Distraction detection project

March 16, 2021

1 Imports

[1]:
```
import os
import pickle

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

from tqdm import tqdm

# Seaborn
import seaborn as sns
import seaborn as sns

# Sci-kit learn
from sklearn.datasets import load_files
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split

# Keras
from keras.utils import np_utils
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
from keras.layers import Dropout, Flatten, Dense
from keras.models import Sequential
from keras.utils.vis_utils import plot_model
from keras.callbacks import ModelCheckpoint
from keras.utils import to_categorical
from keras.preprocessing import image

from PIL import ImageFile
```

2 Load the data

[2]:
```python
# Create path constants
DATA_DIR = r"state-farm-distracted-driver-detection/imgs"
TEST_DIR = os.path.join(DATA_DIR,"test")
TRAIN_DIR = os.path.join(DATA_DIR,"train")
MODEL_PATH = os.path.join(os.getcwd(),"basic_model")
PICKLE_DIR = os.path.join(os.getcwd(),"pickle_files")
CSV_DIR = os.path.join(os.getcwd(),"csv_files")
```

[3]:
```python
# Create the specified directories if it does not exist
if not os.path.exists(TEST_DIR):
    print("Testing data does not exists")
if not os.path.exists(TRAIN_DIR):
    print("Training data does not exists")
if not os.path.exists(MODEL_PATH):
    print("Model path does not exists")
    os.makedirs(MODEL_PATH)
    print("Model path created")
if not os.path.exists(PICKLE_DIR):
    os.makedirs(PICKLE_DIR)
if not os.path.exists(CSV_DIR):
    os.makedirs(CSV_DIR)
```

3 Create data CSVs

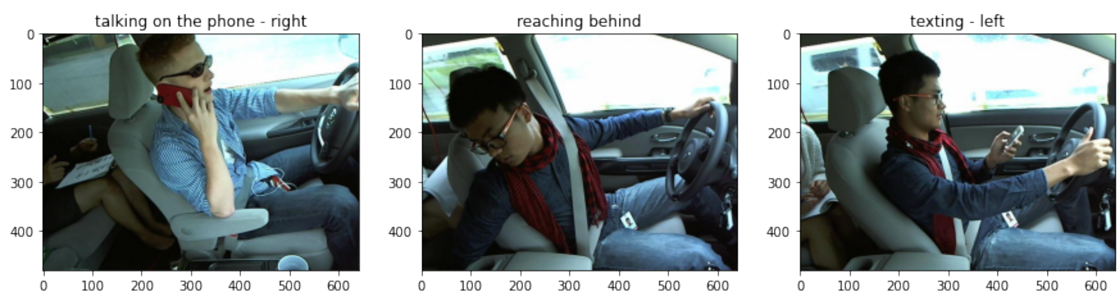
[4]:
```python
def create_csv(DATA_DIR, filename):
    # Get the classes
    class_names = os.listdir(DATA_DIR)
    data = list()
    # Check if the class data folder is found if not we are in test directory
    if(os.path.isdir(os.path.join(DATA_DIR, class_names[0]))):
        # iterate through the classes
        for class_name in class_names:
            file_names = os.listdir(os.path.join(DATA_DIR, class_name))
            for file in file_names:
                data.append({
                    "filename": os.path.join(DATA_DIR,class_name,file),
                    "classname": class_name
                })
    else:
        class_name = "test"
        file_names = os.listdir(DATA_DIR)
        for file in file_names:
            data.append(({
                "filename": os.path.join(DATA_DIR,file),
                "classname": class_name
```

```
            }))
    data = pd.DataFrame(data)
    data.to_csv(os.path.join(os.getcwd(), "csv_files", filename), index=False)
```

[5]:
```
# Create CSVs for train and test
create_csv(TRAIN_DIR,"train.csv")
create_csv(TEST_DIR,"test.csv")
# Load the train and test CSVs
data_train = pd.read_csv(os.path.join(os.getcwd(), "csv_files", "train.csv"))
data_test = pd.read_csv(os.path.join(os.getcwd(), "csv_files", "test.csv"))
```

4 Data visualiztion

[6]:
```
classes = {"c0": "safe 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"
          }
# Take a random sample of the data
df = data_train.sample(frac=1).reset_index(drop=True)
plt.figure(figsize=(15, 15))
for i, row in df.iterrows():
    img_path = row.values[0]
    img = image.load_img(img_path)
    ax = plt.subplot(int(f"23{i+1}"))
    ax.margins(0.05)
    ax.imshow(img)
    label = row.values[1]
    label = classes[label]
    ax.set_title(label)
    if i > 4:
        break
plt.savefig(os.path.join(MODEL_PATH, "data_visualization_basic.png"))
plt.show()
```



4.1 Data exploration

[7]:
```python
data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22424 entries, 0 to 22423
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   filename   22424 non-null  object
 1   classname  22424 non-null  object
dtypes: object(2)
memory usage: 350.5+ KB
```

[8]:
```python
data_train['classname'].value_counts()
```

[8]:
```
c0    2489
c3    2346
c4    2326
c6    2325
```

```
c2    2317
c5    2312
c1    2267
c9    2129
c7    2002
c8    1911
Name: classname, dtype: int64
```

[9]:

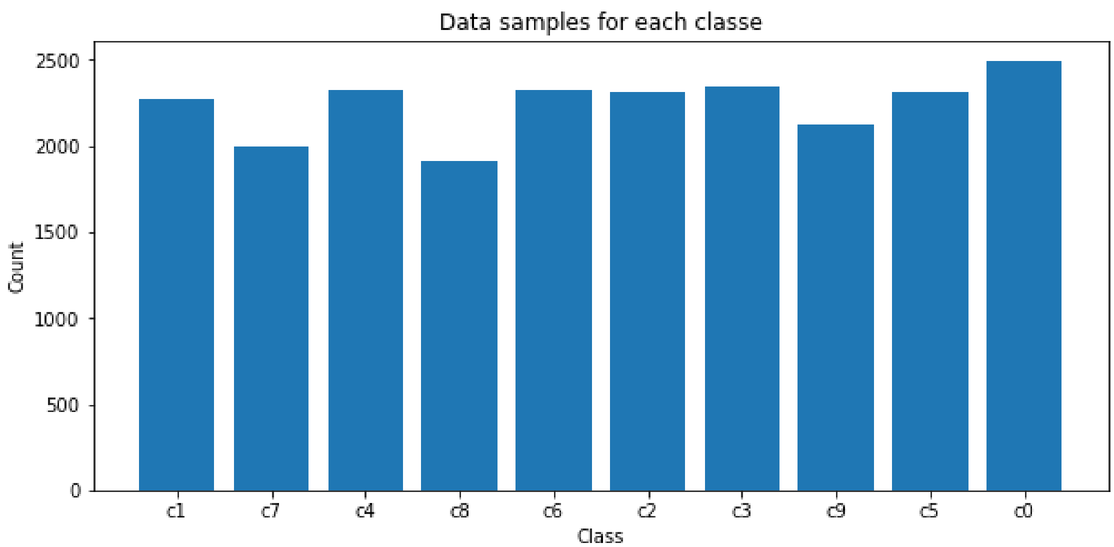
```python
data_train.describe()
```

[9]:

	filename	classname
count	22424	22424
unique	22424	10
top	state-farm-distracted-driver-detection/imgs\tr…	c0
freq	1	2489

[10]:

```python
# Create a bar chart for the data samples for each class
nf = data_train['classname'].value_counts(sort=False)
labels = data_train['classname'].value_counts(sort=False).index.tolist()
y = np.array(nf)
x = range(len(y))
# Create figure
fig = plt.figure(figsize=(10, 10))
ay = fig.add_subplot(211)
plt.xticks(x, labels)
ay.bar(x, y)
plt.title('Data samples for each classe')
plt.xlabel('Class')
plt.ylabel('Count')
plt.savefig(os.path.join(MODEL_PATH, "data_samples_per_class.png"))
plt.show()
```



We can see that the training dataset is equally balanced to a great extent and hence we need not do any downsampling of the data.

