notebook186f17952d

April 30, 2024

1 WEEK 6 FINAL PROJECT - DISTRACTED DRIVER DETECTION USING CNN

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1.1 Gather data, determine the method of data collection and provenance of the data

For the final project, I wanted to work on any object detection/image processing deep learning area. I found a dataset that could help me with this on Kaggle.

While driving on road, it is not uncommon to see drivers who are distracted. They may be texting, scrolling through social media, or in a lively hand-held conversation on their phone.

Quoting from the Kaggle competition: "According to the CDC motor vehicle safety division, one in five car accidents is caused by a distracted driver. Sadly, this translates to 425,000 people injured and 3,000 people killed by distracted driving every year."

The Kaggle challenge was sponsored by State Farm with the intent to better insure their customers, by testing whether dashboard cameras can automatically detect drivers engaging in distracted behaviors.

The challenge's outcomes are evaluated using the multi-class logarithmic loss. Each image has been labeled with one true class. For each image, we must submit a set of predicted probabilities (one for every image). The formula is then,

$logloss = \frac{-1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} log(p_{ij})$,

where

N is the number of images in the test set,

M is the number of image class labels,

log is the natural logarithm,

y_{ij} is 1 if observation i belongs to class j and 0 otherwise,

and p_{ij} is the predicted probability that observation i belongs to class j.

The submitted probabilities for a given image are not required to sum to one because they are rescaled prior to being scored (each row is divided by the row sum). In order to avoid the extremes of the log function, predicted probabilities are replaced with $max(min(p, 1 - 10^{-15}), 10^{-15})$.

To download the data, we have to register for the competion https://www.kaggle.com/competitions/state-farm-distracted-driver-detection/overview

1.2 Identify a Deep Learning Problem

For this project, since the data is from Kaggle, I will be trying different CNN models and comparing their performance.

[2]:
```
import os, cv2, random, shutil

import pandas as pd
import numpy as np



from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import plot_model

from keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense
from keras.models import Sequential, load_model
from keras.callbacks import ModelCheckpoint
from keras.utils import to_categorical
from keras.preprocessing import image


from tqdm import tqdm


from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
from sklearn.datasets import load_files
from sklearn.model_selection import train_test_split


%matplotlib inline
```

1.3 Exploratory Data Analysis (EDA) - Inspect, Visualize, and Clean the Data

[56]:
```
DATA_PATH = "/kaggle"

INPUT_PATH = os.path.join(DATA_PATH, "input/
↪state-farm-distracted-driver-detection")
```

```
IMAGES_PATH = os.path.join(INPUT_PATH, "imgs")
TEST_DIR = os.path.join(IMAGES_PATH, "test")
TRAIN_DIR = os.path.join(IMAGES_PATH, "train")

BASE_MODEL_PATH = os.path.join(DATA_PATH, "working", "model")

MODEL_PATH = os.path.join(BASE_MODEL_PATH, "self_trained")
OUTPUT_CSV_FILES_DIR = os.path.join(DATA_PATH, "working", "output_csv_files")
INPUT_CSV_FILES_DIR = os.path.join(DATA_PATH, "working", "input_csv_files")

if not os.path.exists(INPUT_CSV_FILES_DIR):
    os.makedirs(INPUT_CSV_FILES_DIR)
    print(f"Input CSV path created {INPUT_CSV_FILES_DIR}")

if not os.path.exists(OUTPUT_CSV_FILES_DIR):
    os.makedirs(OUTPUT_CSV_FILES_DIR)
    print(f"Output CSV path created {OUTPUT_CSV_FILES_DIR}")

if not os.path.exists(MODEL_PATH):
    os.makedirs(MODEL_PATH)
    print(f"Model path created {MODEL_PATH}")
```

[20]:
```
train_image = []
image_label = []

img_dim = 64

driver_details = pd.read_csv(os.path.join(INPUT_PATH, "driver_imgs_list.csv"),␣
↪na_values='na')
driver_details.head(5)

for i in range(10):
    print(f'traversing C{i}')
    imgs = os.listdir(os.path.join(TRAIN_DIR, "c"+str(i)))
    for j in range(len(imgs)):
        img_name = os.path.join(TRAIN_DIR, "c"+str(i), imgs[j])
        img = cv2.imread(img_name)
        img = img[50:,120:-50]
        img = cv2.resize(img,(img_dim,img_dim))
        label = i
        driver = driver_details[driver_details['img'] == imgs[j]]['subject'].
↪values[0]
        train_image.append([img,label,driver])
        image_label.append(i)
```

```
traversing C0
traversing C1
traversing C2
```

```
traversing C3
traversing C4
traversing C5
traversing C6
traversing C7
traversing C8
traversing C9
```

[65]:
```python
driver_details.head(5)
```

[65]:

	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

[66]:
```python
driver_details.describe()
```

[66]:

	subject	classname	img
count	22424	22424	22424
unique	26	10	22424
top	p021	c0	img_9684.jpg
freq	1237	2489	1

[68]:
```python
driver_details.isna().sum()
```

[68]:
```
subject      0
classname    0
img          0
dtype: int64
```

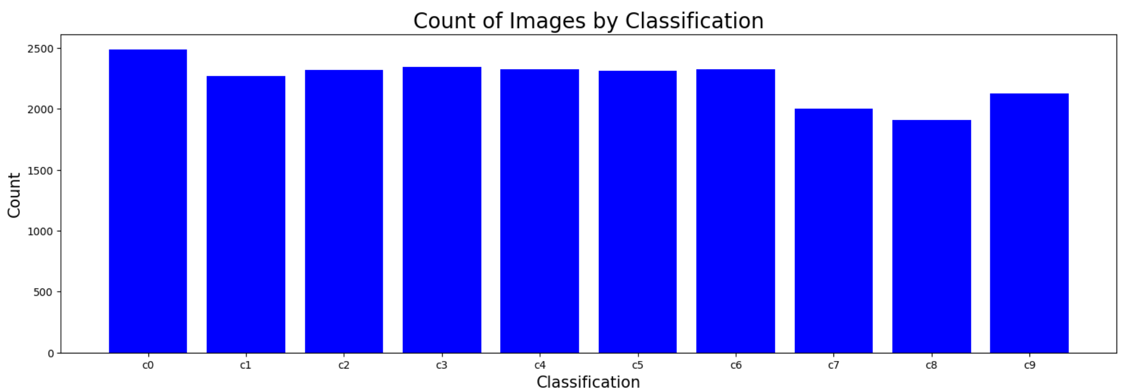
All images seem to be good. We have no null values in csv. So, there is nothing to be cleaned

[21]:
```python
class_value_counts = dict()
for img in train_image:
    class_type = img[1]
    class_value_counts['c'+str(class_type)] = class_value_counts.
 ↪get('c'+str(class_type), 0)+1

print(class_value_counts)
```

```
{'c0': 2489, 'c1': 2267, 'c2': 2317, 'c3': 2346, 'c4': 2326, 'c5': 2312, 'c6':
2325, 'c7': 2002, 'c8': 1911, 'c9': 2129}
```

Let us look at the number of images in each of the different classes

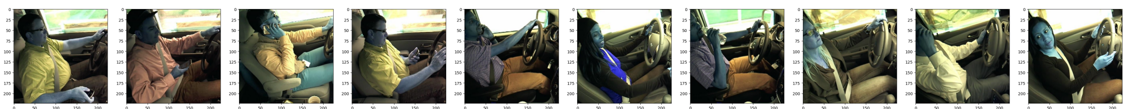
```
[22]: fig = plt.figure(figsize=(18,12))
ay = fig.add_subplot(211)
labels = class_value_counts.keys()
x = range(len(labels))
y = class_value_counts.values()
plt.xticks(x, labels, size=10)
plt.yticks(size=10)

ay.bar(x, y, color="blue")

plt.title('Count of Images by Classification',size=20)
plt.xlabel('Classification', size=15)
plt.ylabel('Count', size=15)

plt.show()
```



