_accuracy: 0.9690  
Epoch 94/100  
281/281 [=====] - 127s 452ms/step - loss: 0.0887 - accuracy: 0.9730 - val\_loss: 0.1110 - val\_accuracy: 0.9661  
Epoch 95/100  
281/281 [=====] - 127s 451ms/step - loss: 0.1044 - accuracy: 0.9690 - val\_loss: 0.1364 - val\_accuracy: 0.9594  
Epoch 96/100  
281/281 [=====] - 128s 454ms/step - loss: 0.0971 - accuracy: 0.9713 - val\_loss: 0.1050 - val\_accuracy: 0.9705  
Epoch 97/100  
281/281 [=====] - 129s 459ms/step - loss: 0.0897 - accuracy: 0.9720 - val\_loss: 0.2181 - val\_accuracy: 0.9391  
Epoch 98/100  
281/281 [=====] - 129s 458ms/step - loss: 0.0870 - accuracy: 0.9746 - val\_loss: 0.1498 - val\_accuracy: 0.9551  
Epoch 99/100  
281/281 [=====] - 129s 460ms/step - loss: 0.0836 - accuracy: 0.9747 - val\_loss: 0.1217 - val\_accuracy: 0.9656  
Epoch 100/100  
281/281 [=====] - 129s 460ms/step - loss: 0.0947 - accuracy: 0.9720 - val\_loss: 0.1144 - val\_accuracy: 0.9683

## 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.

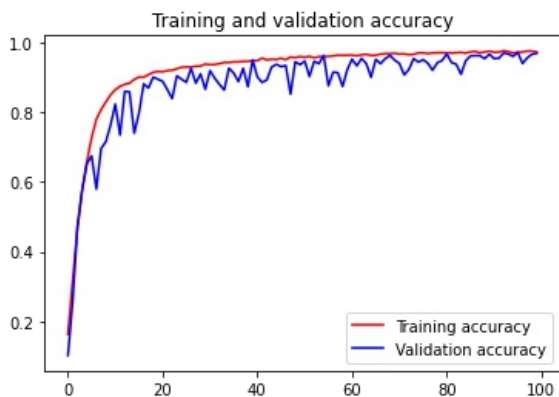
In [7]:

```
accuracy = history.history['accuracy']
validation_accuracy = history.history['val_accuracy']
loss = history.history['loss']
validation_loss = history.history['val_loss']

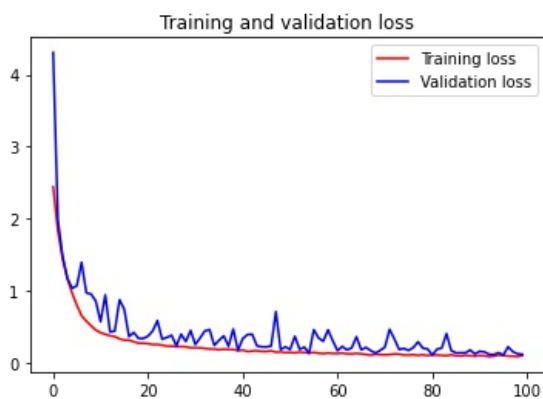
epochs = range(len(accuracy))

plt.plot(epochs, accuracy, 'red', label='Training accuracy')
plt.plot(epochs, validation_accuracy, 'blue', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend(loc=0)
plt.figure()
plt.show()

plt.plot(epochs, loss, 'red', label='Training loss')
plt.plot(epochs, validation_loss, 'blue', 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>

## 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.

In [8]:

```
testparentdirectory = os.path.join(workindir + '/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 [=====] - 425s 170ms/step

## 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.

In [9]:

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

In [10]:

```
testoutput = pd.DataFrame(result)
```

## Exploratory data analysis

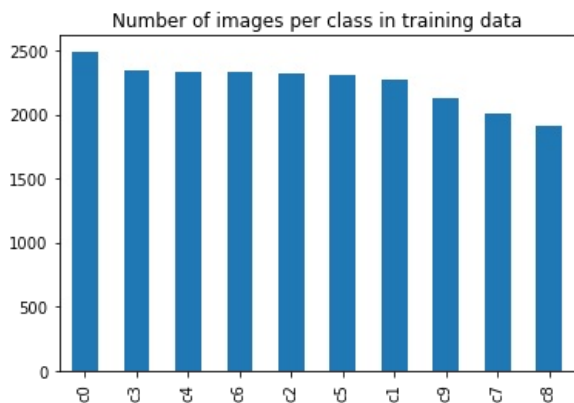
The number of images in each class were depicted with a bar plot.

In [45]:

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

Out[45]:

Text(0.5, 1.0, 'Number of images per class in training data')



In [35]:

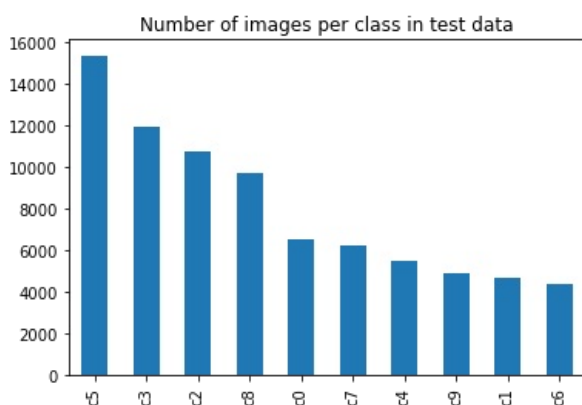
```
testvalue = testoutput[['c0', 'c1', 'c2', 'c3', 'c4', 'c5', 'c6', 'c7', 'c8', 'c9']].idxmax(axis = 1)
```

In [44]:

```
testvalue.value_counts().plot(kind = 'bar')
plt.title('Number of images per class in test data')
```

Out[44]:

Text(0.5, 1.0, 'Number of images per class in test data')





## Preparing output file

Then, the csv had been written from the 'testoutput' dataframe.

In [13]:

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

## Conclusion

We built a model using Convolution Neural Networks with data augmentation, Batch Normalization and Dropout to increase the efficiency of the model. Thus, the prediction of test images from the model with the learning of training and validation images was successfully exported to a csv file with over 97% accuracy.

## References

1. <https://www.tensorflow.org/tutorials/keras/classification> (<https://www.tensorflow.org/tutorials/keras/classification>)
2. <https://www.tensorflow.org/tutorials/images/cnn> (<https://www.tensorflow.org/tutorials/images/cnn>)
3. <https://charon.me/posts/keras/keras2/> (<https://charon.me/posts/keras/keras2/>)
4. [https://www.tensorflow.org/api\\_docs/python/tf/keras/preprocessing/image/ImageDataGenerator](https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image/ImageDataGenerator)  
([https://www.tensorflow.org/api\\_docs/python/tf/keras/preprocessing/image/ImageDataGenerator](https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image/ImageDataGenerator))
5. [https://www.tensorflow.org/guide/keras/train\\_and\\_evaluate](https://www.tensorflow.org/guide/keras/train_and_evaluate) ([https://www.tensorflow.org/guide/keras/train\\_and\\_evaluate](https://www.tensorflow.org/guide/keras/train_and_evaluate))