[11]:
```python
data_test.head()
```

[11]:

	filename	classname
0	state-farm-distracted-driver-detection/imgs\te…	test
1	state-farm-distracted-driver-detection/imgs\te…	test
2	state-farm-distracted-driver-detection/imgs\te…	test
3	state-farm-distracted-driver-detection/imgs\te…	test
4	state-farm-distracted-driver-detection/imgs\te…	test

[12]:
```python
print(f"There are total {data_train.shape[0]} training samples")
print(f"There are total {data_test.shape[0]} testing samples")
```

```
There are total 22424 training samples
There are total 79726 testing samples
```

5 Data preprocessing

5.1 Convert the labels to numerals

[13]:
```python
labels_list = list(set(data_train['classname'].values.tolist()))
labels_id = {label_name:id for id, label_name in enumerate(labels_list)}
print(f"labels_id = {labels_id}")
data_train['classname'].replace(labels_id, inplace=True)
```

```
labels_id = {'c7': 0, 'c4': 1, 'c0': 2, 'c3': 3, 'c8': 4, 'c1': 5, 'c2': 6,
'c5': 7, 'c6': 8, 'c9': 9}
```

[14]:
```python
# Save the labels list to the desk in a pickle file
with open(os.path.join(os.getcwd(),"pickle_files","labels_list.pkl"),"wb") as␣
↪handle:
    pickle.dump(labels_id,handle)
# Categorize the labels
labels = to_categorical(data_train['classname'])
print(f"labels.shape = {labels.shape}")
```

```
labels.shape = (22424, 10)
```

5.2 Splitting training data into train and test (validation) sets

[15]:
```python
# Split the data into 80% train and 20% test
x_train, x_test, y_train, y_test = train_test_split(data_train.iloc[:, 0],␣
↪labels, test_size=0.2, random_state=7)
```

5.3 Dcaling images

We scale the image to be 64 * 64 images instead of 640 * 480

[16]:
```
# A function to load and resize the image
def path_to_tensor(img_path):
    # loads RGB image as PIL.Image.Image type
    img = image.load_img(img_path, target_size=(64, 64))
    # convert PIL.Image.Image type to 3D tensor with shape (64, 64, 3)
    x = image.img_to_array(img)
    # convert 3D tensor to 4D tensor with shape (1, 64,64, 3) and return 4D␣
 ↪tensor
    return np.expand_dims(x, axis=0)

# A function to process all the images
def paths_to_tensor(img_paths):
    list_of_tensors = [path_to_tensor(img_path) for img_path in tqdm(img_paths)]
    return np.vstack(list_of_tensors)
```

[17]:
```
# Preprocess the data for Keras by normalizing the image to be between 0 and 1␣
 ↪with mean of 0.5
train_tensors_path = os.path.join(os.getcwd(), "pickle_files", "train_tensors.
 ↪pkl")
valid_tensors_path = os.path.join(os.getcwd(), "pickle_files", "valid_tensors.
 ↪pkl")

# Save the labels list to the desk in a pickle file
if os.path.isfile(train_tensors_path):
    with open(train_tensors_path, 'rb') as f:
        train_tensors = pickle.load(f)
else:
    train_tensors = paths_to_tensor(x_train).astype('float32')/255 - 0.5
    with open(train_tensors_path, 'wb') as handle:
        pickle.dump(train_tensors, handle)

if os.path.isfile(valid_tensors_path):
    with open(valid_tensors_path, 'rb') as f:
        valid_tensors = pickle.load(f)
else:
    valid_tensors = paths_to_tensor(x_test).astype('float32')/255 - 0.5
    with open(valid_tensors_path, 'wb') as handle:
        pickle.dump(valid_tensors, handle)
```

6 Building the Model

[18]:
```
input_shape = (64, 64, 3)
kernel_initializer = 'glorot_normal'
padding = 'same'
activation = 'relu'

model = Sequential()

model.add(Conv2D(filters=64, kernel_size=2, padding=padding,␣
↪activation=activation,
                 input_shape=input_shape,␣
↪kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Conv2D(filters=128, kernel_size=2, padding=padding,␣
↪activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Conv2D(filters=256, kernel_size=2, padding=padding,␣
↪activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Conv2D(filters=512, kernel_size=2, padding=padding,␣
↪activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(500, activation=activation,␣
↪kernel_initializer=kernel_initializer))
model.add(Dropout(0.5))

model.add(Dense(10, activation='softmax',␣
↪kernel_initializer=kernel_initializer))



model.summary()
```

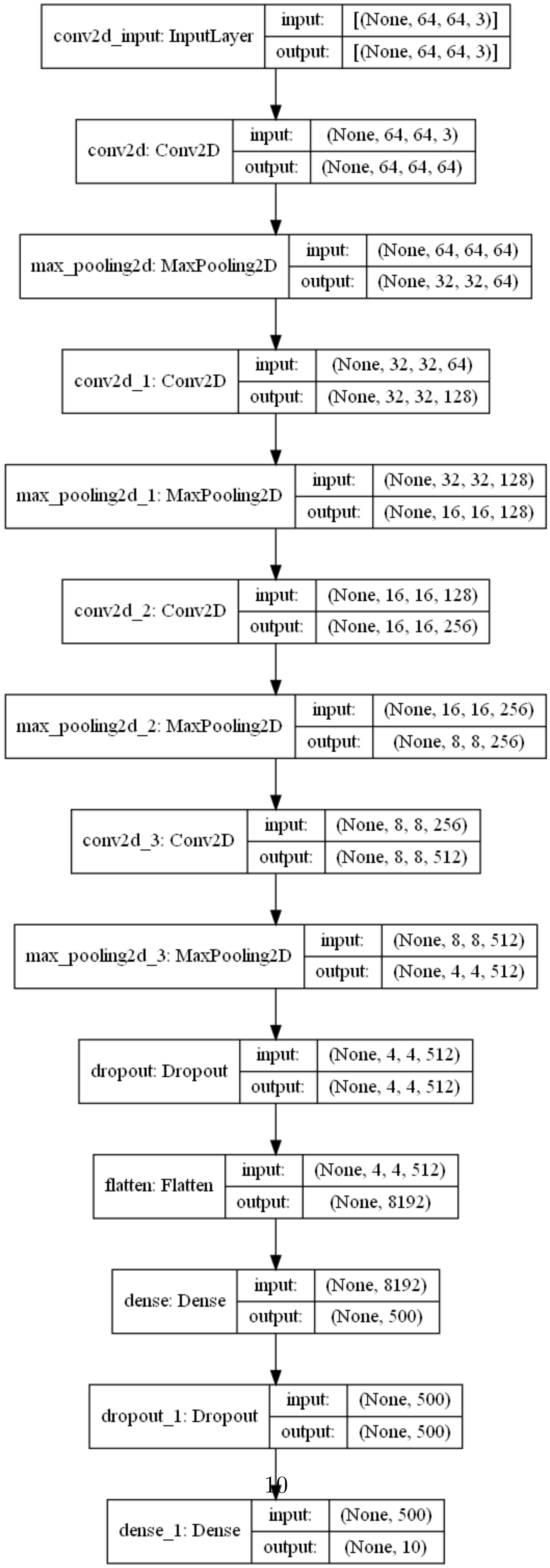
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 64, 64, 64)        832
```