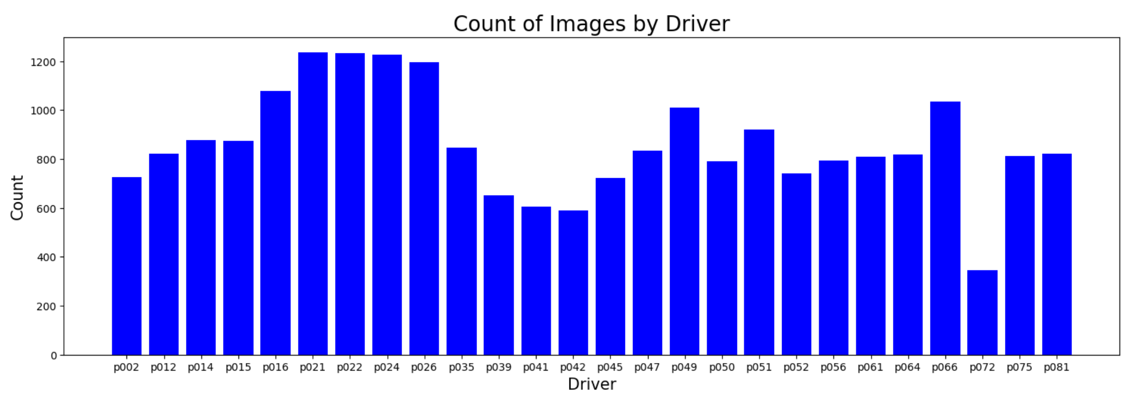
Let us look at one image from each of the different classes

```
[60]: fig, ax = plt.subplots(1, 10, figsize = (50,50 ))
for i in range(10):
    for file in os.listdir(os.path.join(TRAIN_DIR, 'c'+str(i))):
        img = cv2.imread(os.path.join(TRAIN_DIR, 'c'+str(i),file))
        img = img[50:,120:-50]
        img = cv2.resize(img,(224,224))

        ax[i].imshow(img,cmap = 'gray')
        break
plt.show
```

```
[60]: <function matplotlib.pyplot.show(close=None, block=None)>
```



[74]:
```python
# Find the frequency of images per driver
driver_ids = dict()
for dr in driver_details['subject']:
    driver_ids[dr] = driver_ids.get(dr, 0)+1

d = list()
c = list()
for k,v in driver_ids.items():
    d.append(k)
    c.append(v)

fig = plt.figure(figsize=(18,12))
ay = fig.add_subplot(211)
labels = d
x = range(len(labels))
y = c
plt.xticks(x, labels, size=10)
plt.yticks(size=10)

ay.bar(x, y, color="blue")

plt.title('Count of Images by Driver',size=20)
plt.xlabel('Driver', size=15)
plt.ylabel('Count', size=15)

plt.show()
```



1.4 Model Building

I will split the data into 80:20 for training and validation. The CNN model I will start off with is a multi layer one with Conv2D with 64+128+256+512 filters and relu activation, followed by max pooling. After flattening the data and adding dropouts, finally I will add a softmax layer with 10 classes.

[32]:
```
X = list()
y = list()
for features,labels,drivers in train_image:
    X.append(features)
    y.append(labels)


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
print (len(X_train),len(X_test))
print (len(y_train),len(y_test))
X_train = np.array(X_train).reshape(-1,img_dim,img_dim,3)
X_test = np.array(X_test).reshape(-1,img_dim,img_dim,3)
print(f'{X_train.shape} {X_test.shape}')
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
print(f'{y_train.shape} {y_test.shape}')
```

```
17939 4485
17939 4485
(17939, 64, 64, 3) (4485, 64, 64, 3)
(17939, 10) (4485, 10)
```

[33]:
```
def get_model():
    model = Sequential()
    # 64 conv2d filters with relu
    model.add(Conv2D(filters=64, kernel_size=2, padding='same',␣
 ↪activation='relu', input_shape=(64,64,3),␣
 ↪kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 128 conv2d filters with relu
    model.add(Conv2D(filters=128, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 256 conv2d filters with relu
    model.add(Conv2D(filters=256, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 512 conv2d filters with relu
    model.add(Conv2D(filters=512, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))
```

```
    model.add(Dropout(0.5))
    model.add(Flatten())
    model.add(Dense(500, activation='relu', kernel_initializer='glorot_normal'))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation='softmax',␣
↪kernel_initializer='glorot_normal'))

    return model

model = get_model()
model.summary()
```

```
/opt/conda/lib/python3.10/site-
packages/keras/src/layers/convolutional/base_conv.py:99: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 64, 64, 64)	832
max_pooling2d_4 (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_5 (Conv2D)	(None, 32, 32, 128)	32,896
max_pooling2d_5 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_6 (Conv2D)	(None, 16, 16, 256)	131,328
max_pooling2d_6 (MaxPooling2D)	(None, 8, 8, 256)	0
conv2d_7 (Conv2D)	(None, 8, 8, 512)	524,800
max_pooling2d_7 (MaxPooling2D)	(None, 4, 4, 512)	0
dropout_2 (Dropout)	(None, 4, 4, 512)	0
flatten_1 (Flatten)	(None, 8192)	0
dense_2 (Dense)	(None, 500)	4,096,500
dropout_3 (Dropout)	(None, 500)	0

```
dense_3 (Dense)                    (None, 10)                    5,010
```

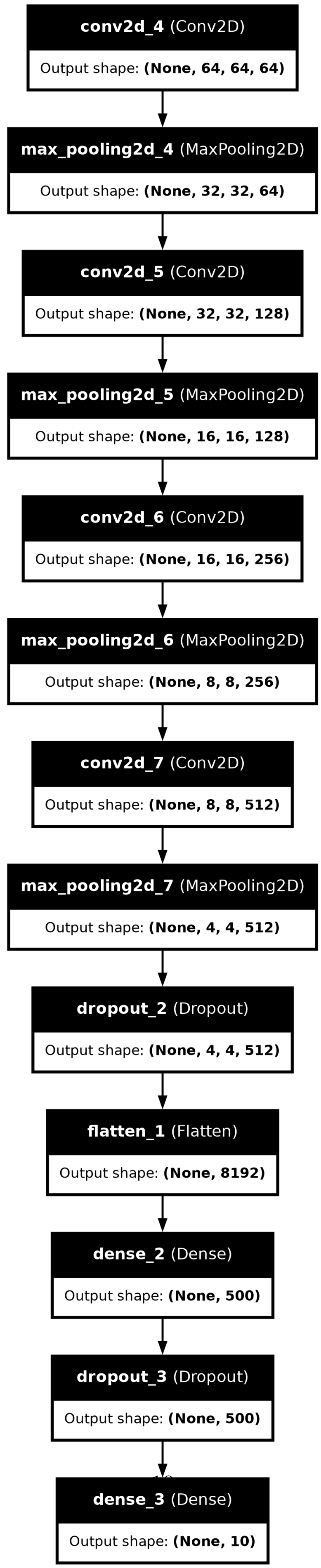
Total params: 4,791,366 (18.28 MB)

Trainable params: 4,791,366 (18.28 MB)

Non-trainable params: 0 (0.00 B)

[34]:
```python
plot_model(model,to_file=os.path.join(MODEL_PATH,"model_distracted_driver.
↪png"),show_shapes=True,show_layer_names=True)
```

[34]:


conv2d_4 (Conv2D)
Output shape: (None, 64, 64, 64)
max_pooling2d_4 (MaxPooling2D)
Output shape: (None, 32, 32, 64)
conv2d_5 (Conv2D)
Output shape: (None, 32, 32, 128)
max_pooling2d_5 (MaxPooling2D)
Output shape: (None, 16, 16, 128)
conv2d_6 (Conv2D)
Output shape: (None, 16, 16, 256)
max_pooling2d_6 (MaxPooling2D)
Output shape: (None, 8, 8, 256)
conv2d_7 (Conv2D)
Output shape: (None, 8, 8, 512)
max_pooling2d_7 (MaxPooling2D)
Output shape: (None, 4, 4, 512)
dropout_2 (Dropout)
Output shape: (None, 4, 4, 512)
flatten_1 (Flatten)
Output shape: (None, 8192)
dense_2 (Dense)
Output shape: (None, 500)
dropout_3 (Dropout)
Output shape: (None, 500)
dense_3 (Dense)
Output shape: (None, 10)

[35]:
```
model.compile(optimizer='rmsprop', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])

filepath = os.path.join(MODEL_PATH,"first-{epoch:02d}-{val_accuracy:.2f}.keras")

img_data_gen = ImageDataGenerator(height_shift_range=0.5, width_shift_range=0.
↪5, zoom_range=0.5, rotation_range=30)

data_generator = img_data_gen.flow(X_train, y_train, batch_size=64)

checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,␣
↪save_best_only=True, mode='max')
callbacks_list = [checkpoint]
epochs = 20

model_history = model.fit(data_generator, validation_data=(X_test, y_test),␣
↪epochs=epochs, batch_size=40, shuffle=True, callbacks=callbacks_list)
```

```
Epoch 1/20

/opt/conda/lib/python3.10/site-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:120:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
  self._warn_if_super_not_called()

  3/281              17s 62ms/step - accuracy:
0.0703 - loss: 94.4282

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1714031376.956743      87 device_compiler.h:186] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.
W0000 00:00:1714031376.973145      87 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

118/281              20s 125ms/step -
accuracy: 0.1038 - loss: 14.2558

W0000 00:00:1714031391.547976      90 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

280/281              0s 102ms/step -
accuracy: 0.1086 - loss: 8.3521

W0000 00:00:1714031407.352311      89 graph_launch.cc:671] Fallback to op-by-op
```

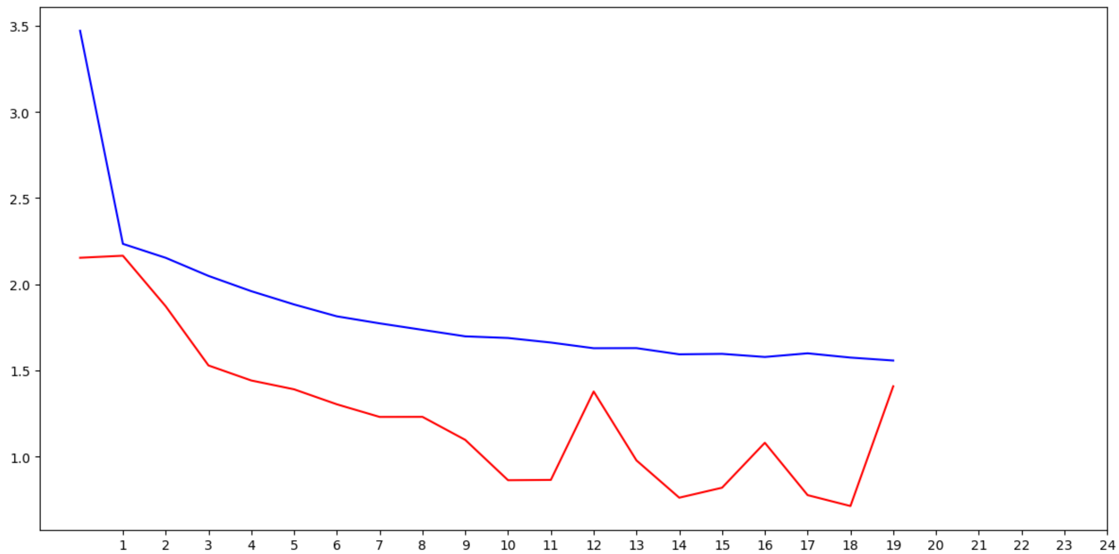
```
mode because memset node breaks graph update

Epoch 1: val_accuracy improved from -inf to 0.22965, saving model to
/kaggle/working/model/self_trained/first-01-0.23.keras
281/281            42s 114ms/step -
accuracy: 0.1087 - loss: 8.3175 - val_accuracy: 0.2297 - val_loss: 2.1536
W0000 00:00:1714031408.718173      88 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
Epoch 2/20
281/281            0s 87ms/step -
accuracy: 0.1476 - loss: 2.2606
Epoch 2: val_accuracy did not improve from 0.22965
281/281            25s 88ms/step -
accuracy: 0.1477 - loss: 2.2605 - val_accuracy: 0.2161 - val_loss: 2.1655
Epoch 3/20
280/281            0s 85ms/step -
accuracy: 0.1801 - loss: 2.1764
Epoch 3: val_accuracy improved from 0.22965 to 0.30814, saving model to
/kaggle/working/model/self_trained/first-03-0.31.keras
281/281            25s 87ms/step -
accuracy: 0.1802 - loss: 2.1762 - val_accuracy: 0.3081 - val_loss: 1.8722
Epoch 4/20
281/281            0s 85ms/step -
accuracy: 0.2192 - loss: 2.0706
Epoch 4: val_accuracy improved from 0.30814 to 0.41427, saving model to
/kaggle/working/model/self_trained/first-04-0.41.keras
281/281            25s 87ms/step -
accuracy: 0.2193 - loss: 2.0706 - val_accuracy: 0.4143 - val_loss: 1.5288
Epoch 5/20
280/281            0s 86ms/step -
accuracy: 0.2676 - loss: 1.9692
Epoch 5: val_accuracy improved from 0.41427 to 0.42876, saving model to
/kaggle/working/model/self_trained/first-05-0.43.keras
281/281            25s 88ms/step -
accuracy: 0.2676 - loss: 1.9692 - val_accuracy: 0.4288 - val_loss: 1.4417
Epoch 6/20
281/281            0s 84ms/step -
accuracy: 0.2957 - loss: 1.9029
Epoch 6: val_accuracy improved from 0.42876 to 0.52263, saving model to
/kaggle/working/model/self_trained/first-06-0.52.keras
281/281            25s 86ms/step -
accuracy: 0.2957 - loss: 1.9028 - val_accuracy: 0.5226 - val_loss: 1.3904
Epoch 7/20
280/281            0s 85ms/step -
accuracy: 0.3237 - loss: 1.8160
Epoch 7: val_accuracy did not improve from 0.52263
```

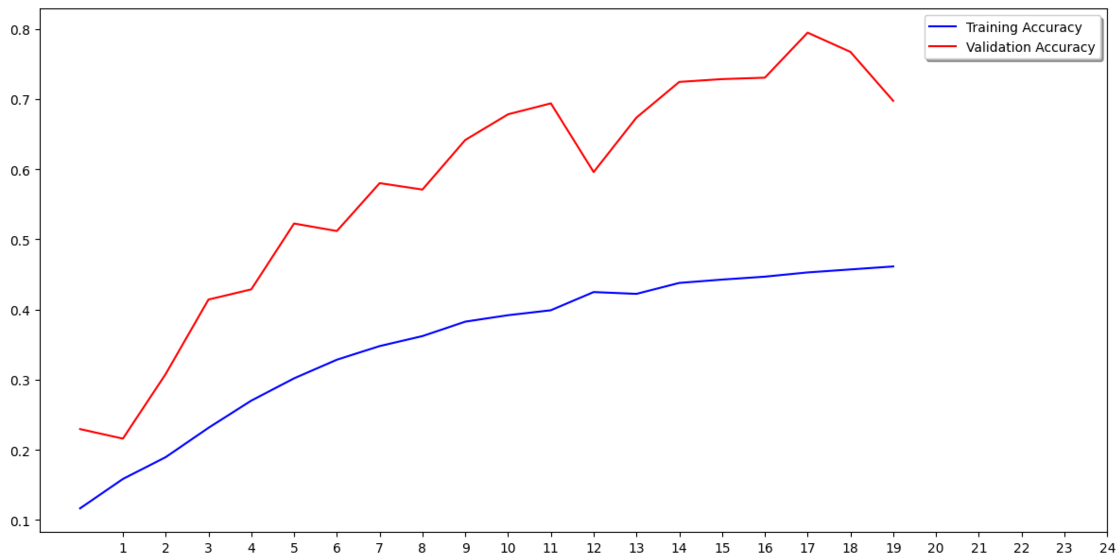
```
281/281              25s 87ms/step -
accuracy: 0.3238 - loss: 1.8160 - val_accuracy: 0.5119 - val_loss: 1.3034
Epoch 8/20
280/281              0s 84ms/step -
accuracy: 0.3498 - loss: 1.7702
Epoch 8: val_accuracy improved from 0.52263 to 0.58016, saving model to
/kaggle/working/model/self_trained/first-08-0.58.keras
281/281              25s 86ms/step -
accuracy: 0.3498 - loss: 1.7702 - val_accuracy: 0.5802 - val_loss: 1.2302
Epoch 9/20
281/281              0s 85ms/step -
accuracy: 0.3596 - loss: 1.7301
Epoch 9: val_accuracy did not improve from 0.58016
281/281              25s 86ms/step -
accuracy: 0.3596 - loss: 1.7301 - val_accuracy: 0.5710 - val_loss: 1.2306
Epoch 10/20
280/281              0s 86ms/step -
accuracy: 0.3777 - loss: 1.7069
Epoch 10: val_accuracy improved from 0.58016 to 0.64169, saving model to
/kaggle/working/model/self_trained/first-10-0.64.keras
281/281              25s 88ms/step -
accuracy: 0.3778 - loss: 1.7068 - val_accuracy: 0.6417 - val_loss: 1.0969
Epoch 11/20
280/281              0s 84ms/step -
accuracy: 0.3860 - loss: 1.6998
Epoch 11: val_accuracy improved from 0.64169 to 0.67826, saving model to
/kaggle/working/model/self_trained/first-11-0.68.keras
281/281              25s 86ms/step -
accuracy: 0.3861 - loss: 1.6998 - val_accuracy: 0.6783 - val_loss: 0.8630
Epoch 12/20
280/281              0s 84ms/step -
accuracy: 0.3956 - loss: 1.6780
Epoch 12: val_accuracy improved from 0.67826 to 0.69387, saving model to
/kaggle/working/model/self_trained/first-12-0.69.keras
281/281              25s 86ms/step -
accuracy: 0.3957 - loss: 1.6779 - val_accuracy: 0.6939 - val_loss: 0.8647
Epoch 13/20
280/281              0s 86ms/step -
accuracy: 0.4205 - loss: 1.6266
Epoch 13: val_accuracy did not improve from 0.69387
281/281              25s 88ms/step -
accuracy: 0.4205 - loss: 1.6266 - val_accuracy: 0.5960 - val_loss: 1.3777
Epoch 14/20
281/281              0s 86ms/step -
accuracy: 0.4155 - loss: 1.6389
Epoch 14: val_accuracy did not improve from 0.69387
281/281              25s 87ms/step -
accuracy: 0.4155 - loss: 1.6389 - val_accuracy: 0.6736 - val_loss: 0.9780
```