```
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 128)       32896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 256)       131328
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 512)         524800
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 512)         0
_________________________________________________________________
dropout (Dropout)            (None, 4, 4, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 8192)              0
_________________________________________________________________
dense (Dense)                (None, 500)               4096500
_________________________________________________________________
dropout_1 (Dropout)          (None, 500)               0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                5010
=================================================================
Total params: 4,791,366
Trainable params: 4,791,366
Non-trainable params: 0

_________________________________________________________________
```

[19]:

```
# Plot the model
plot_model(model, to_file=os.path.join(MODEL_PATH, "distraction_basic_model.
→png"), show_shapes=True, show_layer_names=True)
```

[19]:


conv2d_input: InputLayer
input: [(None, 64, 64, 3)]
output: [(None, 64, 64, 3)]
conv2d: Conv2D
input: (None, 64, 64, 3)
output: (None, 64, 64, 64)
max_pooling2d: MaxPooling2D
input: (None, 64, 64, 64)
output: (None, 32, 32, 64)
conv2d_1: Conv2D
input: (None, 32, 32, 64)
output: (None, 32, 32, 128)
max_pooling2d_1: MaxPooling2D
input: (None, 32, 32, 128)
output: (None, 16, 16, 128)
conv2d_2: Conv2D
input: (None, 16, 16, 128)
output: (None, 16, 16, 256)
max_pooling2d_2: MaxPooling2D
input: (None, 16, 16, 256)
output: (None, 8, 8, 256)
conv2d_3: Conv2D
input: (None, 8, 8, 256)
output: (None, 8, 8, 512)
max_pooling2d_3: MaxPooling2D
input: (None, 8, 8, 512)
output: (None, 4, 4, 512)
dropout: Dropout
input: (None, 4, 4, 512)
output: (None, 4, 4, 512)
flatten: Flatten
input: (None, 4, 4, 512)
output: (None, 8192)
dense: Dense
input: (None, 8192)
output: (None, 500)
dropout_1: Dropout
input: (None, 500)
output: (None, 500)
dense_1: Dense
input: (None, 500)
output: (None, 10)

[20]:
```
# Compile the model
model.compile(optimizer='rmsprop', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
```

[21]:
```
epochs = 5
batch_size = 32
# Save the model with the best accuracy during the training process
filepath = os.path.join(MODEL_PATH, "distraction-{epoch:02d}-{val_accuracy:.2f}.
↪hdf5")
checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,␣
↪save_best_only=True, mode='max', period=1)
callbacks_list = [checkpoint]
# Start the training process
model_history = model.fit(train_tensors, y_train,␣
↪validation_data=(valid_tensors, y_test),
                          epochs=epochs, batch_size=batch_size, shuffle=True,␣
↪callbacks=callbacks_list)
```

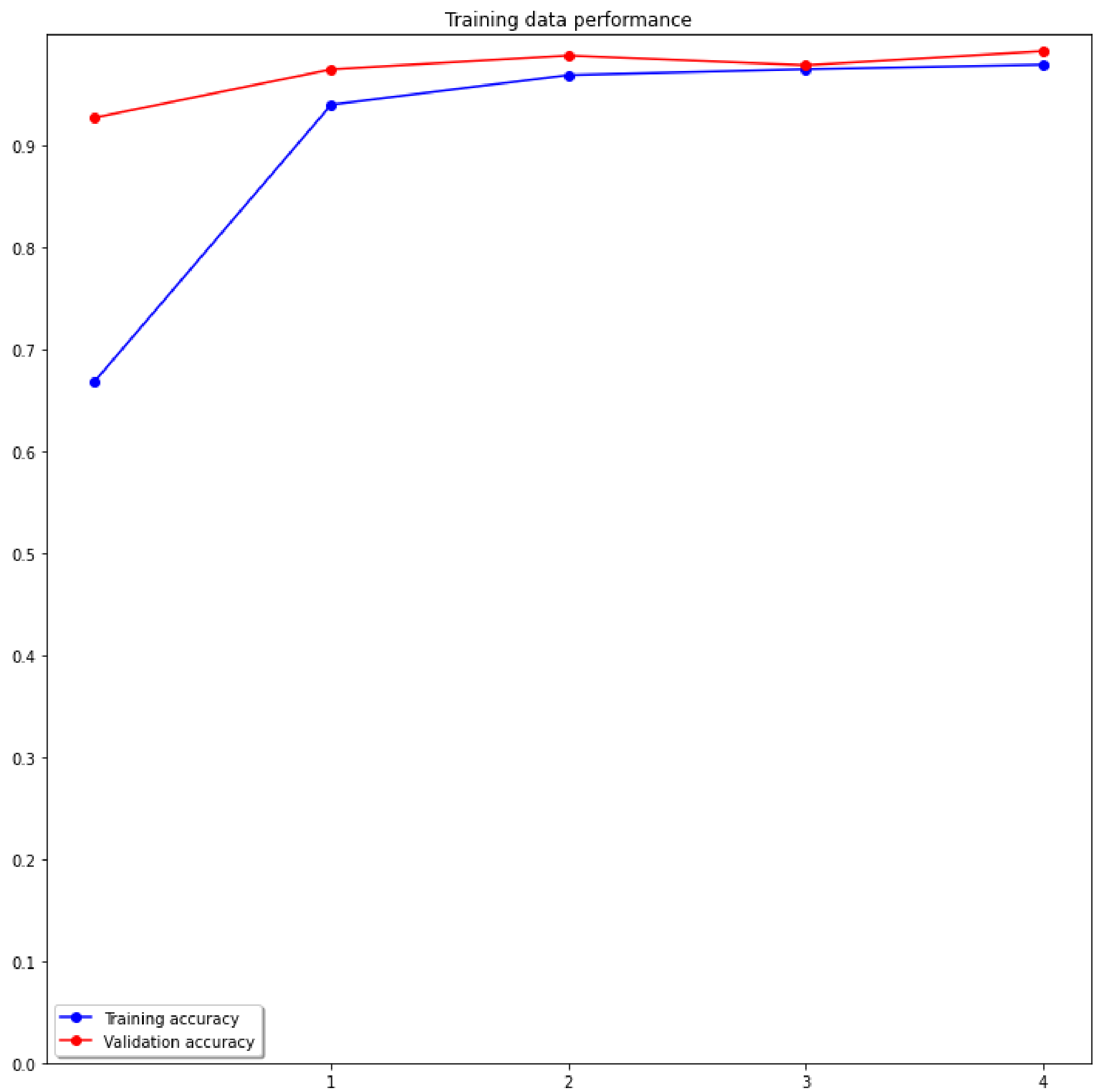
```
WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to
specify the frequency in number of batches seen.
Epoch 1/5
561/561 [==============================] - 101s 178ms/step - loss: 1.5078 -
accuracy: 0.4456 - val_loss: 0.2189 - val_accuracy: 0.9269

Epoch 00001: val_accuracy improved from -inf to 0.92687, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-01-0.93.hdf5
Epoch 2/5
561/561 [==============================] - 99s 176ms/step - loss: 0.2369 -
accuracy: 0.9267 - val_loss: 0.0915 - val_accuracy: 0.9744

Epoch 00002: val_accuracy improved from 0.92687 to 0.97436, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-02-0.97.hdf5
Epoch 3/5
561/561 [==============================] - 97s 173ms/step - loss: 0.1144 -
accuracy: 0.9669 - val_loss: 0.0432 - val_accuracy: 0.9880