```
Epoch 15/20
280/281              0s 85ms/step -
accuracy: 0.4434 - loss: 1.5828
Epoch 15: val_accuracy improved from 0.69387 to 0.72441, saving model to
/kaggle/working/model/self_trained/first-15-0.72.keras
281/281              25s 87ms/step -
accuracy: 0.4433 - loss: 1.5828 - val_accuracy: 0.7244 - val_loss: 0.7616
Epoch 16/20
281/281              0s 85ms/step -
accuracy: 0.4432 - loss: 1.5894
Epoch 16: val_accuracy improved from 0.72441 to 0.72843, saving model to
/kaggle/working/model/self_trained/first-16-0.73.keras
281/281              25s 87ms/step -
accuracy: 0.4432 - loss: 1.5894 - val_accuracy: 0.7284 - val_loss: 0.8195
Epoch 17/20
280/281              0s 87ms/step -
accuracy: 0.4434 - loss: 1.5874
Epoch 17: val_accuracy improved from 0.72843 to 0.73043, saving model to
/kaggle/working/model/self_trained/first-17-0.73.keras
281/281              25s 88ms/step -
accuracy: 0.4434 - loss: 1.5874 - val_accuracy: 0.7304 - val_loss: 1.0802
Epoch 18/20
281/281              0s 84ms/step -
accuracy: 0.4512 - loss: 1.6058
Epoch 18: val_accuracy improved from 0.73043 to 0.79465, saving model to
/kaggle/working/model/self_trained/first-18-0.79.keras
281/281              25s 86ms/step -
accuracy: 0.4512 - loss: 1.6058 - val_accuracy: 0.7946 - val_loss: 0.7764
Epoch 19/20
281/281              0s 87ms/step -
accuracy: 0.4460 - loss: 1.5926
Epoch 19: val_accuracy did not improve from 0.79465
281/281              25s 88ms/step -
accuracy: 0.4461 - loss: 1.5925 - val_accuracy: 0.7672 - val_loss: 0.7132
Epoch 20/20
280/281              0s 86ms/step -
accuracy: 0.4535 - loss: 1.5571
Epoch 20: val_accuracy did not improve from 0.79465
281/281              25s 87ms/step -
accuracy: 0.4536 - loss: 1.5571 - val_accuracy: 0.6974 - val_loss: 1.4080
```

[38]:
```python
def show_loss_and_accuracy_plots(model_history):
    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 12))
    ax1.plot(model_history.history['loss'], color='b', label="Training Loss")
    ax1.plot(model_history.history['val_loss'], color='r', label="Validation␣
↪Loss")
    ax1.set_xticks(np.arange(1, 25, 1))
```

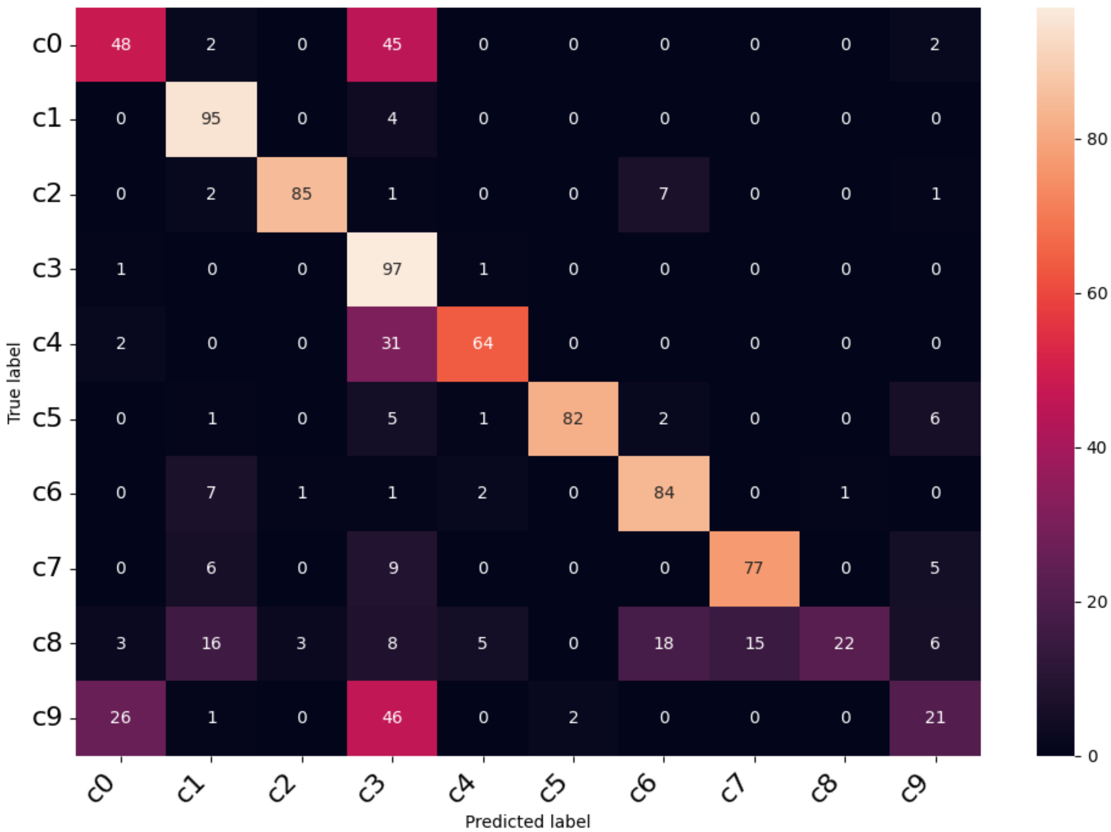
```
    ax2.plot(model_history.history['accuracy'], color='b', label="Training␣
↪Accuracy")
    ax2.plot(model_history.history['val_accuracy'], color='r',label="Validation␣
↪Accuracy")
    ax2.set_xticks(np.arange(1, 25, 1))

    legend = plt.legend(loc='best', shadow=True)
    plt.tight_layout()
    plt.show()

show_loss_and_accuracy_plots(model_history)
```





[39]:
```
def print_confusion_matrix(confusion_matrix, class_names, figsize=(10,7),␣
↪fontsize=14):
    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', fontsize=fontsize)
    heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45,␣
↪ha='right', fontsize=fontsize)
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    fig.savefig(os.path.join(MODEL_PATH,"confusion_matrix.png"))
    return fig

def print_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 = print_confusion_matrix(c, class_names, figsize=(12,8),␣
↪fontsize=16)

class_names = ['c0', 'c1', 'c2', 'c3', 'c4', 'c5', 'c6', 'c7', 'c8', 'c9']
y_pred = model.predict(X_test)

print_heatmap(y_test,y_pred,class_names)
```

```
 66/141            0s 2ms/step

W0000 00:00:1714032332.210508      90 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

141/141            2s 5ms/step

W0000 00:00:1714032332.911818      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
```



[41]:
```
y_pred_class = np.argmax(y_pred, axis=1)

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

accuracy = accuracy_score(y_test, y_pred_class)
print('Accuracy: %f' % accuracy)

precision = precision_score(y_test, y_pred_class, average='weighted')
print('Precision: %f' % precision)

recall = recall_score(y_test, y_pred_class, average='weighted')
print('Recall: %f' % recall)

f1 = f1_score(y_test, y_pred_class, average='weighted')
print('F1 score: %f' % f1)
```

```
Accuracy: 0.697436
Precision: 0.744432
Recall: 0.697436
F1 score: 0.683957
```

[42]:
```python
#load checkpoint with best val_accuracy
BEST_MODEL = os.path.join(MODEL_PATH,"first-18-0.79.keras")
model = load_model(BEST_MODEL)
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 64, 64, 64)	832
max_pooling2d_4 (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_5 (Conv2D)	(None, 32, 32, 128)	32,896
max_pooling2d_5 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_6 (Conv2D)	(None, 16, 16, 256)	131,328
max_pooling2d_6 (MaxPooling2D)	(None, 8, 8, 256)	0
conv2d_7 (Conv2D)	(None, 8, 8, 512)	524,800
max_pooling2d_7 (MaxPooling2D)	(None, 4, 4, 512)	0
dropout_2 (Dropout)	(None, 4, 4, 512)	0
flatten_1 (Flatten)	(None, 8192)	0
dense_2 (Dense)	(None, 500)	4,096,500
dropout_3 (Dropout)	(None, 500)	0
dense_3 (Dense)	(None, 10)	5,010

Total params: 9,582,734 (36.56 MB)

Trainable params: 4,791,366 (18.28 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 4,791,368 (18.28 MB)

[43]:
```
files = os.listdir(TEST_DIR)
test_images = []
for i in range(len(files)):
    img = cv2.imread(os.path.join(TEST_DIR, files[i]))
    img = img[50:,120:-50]
    img = cv2.resize(img,(64,64))
    test_images.append(img)

test_images = np.array(test_images).reshape(-1,64,64,3)
test_image.shape
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[43], line 10
      7     test_images.append(img)
      9 test_images = np.array(test_images).reshape(-1,64,64,3)
---> 10 test_image.shape

NameError: name 'test_image' is not defined
```

[44]:
```
test_images.shape
```

[44]:
```
(79726, 64, 64, 3)
```

[47]:
```
def predict_and_write_results(model, test_images, files, out_file_name):
    df = pd.DataFrame(columns=['img', 'c0', 'c1', 'c2', 'c3', 'c4', 'c5', 'c6',␣
 ↪'c7', 'c8', 'c9'])
    ypred_test = model.predict(test_images, verbose=1)
    for i in range(len(files)):
        new_row = {
            "img":files[i],
            'c0':ypred_test[i][0],
            'c1':ypred_test[i][1],
            'c2':ypred_test[i][2],
            'c3':ypred_test[i][3],
            'c4':ypred_test[i][4],
            'c5':ypred_test[i][5],
            'c6':ypred_test[i][6],
            'c7':ypred_test[i][7],
            'c8':ypred_test[i][8],
            'c9':ypred_test[i][9]
        }
        df = pd.concat([df, pd.DataFrame([new_row])], ignore_index=True)
    df.to_csv(os.path.join(OUTPUT_CSV_FILES_DIR,out_file_name),index=False)
```

```
predict_and_write_results(model, test_images, files,␣
↪'kaggle_self_trained_first_model.csv')
```

```
2492/2492              6s 2ms/step

/tmp/ipykernel_34/950582733.py:18: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  df = pd.concat([df, pd.DataFrame([new_row])], ignore_index=True)
```

Submission and Description	Private Score	Public Score	Selected
kaggle_self_trained_first_model.csv Complete (after deadline) · now	2.24537	2.46848	☐

1.5 Tuning training process

This score is good. However, when the images are split randomly, different images of the same person will end up in training and validation and there appears to be a leak in the model. Let us try if the same model will work better if we split our training data according to driver instead of random split

[48]:
```
driv_selected = ['p050', 'p015', 'p022', 'p056']
## Split the data into training and validation

X_train= []
y_train = []
X_test = []
y_test = []
D_train = []
D_test = []

for features,labels,drivers in train_image:
    if drivers in driv_selected:
        X_test.append(features)
        y_test.append(labels)
        D_test.append(drivers)

    else:
        X_train.append(features)
        y_train.append(labels)
        D_train.append(drivers)

print (len(X_train),len(X_test))
print (len(y_train),len(y_test))
```

18732 3692
18732 3692

[49]:
```
X_train = np.array(X_train).reshape(-1,img_dim,img_dim,3)
X_test = np.array(X_test).reshape(-1,img_dim,img_dim,3)
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)


print (X_train.shape)
```

```
(18732, 64, 64, 3)
```

[50]:
```
model = get_model()
model.summary()
```

```
/opt/conda/lib/python3.10/site-
packages/keras/src/layers/convolutional/base_conv.py:99: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 64, 64, 64)	832
max_pooling2d_8 (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_9 (Conv2D)	(None, 32, 32, 128)	32,896
max_pooling2d_9 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_10 (Conv2D)	(None, 16, 16, 256)	131,328
max_pooling2d_10 (MaxPooling2D)	(None, 8, 8, 256)	0
conv2d_11 (Conv2D)	(None, 8, 8, 512)	524,800
max_pooling2d_11 (MaxPooling2D)	(None, 4, 4, 512)	0
dropout_4 (Dropout)	(None, 4, 4, 512)	0
flatten_2 (Flatten)	(None, 8192)	0
dense_4 (Dense)	(None, 500)	4,096,500

```
 dropout_5 (Dropout)              (None, 500)                      0

 dense_5 (Dense)                  (None, 10)                   5,010
```

Total params: 4,791,366 (18.28 MB)

Trainable params: 4,791,366 (18.28 MB)

Non-trainable params: 0 (0.00 B)

[51]:
```python
model.compile(optimizer='rmsprop', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])

filepath = os.path.join(MODEL_PATH,"second-{epoch:02d}-{val_accuracy:.2f}.
↪keras")

checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,␣
↪save_best_only=True, mode='max')
callbacks_list = [checkpoint]


img_data_gen = ImageDataGenerator(height_shift_range=0.5, width_shift_range = 0.
↪5, zoom_range = 0.5, rotation_range=30)

data_generator = img_data_gen.flow(X_train, y_train, batch_size=64)

history = model.fit(data_generator, callbacks=callbacks_list, epochs=20,␣
↪verbose=1, validation_data=(X_test, y_test), batch_size=40, shuffle=True)
```

```
Epoch 1/20

/opt/conda/lib/python3.10/site-
packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:120:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
  self._warn_if_super_not_called()

  3/293              17s 62ms/step - accuracy:
0.0972 - loss: 76.3583

W0000 00:00:1714037371.592966      87 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
```

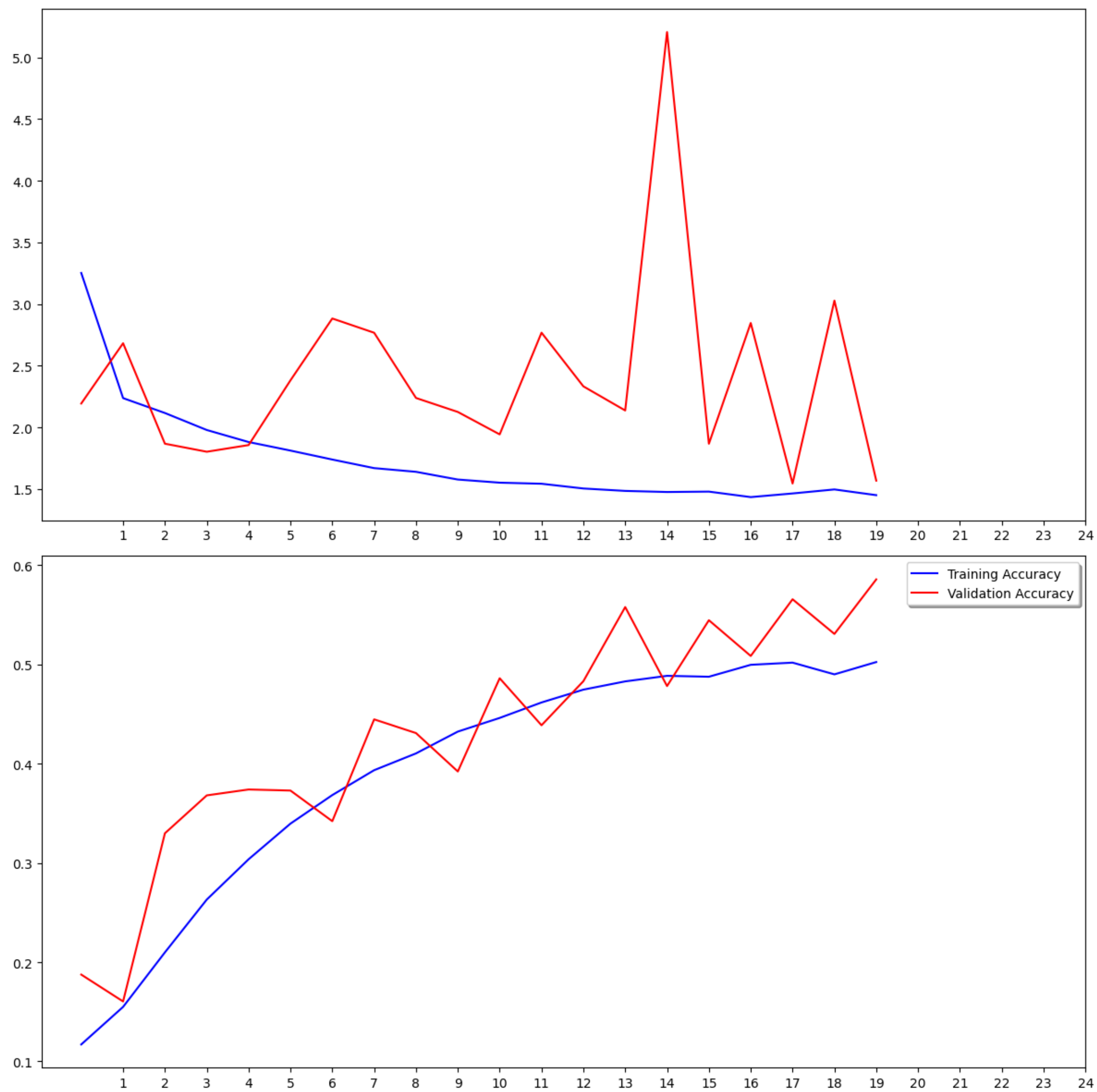
```
124/293           22s 134ms/step -
accuracy: 0.0970 - loss: 11.9435