Epoch 00003: val_accuracy improved from 0.97436 to 0.98796, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-03-0.99.hdf5
Epoch 4/5
561/561 [==============================] - 97s 173ms/step - loss: 0.0906 -
accuracy: 0.9741 - val_loss: 0.0716 - val_accuracy: 0.9784

Epoch 00004: val_accuracy did not improve from 0.98796
Epoch 5/5
561/561 [==============================] - 98s 175ms/step - loss: 0.0692 -
```

```
accuracy: 0.9782 - val_loss: 0.0387 - val_accuracy: 0.9922

Epoch 00005: val_accuracy improved from 0.98796 to 0.99220, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-05-0.99.hdf5
```

7 Plot performance graphs

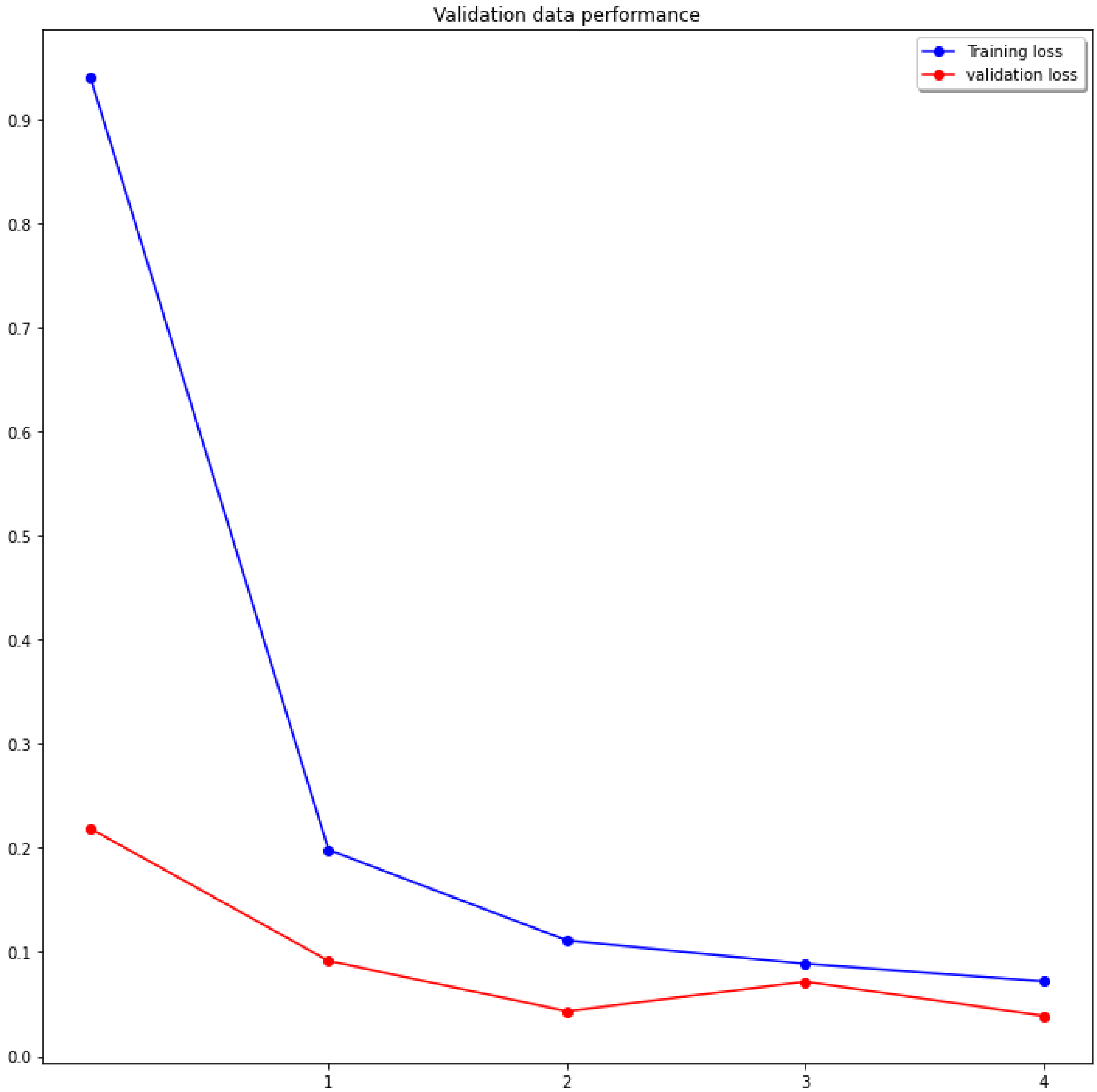
[22]:

```
# Training date
fig = plt.figure(figsize=(10, 10))
plt.plot(model_history.history['accuracy'], '-bo', label="Training accuracy")
plt.plot(model_history.history['val_accuracy'], '-ro',label="Validation␣
↪accuracy")
plt.xticks(np.arange(1, epochs, 1))
plt.yticks(np.arange(0, 1, 0.1))
legend = plt.legend(loc='best', shadow=True)
plt.title("Training data performance")
plt.tight_layout()
plt.savefig(os.path.join(MODEL_PATH, "basic_model_training.png"))
plt.show()
```



[23]:

```
# Validation date
fig = plt.figure(figsize=(10, 10))
plt.plot(model_history.history['loss'], '-bo', label="Training loss")
plt.plot(model_history.history['val_loss'], '-ro', label="validation loss")
plt.xticks(np.arange(1, epochs, 1))
plt.yticks(np.arange(0, 1, 0.1))
legend = plt.legend(loc='best', shadow=True)
plt.title("Validation data performance")
plt.tight_layout()
plt.savefig(os.path.join(MODEL_PATH, "basic_model_validation.png"))
plt.show()
```



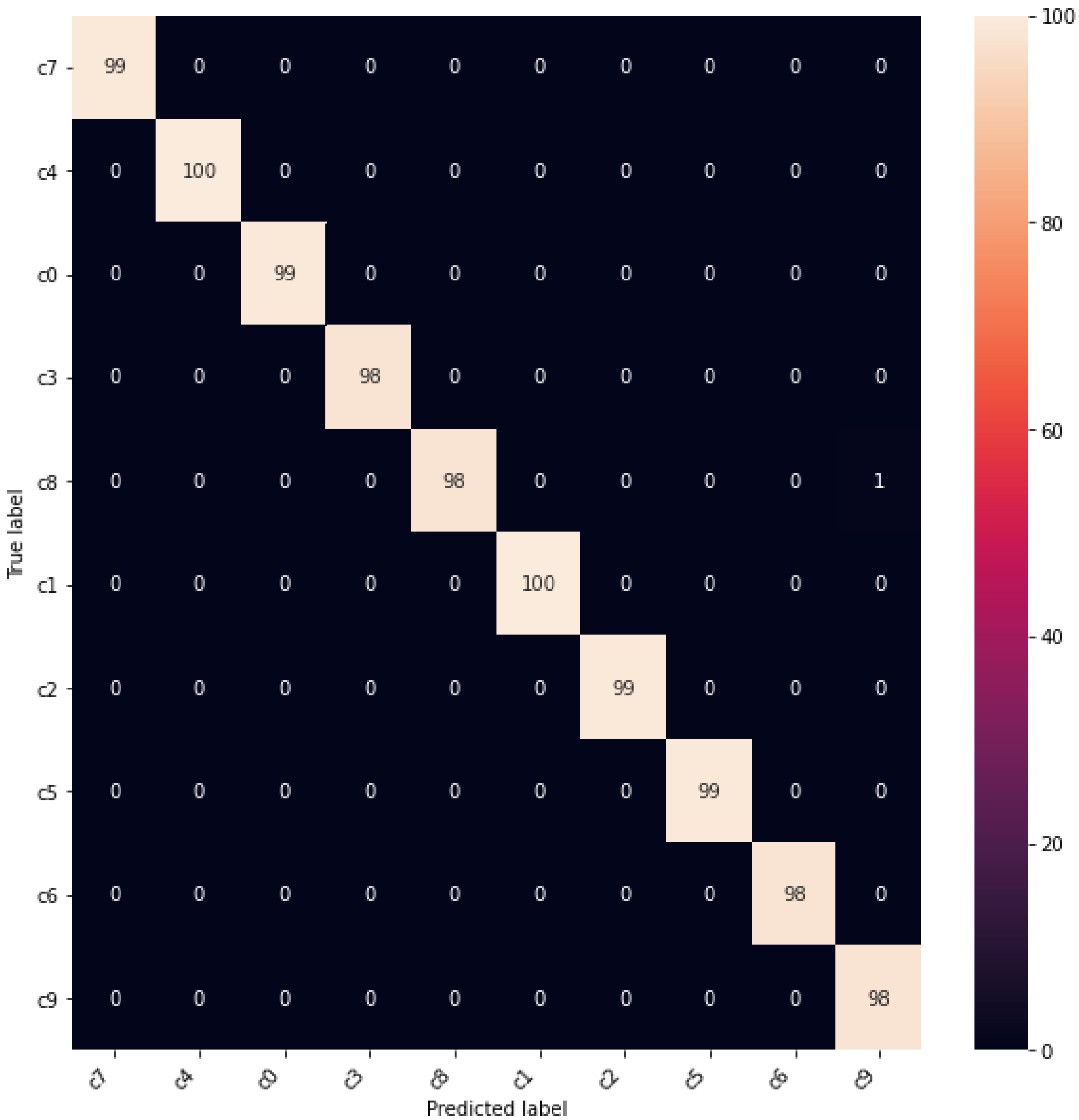
8 Model Analysis

Finding the Confusion matrix, Precision, Recall and F1 score to analyse the model performance

[24]:
```
def show_confusion_matrix(confusion_matrix, class_names):
    figsize = (10,10)
    df_cm = pd.DataFrame(confusion_matrix, index=class_names,␣
 ↪columns=class_names)
    fig = plt.figure(figsize=figsize)

    try:
        heatmap = sns.heatmap(df_cm, annot=True, fmt="d")
```

```
    except ValueError:
        raise ValueError("Confusion matrix values must be integers.")

    heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0,␣
 ↪ha='right')
    heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45,␣
 ↪ha='right')
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    fig.savefig(os.path.join(MODEL_PATH, "basic_model_confusion_matrix.png"))
    return fig

def show_heatmap(n_labels, n_predictions, class_names):
    labels = n_labels
    predictions = n_predictions
    matrix = confusion_matrix(labels.argmax(axis=1), predictions.argmax(axis=1))
    row_sum = np.sum(matrix, axis=1)
    w, h = matrix.shape
    c_m = np.zeros((w, h))
    for i in range(h):
        c_m[i] = matrix[i] * 100 / row_sum[i]
    c = c_m.astype(dtype = np.uint8)
    heatmap = show_confusion_matrix(c, class_names)
```

[25]:
```
class_names = list()
for name, idx in labels_id.items():
    class_names.append(name)

y_pred = model.predict(valid_tensors)
show_heatmap(y_test, y_pred, class_names)
```



9 Precision, recall, and F1 score

[26]:
```
y_pred = np.argmax(y_pred, axis=1)
y_test = np.argmax(y_test, axis=1)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {round(accuracy, 3)}")

# precision = tp / (tp + fp)
precision = precision_score(y_test, y_pred, average='weighted')
print(f"Precision: {round(precision, 3)}")
```

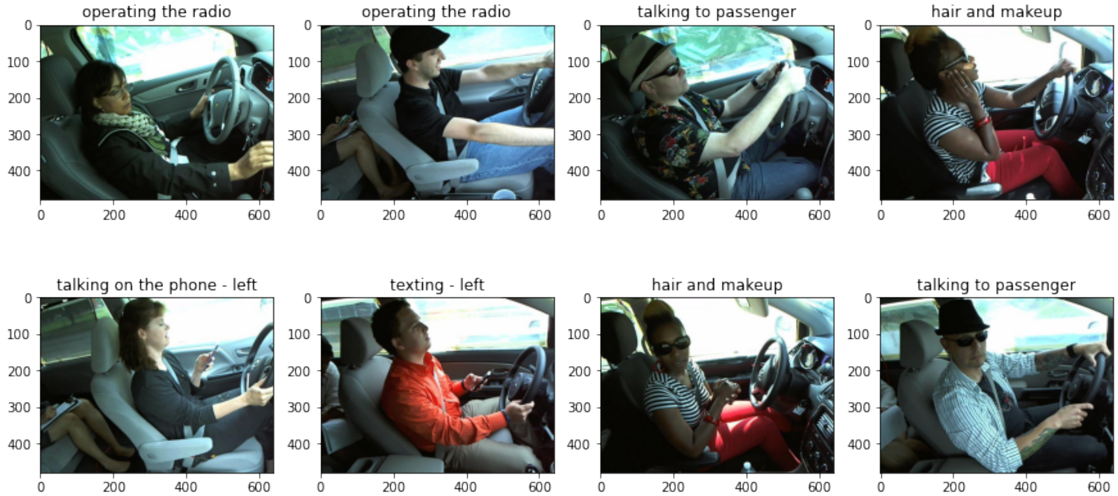
```python
# recall = tp / (tp + fn)
recall = recall_score(y_test, y_pred, average='weighted')
print(f"Recall: {round(recall, 3)}")

# f1 = 2 tp / (2 tp + fp + fn)
f1 = f1_score(y_test, y_pred, average='weighted')
print(f"F1 score: {round(f1, 3)}")
```

```
Accuracy: 0.992
Precision: 0.992
Recall: 0.992
F1 score: 0.992
```

10 Test model on test data (Unlabeled data)

Actually this is do good to be true so let's see how the model perform on the unlabeled data

[27]:
```python
classes = {"c0": "safe 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"
          }

plt.figure(figsize=(15, 15))
for i, img_path in data_test.iterrows():
    img_path = img_path.values[0]
    img = image.load_img(img_path)
    ax = plt.subplot(int(f"44{i+1}"))
    ax.margins(0.05)
    ax.imshow(img)
    img_tensor = path_to_tensor(img_path).astype('float32')/255 - 0.5
    label = np.argmax(model.predict(img_tensor))
    label = classes[labels_list[label]]
    ax.set_title(label)
    if i > 6:
        break
plt.savefig(os.path.join(MODEL_PATH, "basic_model_test_samples.png"))
plt.show()
```



11 I think we have a serious problem which require data investigation

12 ...

13 After careful investigation we found that we have a data leakage problem

14 Re-define the model

[28]:
```
input_shape = (64, 64, 3)
kernel_initializer = 'glorot_normal'
padding = 'same'
activation = 'relu'

model = Sequential()

model.add(Conv2D(filters=64, kernel_size=2, padding=padding, activation=activation,
                 input_shape=input_shape, kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Conv2D(filters=128, kernel_size=2, padding=padding, activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))
```

```
model.add(Conv2D(filters=256, kernel_size=2, padding=padding,␣
↪activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Conv2D(filters=512, kernel_size=2, padding=padding,␣
↪activation=activation,
                 kernel_initializer=kernel_initializer))
model.add(MaxPooling2D(pool_size=2))

model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(500, activation=activation,␣
↪kernel_initializer=kernel_initializer))
model.add(Dropout(0.5))

model.add(Dense(10, activation='softmax',␣
↪kernel_initializer=kernel_initializer))


model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 64, 64, 64)        832
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 32, 32, 128)       32896
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 16, 16, 256)       131328
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 8, 8, 512)         524800
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 4, 4, 512)         0
_________________________________________________________________
dropout_2 (Dropout)          (None, 4, 4, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_2 (Dense)              (None, 500)               4096500
```

```
_________________________________________________________________
dropout_3 (Dropout)          (None, 500)               0

_________________________________________________________________
dense_3 (Dense)              (None, 10)                5010
=================================================================
Total params: 4,791,366
Trainable params: 4,791,366
Non-trainable params: 0

_________________________________________________________________
```

15 Perform stratified sampling

[29]:
```python
# Create path constants
DATA_DIR = "state-farm-distracted-driver-detection\\imgs\\train\\"
images_df = pd.
 ↪read_csv("state-farm-distracted-driver-detection\\driver_imgs_list.csv")
images_df.head()
```

[29]:

	subject	classname	img
0	p002	c0	img_44733.jpg
1	p002	c0	img_72999.jpg
2	p002	c0	img_25094.jpg
3	p002	c0	img_69092.jpg
4	p002	c0	img_92629.jpg

[30]:
```python
# Add the full path to the image name
for i, row in images_df.iterrows():
    row["img"] = DATA_DIR + row["classname"] + "\\" + row["img"]

# Count the number of sample in each class
images_df["subject"].value_counts()
```

[30]:
```
p021    1237
p022    1233
p024    1226
p026    1196
p016    1078
p066    1034
p049    1011
p051     920
p014     876
p015     875
p035     848
p047     835
p012     823
p081     823
p064     820
```

```
p075     814
p061     809
p056     794
p050     790
p052     740
p002     725
p045     724
p039     651
p041     605
p042     591
p072     346
Name: subject, dtype: int64
```

[31]:

```
labels_list = list(set(images_df["classname"].values.tolist()))
labels_id = {label_name:id for id, label_name in enumerate(labels_list)}
print(f"labels_id = {labels_id}")
images_df["classname"].replace(labels_id, inplace=True)
labels = to_categorical(images_df["classname"])
print(f"labels.shape = {labels.shape}")
```

```
labels_id = {'c7': 0, 'c4': 1, 'c0': 2, 'c3': 3, 'c8': 4, 'c1': 5, 'c2': 6,
'c5': 7, 'c6': 8, 'c9': 9}
labels.shape = (22424, 10)
```

[32]:

```
# A function to load and resize the image
def path_to_tensor(img_path):
    # loads RGB image as PIL.Image.Image type
    img = image.load_img(img_path, target_size=(64, 64))
    # convert PIL.Image.Image type to 3D tensor with shape (64, 64, 3)
    x = image.img_to_array(img)
    # convert 3D tensor to 4D tensor with shape (1, 64,64, 3) and return 4D␣
↪tensor
    return np.expand_dims(x, axis=0)

# A function to process all the images
def paths_to_tensor(img_paths):
    list_of_tensors = [path_to_tensor(img_path) for img_path in tqdm(img_paths)]
    return np.vstack(list_of_tensors)
```

[33]:

```
# Split the data into 80% train and 20% test (stratified)
test_df = images_df.loc[(images_df["subject"] == "p021") |␣
↪(images_df["subject"] == "p022") | \
                        (images_df["subject"] == "p024") |␣
↪(images_df["subject"] == "p026")]


mask = images_df["img"].isin(test_df["img"])
```

```
train_df = images_df.drop(images_df[mask].index)

print(f"images_df.shape = {images_df.shape}")
print(f"train_df.shape = {train_df.shape}")
print(f"test_df.shape = {test_df.shape}")
```

```
images_df.shape = (22424, 3)
train_df.shape = (17532, 3)
test_df.shape = (4892, 3)
```

[34]:
```
x_train = list(train_df["img"])
y_train = to_categorical(train_df["classname"])

x_test = list(test_df["img"])
y_test = to_categorical(test_df["classname"])
```

[35]:
```
train_tensors = paths_to_tensor(x_train).astype('float32')/255
valid_tensors = paths_to_tensor(x_test).astype('float32')/255
```

```
100%|
| 17532/17532 [01:09<00:00, 253.71it/s]
100%|
 | 4892/4892 [00:18<00:00, 262.38it/s]
```

16 Re-train the model

[36]:
```
# Compile the model
model.compile(optimizer='sgd', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

epochs = 10
batch_size = 32
# Save the model with the best accuracy during the training process
filepath = os.path.join(MODEL_PATH, "distraction-{epoch:02d}-{val_accuracy:.2f}.
 ↪hdf5")
checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,␣
 ↪save_best_only=True, mode='max', period=1)
callbacks_list = [checkpoint]
# Start the training process
model_history = model.fit(train_tensors, y_train,␣
 ↪validation_data=(valid_tensors, y_test),
                          epochs=epochs, batch_size=batch_size, shuffle=True,␣
 ↪callbacks=callbacks_list)
```

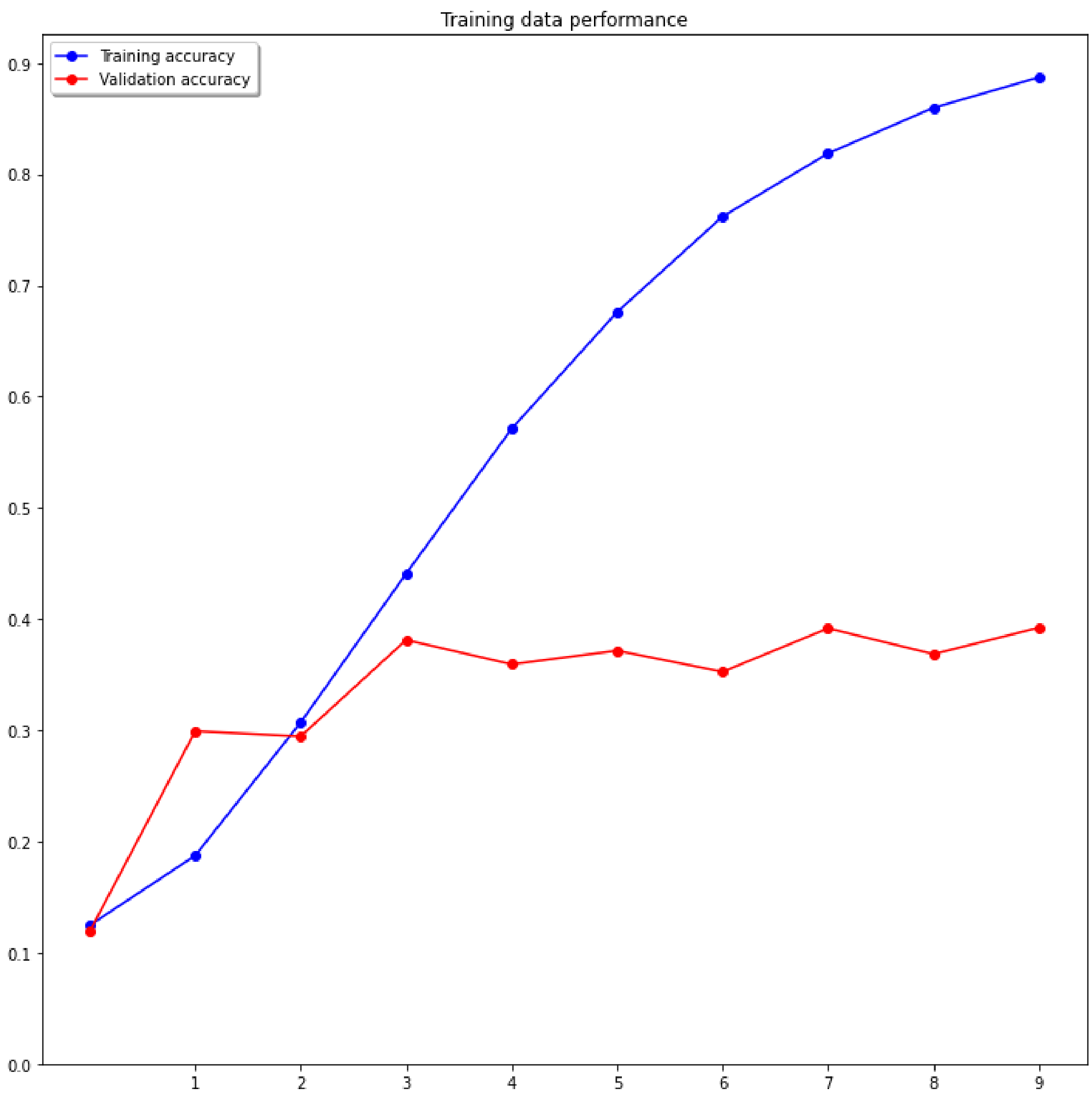
```
WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to
specify the frequency in number of batches seen.
Epoch 1/10
548/548 [==============================] - 88s 159ms/step - loss: 2.3008 -
```