W0000 00:00:1714037387.950956      90 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

293/293           0s 106ms/step -
accuracy: 0.1049 - loss: 7.2001

W0000 00:00:1714037403.532477      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update


Epoch 1: val_accuracy improved from -inf to 0.18743, saving model to
/kaggle/working/model/self_trained/second-01-0.19.keras
293/293           39s 115ms/step -
accuracy: 0.1049 - loss: 7.1867 - val_accuracy: 0.1874 - val_loss: 2.1930
Epoch 2/20

W0000 00:00:1714037404.999101      87 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

292/293           0s 86ms/step -
accuracy: 0.1452 - loss: 2.2601
Epoch 2: val_accuracy did not improve from 0.18743
293/293           26s 87ms/step -
accuracy: 0.1452 - loss: 2.2600 - val_accuracy: 0.1603 - val_loss: 2.6819
Epoch 3/20
293/293           0s 86ms/step -
accuracy: 0.1961 - loss: 2.1519
Epoch 3: val_accuracy improved from 0.18743 to 0.32990, saving model to
/kaggle/working/model/self_trained/second-03-0.33.keras
293/293           26s 88ms/step -
accuracy: 0.1961 - loss: 2.1518 - val_accuracy: 0.3299 - val_loss: 1.8668
Epoch 4/20
292/293           0s 87ms/step -
accuracy: 0.2519 - loss: 2.0038
Epoch 4: val_accuracy improved from 0.32990 to 0.36809, saving model to
/kaggle/working/model/self_trained/second-04-0.37.keras
293/293           27s 89ms/step -
accuracy: 0.2520 - loss: 2.0037 - val_accuracy: 0.3681 - val_loss: 1.8019
Epoch 5/20
292/293           0s 86ms/step -
accuracy: 0.2955 - loss: 1.9057
Epoch 5: val_accuracy improved from 0.36809 to 0.37405, saving model to
/kaggle/working/model/self_trained/second-05-0.37.keras
293/293           26s 87ms/step -
accuracy: 0.2955 - loss: 1.9055 - val_accuracy: 0.3741 - val_loss: 1.8558
Epoch 6/20
292/293           0s 86ms/step -
accuracy: 0.3329 - loss: 1.8245
```

```
Epoch 6: val_accuracy did not improve from 0.37405
293/293            26s 87ms/step -
accuracy: 0.3329 - loss: 1.8244 - val_accuracy: 0.3730 - val_loss: 2.3810
Epoch 7/20
292/293            0s 87ms/step -
accuracy: 0.3574 - loss: 1.7612
Epoch 7: val_accuracy did not improve from 0.37405
293/293            26s 88ms/step -
accuracy: 0.3575 - loss: 1.7611 - val_accuracy: 0.3421 - val_loss: 2.8826
Epoch 8/20
292/293            0s 86ms/step -
accuracy: 0.3840 - loss: 1.6995
Epoch 8: val_accuracy improved from 0.37405 to 0.44475, saving model to
/kaggle/working/model/self_trained/second-08-0.44.keras
293/293            26s 87ms/step -
accuracy: 0.3841 - loss: 1.6993 - val_accuracy: 0.4447 - val_loss: 2.7669
Epoch 9/20
292/293            0s 86ms/step -
accuracy: 0.4049 - loss: 1.6577
Epoch 9: val_accuracy did not improve from 0.44475
293/293            26s 87ms/step -
accuracy: 0.4049 - loss: 1.6576 - val_accuracy: 0.4309 - val_loss: 2.2379
Epoch 10/20
292/293            0s 86ms/step -
accuracy: 0.4282 - loss: 1.5863
Epoch 10: val_accuracy did not improve from 0.44475
293/293            26s 87ms/step -
accuracy: 0.4282 - loss: 1.5862 - val_accuracy: 0.3922 - val_loss: 2.1245
Epoch 11/20
292/293            0s 85ms/step -
accuracy: 0.4326 - loss: 1.5790
Epoch 11: val_accuracy improved from 0.44475 to 0.48619, saving model to
/kaggle/working/model/self_trained/second-11-0.49.keras
293/293            26s 86ms/step -
accuracy: 0.4327 - loss: 1.5788 - val_accuracy: 0.4862 - val_loss: 1.9426
Epoch 12/20
293/293            0s 86ms/step -
accuracy: 0.4553 - loss: 1.5594
Epoch 12: val_accuracy did not improve from 0.48619
293/293            26s 87ms/step -
accuracy: 0.4553 - loss: 1.5593 - val_accuracy: 0.4388 - val_loss: 2.7675
Epoch 13/20
293/293            0s 86ms/step -
accuracy: 0.4757 - loss: 1.4924
Epoch 13: val_accuracy did not improve from 0.48619
293/293            26s 87ms/step -
accuracy: 0.4757 - loss: 1.4924 - val_accuracy: 0.4832 - val_loss: 2.3321
Epoch 14/20
```

```
293/293               0s 86ms/step -
accuracy: 0.4754 - loss: 1.4867
Epoch 14: val_accuracy improved from 0.48619 to 0.55796, saving model to
/kaggle/working/model/self_trained/second-14-0.56.keras
293/293               26s 87ms/step -
accuracy: 0.4754 - loss: 1.4867 - val_accuracy: 0.5580 - val_loss: 2.1365
Epoch 15/20
292/293               0s 85ms/step -
accuracy: 0.4922 - loss: 1.4839
Epoch 15: val_accuracy did not improve from 0.55796
293/293               26s 86ms/step -
accuracy: 0.4922 - loss: 1.4838 - val_accuracy: 0.4783 - val_loss: 5.2060
Epoch 16/20
293/293               0s 86ms/step -
accuracy: 0.4852 - loss: 1.4737
Epoch 16: val_accuracy did not improve from 0.55796
293/293               26s 87ms/step -
accuracy: 0.4852 - loss: 1.4737 - val_accuracy: 0.5447 - val_loss: 1.8665
Epoch 17/20
293/293               0s 86ms/step -
accuracy: 0.4961 - loss: 1.4276
Epoch 17: val_accuracy did not improve from 0.55796
293/293               26s 87ms/step -
accuracy: 0.4962 - loss: 1.4276 - val_accuracy: 0.5087 - val_loss: 2.8459
Epoch 18/20
292/293               0s 86ms/step -
accuracy: 0.5116 - loss: 1.4315
Epoch 18: val_accuracy improved from 0.55796 to 0.56582, saving model to
/kaggle/working/model/self_trained/second-18-0.57.keras
293/293               26s 87ms/step -
accuracy: 0.5116 - loss: 1.4317 - val_accuracy: 0.5658 - val_loss: 1.5440
Epoch 19/20
291/293               0s 87ms/step -
accuracy: 0.4902 - loss: 1.5011
Epoch 19: val_accuracy did not improve from 0.56582
293/293               26s 87ms/step -
accuracy: 0.4902 - loss: 1.5010 - val_accuracy: 0.5309 - val_loss: 3.0278
Epoch 20/20
293/293               0s 85ms/step -
accuracy: 0.4959 - loss: 1.4667
Epoch 20: val_accuracy improved from 0.56582 to 0.58586, saving model to
/kaggle/working/model/self_trained/second-20-0.59.keras
293/293               26s 87ms/step -
accuracy: 0.4960 - loss: 1.4666 - val_accuracy: 0.5859 - val_loss: 1.5672
```

[53]:

```
show_loss_and_accuracy_plots(history)
```



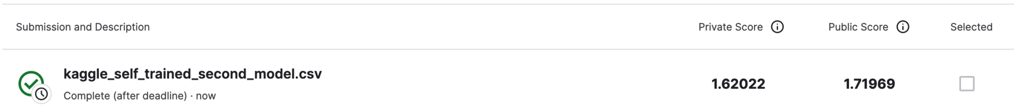
[52]:
```
#load checkpoint with best val_accuracy
BEST_MODEL = os.path.join(MODEL_PATH,"second-20-0.59.keras")
model = load_model(BEST_MODEL)
model.summary()
predict_and_write_results(model, test_images, files,␣
 ↪'kaggle_self_trained_second_model.csv')
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 64, 64, 64)	832

```
 max_pooling2d_8 (MaxPooling2D)    (None, 32, 32, 64)                  0

 conv2d_9 (Conv2D)                 (None, 32, 32, 128)            32,896

 max_pooling2d_9 (MaxPooling2D)    (None, 16, 16, 128)                 0

 conv2d_10 (Conv2D)                (None, 16, 16, 256)           131,328

 max_pooling2d_10 (MaxPooling2D)   (None, 8, 8, 256)                   0

 conv2d_11 (Conv2D)                (None, 8, 8, 512)             524,800

 max_pooling2d_11 (MaxPooling2D)   (None, 4, 4, 512)                   0

 dropout_4 (Dropout)               (None, 4, 4, 512)                   0

 flatten_2 (Flatten)               (None, 8192)                        0

 dense_4 (Dense)                   (None, 500)                 4,096,500

 dropout_5 (Dropout)               (None, 500)                         0

 dense_5 (Dense)                   (None, 10)                      5,010


 Total params: 9,582,734 (36.56 MB)

 Trainable params: 4,791,366 (18.28 MB)

 Non-trainable params: 0 (0.00 B)

 Optimizer params: 4,791,368 (18.28 MB)

  42/2492             9s 4ms/step
W0000 00:00:1714038070.214186      87 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
2492/2492             7s 3ms/step
W0000 00:00:1714038076.708742      90 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
/tmp/ipykernel_34/950582733.py:18: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
```

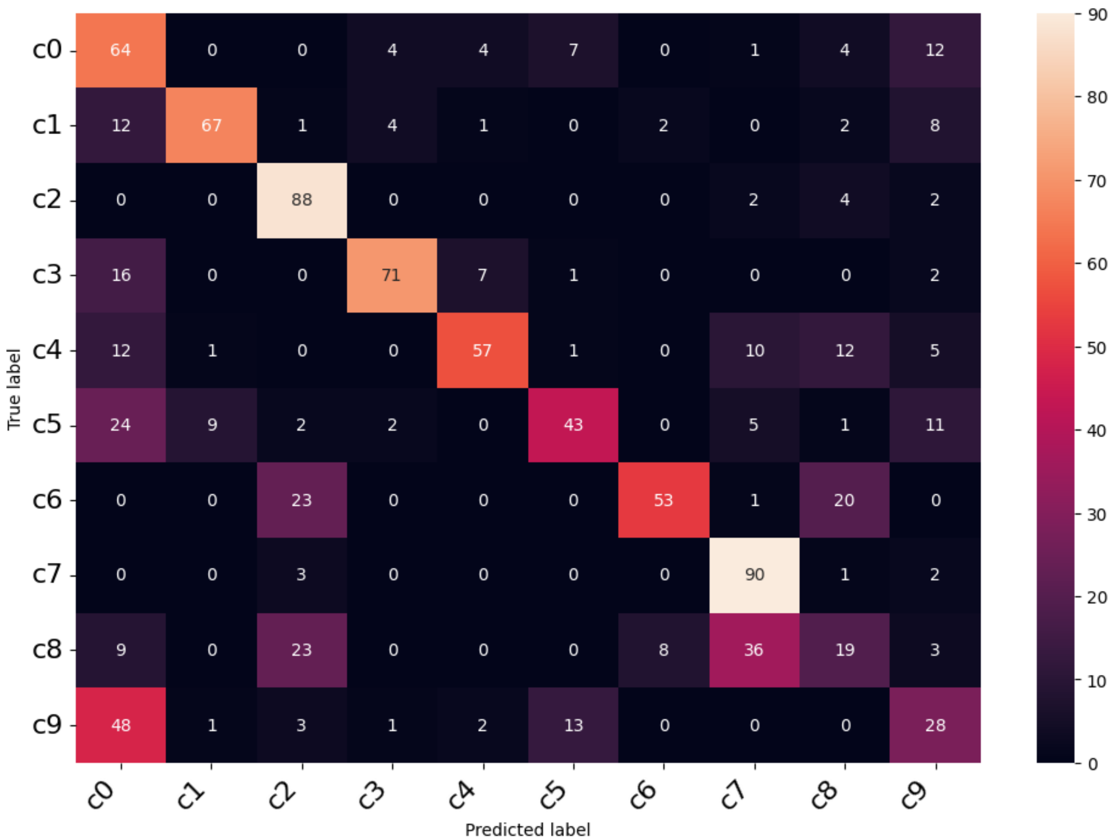
concat operation.
  df = pd.concat([df, pd.DataFrame([new_row])], ignore_index=True)



[54]:
```python
y_pred = model.predict(X_test)

print_heatmap(y_test,y_pred,class_names)
```

```
116/116              1s 6ms/step
```

```
W0000 00:00:1714041371.230180      87 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
```



[55]:
```python
y_pred_class = np.argmax(y_pred, axis=1)

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

```
accuracy = accuracy_score(y_test, y_pred_class)
print('Accuracy: %f' % accuracy)

precision = precision_score(y_test, y_pred_class, average='weighted')
print('Precision: %f' % precision)

recall = recall_score(y_test, y_pred_class, average='weighted')
print('Recall: %f' % recall)

f1 = f1_score(y_test, y_pred_class, average='weighted')
print('F1 score: %f' % f1)
```

```
Accuracy: 0.585861
Precision: 0.618950
Recall: 0.585861
F1 score: 0.582167
```

The same model performed better when training data is split according to driver instead of random split. A comparision between the two models is given below

	accuracy	loss	val_accuracy	val_loss	Kaggle Private Score	Kaggle Public Score
Model 1	0.4512	1.6058	0.7946	0.7764	2.24537	2.46848
Model 2	0.4960	1.4666	0.5859	1.5672	1.62022	1.71969

1.6 Hyperparameter Tuning

I will add a new layer with 1024 filters and use Adam optimizer to see how this model performs

[63]:
```
def get_new_model():
    model = Sequential()
    # 64 conv2d filters with relu
    model.add(Conv2D(filters=64, kernel_size=2, padding='same',␣
 ↪activation='relu', input_shape=(64,64,3),␣
 ↪kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 128 conv2d filters with relu
    model.add(Conv2D(filters=128, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 256 conv2d filters with relu
    model.add(Conv2D(filters=256, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))
```

```
    # 512 conv2d filters with relu
    model.add(Conv2D(filters=512, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    # 1024 conv2d filters with relu
    model.add(Conv2D(filters=1024, kernel_size=2, padding='same',␣
 ↪activation='relu', kernel_initializer='glorot_normal'))
    model.add(MaxPooling2D(pool_size=2))

    model.add(Dropout(0.5))
    model.add(Flatten())
    model.add(Dense(500, activation='relu', kernel_initializer='glorot_normal'))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation='softmax',␣
 ↪kernel_initializer='glorot_normal'))
    return model

driv_selected = ['p050', 'p015', 'p022', 'p056']
## Split the data into training and validation

X_train= []
y_train = []
X_test = []
y_test = []
D_train = []
D_test = []

for features,labels,drivers in train_image:
    if drivers in driv_selected:
        X_test.append(features)
        y_test.append(labels)
        D_test.append(drivers)

    else:
        X_train.append(features)
        y_train.append(labels)
        D_train.append(drivers)

X_train = np.array(X_train).reshape(-1,img_dim,img_dim,3)
X_test = np.array(X_test).reshape(-1,img_dim,img_dim,3)
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

model = get_new_model()
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
```