```
accuracy: 0.1111 - val_loss: 2.2754 - val_accuracy: 0.1192

Epoch 00001: val_accuracy improved from -inf to 0.11917, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-01-0.12.hdf5
Epoch 2/10
548/548 [==============================] - 89s 162ms/step - loss: 2.2605 -
accuracy: 0.1653 - val_loss: 2.0255 - val_accuracy: 0.2993

Epoch 00002: val_accuracy improved from 0.11917 to 0.29926, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-02-0.30.hdf5
Epoch 3/10
548/548 [==============================] - 87s 158ms/step - loss: 1.9967 -
accuracy: 0.2764 - val_loss: 1.6563 - val_accuracy: 0.2946

Epoch 00003: val_accuracy did not improve from 0.29926
Epoch 4/10
548/548 [==============================] - 91s 165ms/step - loss: 1.6174 -
accuracy: 0.4051 - val_loss: 1.6224 - val_accuracy: 0.3812

Epoch 00004: val_accuracy improved from 0.29926 to 0.38123, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-04-0.38.hdf5
Epoch 5/10
548/548 [==============================] - 91s 165ms/step - loss: 1.2903 -
accuracy: 0.5384 - val_loss: 1.7610 - val_accuracy: 0.3594

Epoch 00005: val_accuracy did not improve from 0.38123
Epoch 6/10
548/548 [==============================] - 88s 161ms/step - loss: 0.9839 -
accuracy: 0.6584 - val_loss: 1.8463 - val_accuracy: 0.3716

Epoch 00006: val_accuracy did not improve from 0.38123
Epoch 7/10
548/548 [==============================] - 99s 180ms/step - loss: 0.7404 -
accuracy: 0.7476 - val_loss: 2.2985 - val_accuracy: 0.3526

Epoch 00007: val_accuracy did not improve from 0.38123
Epoch 8/10
548/548 [==============================] - 123s 224ms/step - loss: 0.5765 -
accuracy: 0.8081 - val_loss: 2.0623 - val_accuracy: 0.3917

Epoch 00008: val_accuracy improved from 0.38123 to 0.39166, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-08-0.39.hdf5
Epoch 9/10
548/548 [==============================] - 123s 224ms/step - loss: 0.4561 -
accuracy: 0.8508 - val_loss: 2.2393 - val_accuracy: 0.3686

Epoch 00009: val_accuracy did not improve from 0.39166
Epoch 10/10
```

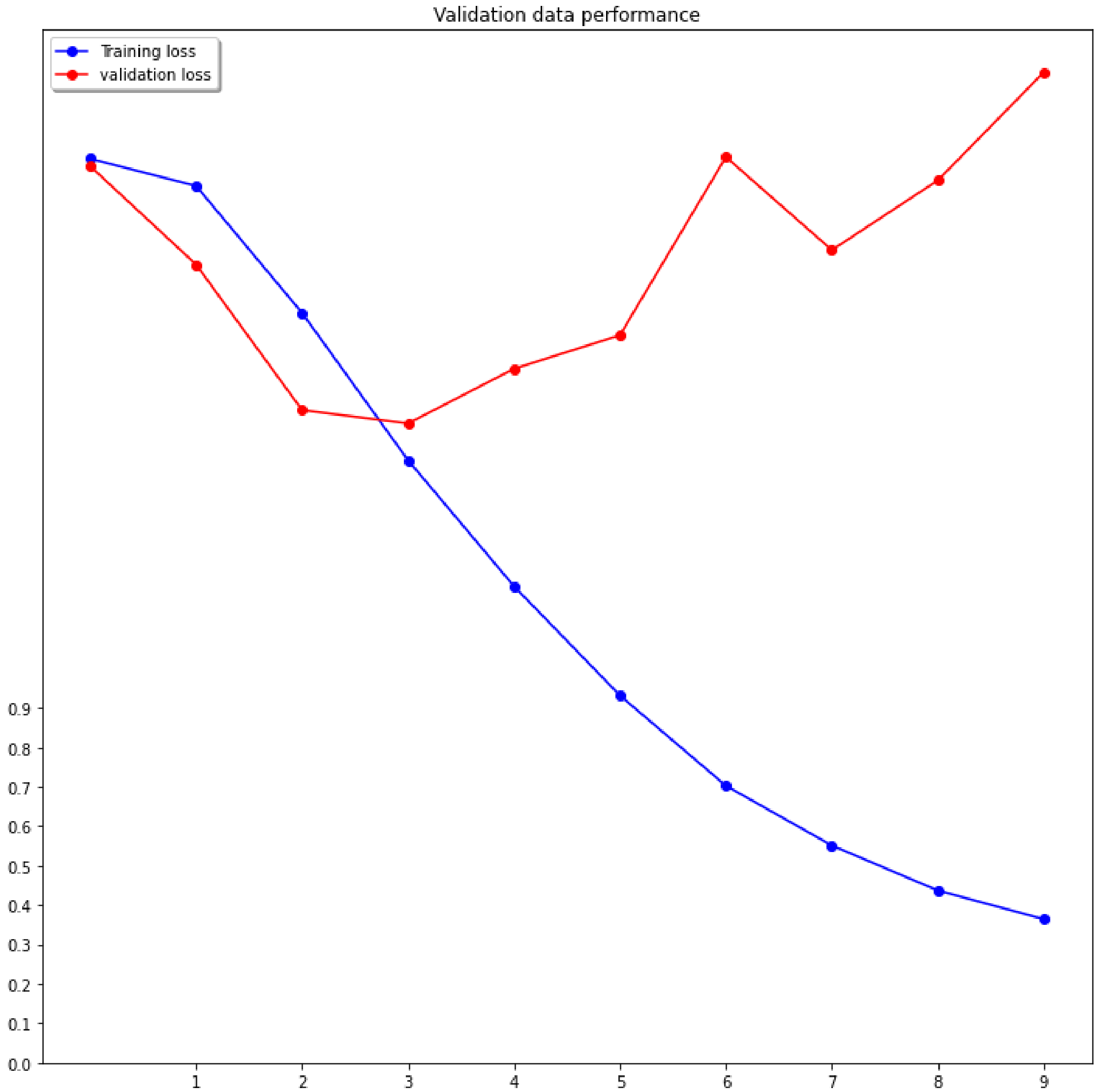
```
548/548 [==============================] - 121s 220ms/step - loss: 0.3845 -
accuracy: 0.8811 - val_loss: 2.5137 - val_accuracy: 0.3923

Epoch 00010: val_accuracy improved from 0.39166 to 0.39227, saving model to
C:\Users\asebaq\distraction-detection\basic_model\distraction-10-0.39.hdf5
```

17 Plot performance graphs

[37]:
```
# Training date
fig = plt.figure(figsize=(10, 10))
plt.plot(model_history.history['accuracy'], '-bo', label="Training accuracy")
plt.plot(model_history.history['val_accuracy'], '-ro',label="Validation␣
 ↪accuracy")
plt.xticks(np.arange(1, epochs, 1))
plt.yticks(np.arange(0, 1, 0.1))
legend = plt.legend(loc='best', shadow=True)
plt.title("Training data performance")
plt.tight_layout()
plt.savefig(os.path.join(MODEL_PATH, "basic_model_training.png"))
plt.show()

# Validation date
fig = plt.figure(figsize=(10, 10))
plt.plot(model_history.history['loss'], '-bo', label="Training loss")
plt.plot(model_history.history['val_loss'], '-ro', label="validation loss")
plt.xticks(np.arange(1, epochs, 1))
plt.yticks(np.arange(0, 1, 0.1))
legend = plt.legend(loc='best', shadow=True)
plt.title("Validation data performance")
plt.tight_layout()
plt.savefig(os.path.join(MODEL_PATH, "basic_model_validation.png"))
plt.show()
```



Training data performance
Training accuracy
Validation accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
1
2
3
4
5
6
7
8
9



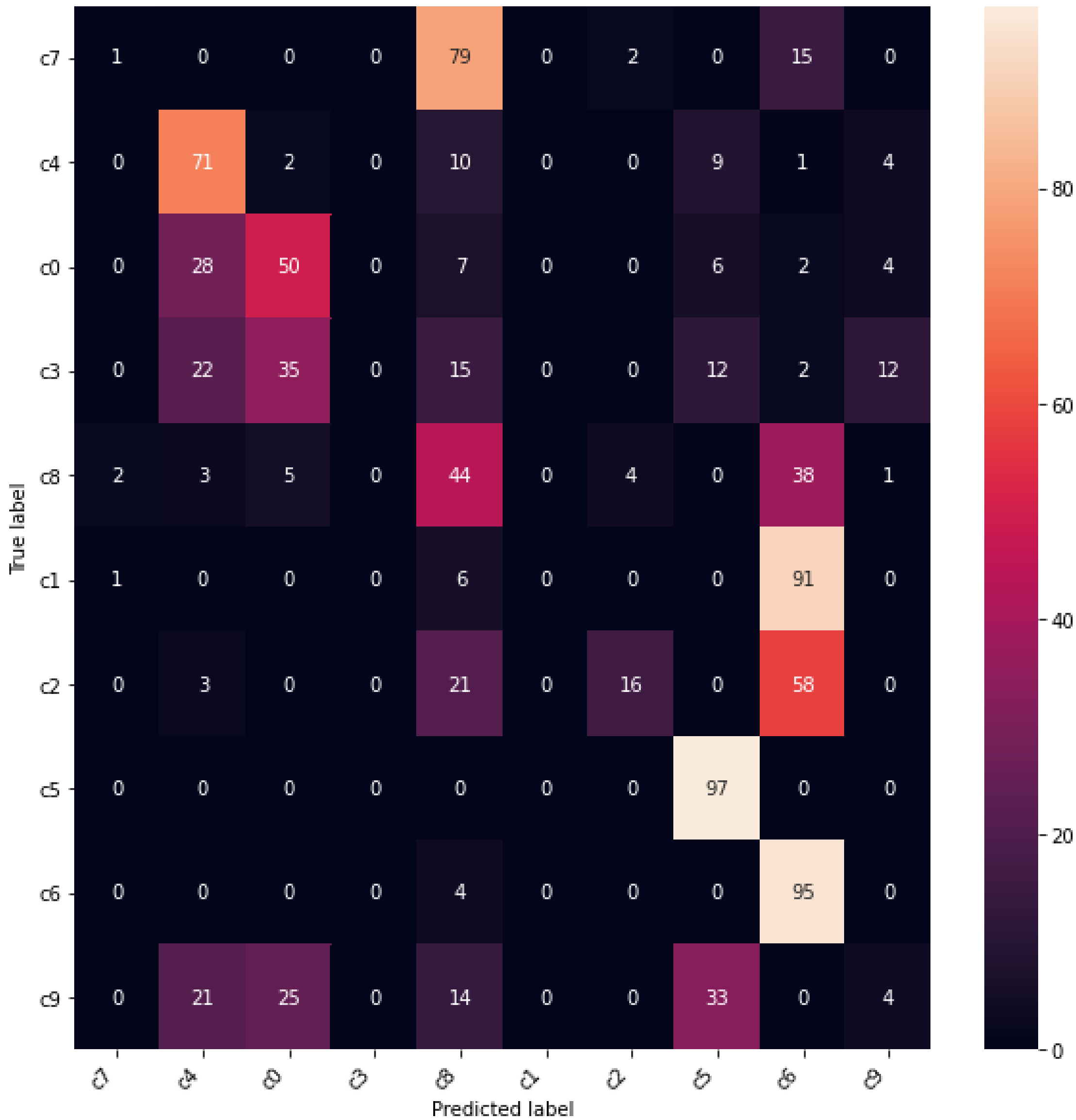
18 Model analysis

[38]:
```
class_names = list()
for name, idx in labels_id.items():
    class_names.append(name)

y_pred = model.predict(valid_tensors)
show_heatmap(y_test, y_pred, class_names)

y_pred = np.argmax(y_pred, axis=1)
y_test = np.argmax(y_test, axis=1)
```

```python
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {round(accuracy, 3)}")

# precision = tp / (tp + fp)
precision = precision_score(y_test, y_pred, average='weighted')
print(f"Precision: {round(precision, 3)}")

# recall = tp / (tp + fn)
recall = recall_score(y_test, y_pred, average='weighted')
print(f"Recall: {round(recall, 3)}")

# f1 = 2 tp / (2 tp + fp + fn)
f1 = f1_score(y_test, y_pred, average='weighted')
print(f"F1 score: {round(f1, 3)}")
```

```
Accuracy: 0.392
Precision: 0.427
Recall: 0.392
F1 score: 0.301
```

```
C:\Users\asebaq\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



[39]:
```
classes = {"c0": "safe 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"
          }
```

```python
plt.figure(figsize=(15, 15))
for i, img_path in data_test.iterrows():
    img_path = img_path.values[0]
    img = image.load_img(img_path)
    ax = plt.subplot(int(f"44{i+1}"))
    ax.margins(0.05)
    ax.imshow(img)
    img_tensor = path_to_tensor(img_path).astype('float32')/255 - 0.5
    label = np.argmax(model.predict(img_tensor))
    label = classes[labels_list[label]]
    ax.set_title(label)
    if i > 6:
        break
plt.savefig(os.path.join(MODEL_PATH, "basic_model_test_samples.png"))
plt.show()
```


```
[ ]:
```