```
filepath = os.path.join(MODEL_PATH,"third-{epoch:02d}-{val_accuracy:.2f}.keras")

checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,␣
↪save_best_only=True, mode='max')
callbacks_list = [checkpoint]


img_data_gen = ImageDataGenerator(height_shift_range=0.5, width_shift_range=0.
↪5, zoom_range=0.5, rotation_range=30)

data_generator = img_data_gen.flow(X_train, y_train, batch_size=64)

history = model.fit(data_generator, callbacks=callbacks_list, epochs=20,␣
↪verbose=1, validation_data=(X_test, y_test), batch_size=40, shuffle=True)
```

```
Epoch 1/20
  3/293              18s 63ms/step - accuracy:
0.0920 - loss: 37.1295

W0000 00:00:1714042736.664572      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

199/293              9s 106ms/step -
accuracy: 0.0994 - loss: 6.1566

W0000 00:00:1714042757.530636      88 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

292/293              0s 99ms/step -
accuracy: 0.1044 - loss: 5.1429

W0000 00:00:1714042767.041167      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update


Epoch 1: val_accuracy improved from -inf to 0.21560, saving model to
/kaggle/working/model/self_trained/third-01-0.22.keras
293/293              38s 109ms/step -
accuracy: 0.1045 - loss: 5.1273 - val_accuracy: 0.2156 - val_loss: 2.1515
Epoch 2/20

W0000 00:00:1714042768.259210      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update

292/293              0s 89ms/step -
accuracy: 0.1725 - loss: 2.1766
Epoch 2: val_accuracy improved from 0.21560 to 0.31717, saving model to
/kaggle/working/model/self_trained/third-02-0.32.keras
293/293              27s 90ms/step -
accuracy: 0.1726 - loss: 2.1762 - val_accuracy: 0.3172 - val_loss: 1.9443
```

```
Epoch 3/20
292/293              0s 88ms/step -
accuracy: 0.2603 - loss: 1.9625
Epoch 3: val_accuracy improved from 0.31717 to 0.38164, saving model to
/kaggle/working/model/self_trained/third-03-0.38.keras
293/293              27s 90ms/step -
accuracy: 0.2604 - loss: 1.9622 - val_accuracy: 0.3816 - val_loss: 1.6303
Epoch 4/20
292/293              0s 87ms/step -
accuracy: 0.3241 - loss: 1.7817
Epoch 4: val_accuracy improved from 0.38164 to 0.38218, saving model to
/kaggle/working/model/self_trained/third-04-0.38.keras
293/293              27s 89ms/step -
accuracy: 0.3242 - loss: 1.7816 - val_accuracy: 0.3822 - val_loss: 2.0792
Epoch 5/20
292/293              0s 88ms/step -
accuracy: 0.3660 - loss: 1.6883
Epoch 5: val_accuracy improved from 0.38218 to 0.38651, saving model to
/kaggle/working/model/self_trained/third-05-0.39.keras
293/293              27s 90ms/step -
accuracy: 0.3661 - loss: 1.6881 - val_accuracy: 0.3865 - val_loss: 2.1545
Epoch 6/20
293/293              0s 90ms/step -
accuracy: 0.4054 - loss: 1.5723
Epoch 6: val_accuracy did not improve from 0.38651
293/293              27s 91ms/step -
accuracy: 0.4055 - loss: 1.5722 - val_accuracy: 0.3692 - val_loss: 1.9330
Epoch 7/20
292/293              0s 88ms/step -
accuracy: 0.4363 - loss: 1.5113
Epoch 7: val_accuracy improved from 0.38651 to 0.44664, saving model to
/kaggle/working/model/self_trained/third-07-0.45.keras
293/293              27s 90ms/step -
accuracy: 0.4364 - loss: 1.5110 - val_accuracy: 0.4466 - val_loss: 1.7210
Epoch 8/20
292/293              0s 88ms/step -
accuracy: 0.4725 - loss: 1.4416
Epoch 8: val_accuracy did not improve from 0.44664
293/293              27s 89ms/step -
accuracy: 0.4726 - loss: 1.4413 - val_accuracy: 0.4382 - val_loss: 2.0683
Epoch 9/20
292/293              0s 88ms/step -
accuracy: 0.5155 - loss: 1.3403
Epoch 9: val_accuracy improved from 0.44664 to 0.52140, saving model to
/kaggle/working/model/self_trained/third-09-0.52.keras
293/293              27s 89ms/step -
accuracy: 0.5155 - loss: 1.3401 - val_accuracy: 0.5214 - val_loss: 1.4598
Epoch 10/20
```

```
293/293              0s 87ms/step -
accuracy: 0.5410 - loss: 1.2710
Epoch 10: val_accuracy did not improve from 0.52140
293/293              26s 88ms/step -
accuracy: 0.5410 - loss: 1.2709 - val_accuracy: 0.5008 - val_loss: 2.3497
Epoch 11/20
292/293              0s 88ms/step -
accuracy: 0.5817 - loss: 1.1643
Epoch 11: val_accuracy improved from 0.52140 to 0.56771, saving model to
/kaggle/working/model/self_trained/third-11-0.57.keras
293/293              27s 89ms/step -
accuracy: 0.5817 - loss: 1.1643 - val_accuracy: 0.5677 - val_loss: 1.7413
Epoch 12/20
292/293              0s 86ms/step -
accuracy: 0.6065 - loss: 1.1117
Epoch 12: val_accuracy improved from 0.56771 to 0.57042, saving model to
/kaggle/working/model/self_trained/third-12-0.57.keras
293/293              26s 88ms/step -
accuracy: 0.6066 - loss: 1.1116 - val_accuracy: 0.5704 - val_loss: 1.4773
Epoch 13/20
292/293              0s 88ms/step -
accuracy: 0.6101 - loss: 1.0923
Epoch 13: val_accuracy improved from 0.57042 to 0.61701, saving model to
/kaggle/working/model/self_trained/third-13-0.62.keras
293/293              27s 89ms/step -
accuracy: 0.6102 - loss: 1.0923 - val_accuracy: 0.6170 - val_loss: 1.4870
Epoch 14/20
292/293              0s 87ms/step -
accuracy: 0.6284 - loss: 1.0530
Epoch 14: val_accuracy improved from 0.61701 to 0.62378, saving model to
/kaggle/working/model/self_trained/third-14-0.62.keras
293/293              27s 89ms/step -
accuracy: 0.6284 - loss: 1.0529 - val_accuracy: 0.6238 - val_loss: 1.2259
Epoch 15/20
292/293              0s 90ms/step -
accuracy: 0.6365 - loss: 1.0242
Epoch 15: val_accuracy improved from 0.62378 to 0.62920, saving model to
/kaggle/working/model/self_trained/third-15-0.63.keras
293/293              27s 91ms/step -
accuracy: 0.6365 - loss: 1.0242 - val_accuracy: 0.6292 - val_loss: 1.2469
Epoch 16/20
292/293              0s 87ms/step -
accuracy: 0.6552 - loss: 0.9848
Epoch 16: val_accuracy did not improve from 0.62920
293/293              27s 88ms/step -
accuracy: 0.6552 - loss: 0.9847 - val_accuracy: 0.5756 - val_loss: 2.1654
Epoch 17/20
292/293              0s 87ms/step -
```

```
accuracy: 0.6715 - loss: 0.9381
Epoch 17: val_accuracy improved from 0.62920 to 0.65791, saving model to
/kaggle/working/model/self_trained/third-17-0.66.keras
293/293              27s 89ms/step -
accuracy: 0.6715 - loss: 0.9381 - val_accuracy: 0.6579 - val_loss: 1.2424
Epoch 18/20
292/293              0s 87ms/step -
accuracy: 0.6791 - loss: 0.9219
Epoch 18: val_accuracy did not improve from 0.65791
293/293              27s 89ms/step -
accuracy: 0.6791 - loss: 0.9220 - val_accuracy: 0.6029 - val_loss: 2.6826
Epoch 19/20
292/293              0s 88ms/step -
accuracy: 0.6745 - loss: 0.9365
Epoch 19: val_accuracy did not improve from 0.65791
293/293              27s 89ms/step -
accuracy: 0.6746 - loss: 0.9364 - val_accuracy: 0.5320 - val_loss: 2.1930
Epoch 20/20
293/293              0s 88ms/step -
accuracy: 0.6890 - loss: 0.8920
Epoch 20: val_accuracy did not improve from 0.65791
293/293              27s 89ms/step -
accuracy: 0.6890 - loss: 0.8920 - val_accuracy: 0.6227 - val_loss: 1.5915
```

[64]:

```
#load checkpoint with best val_accuracy
BEST_MODEL = os.path.join(MODEL_PATH,"third-17-0.66.keras")
model = load_model(BEST_MODEL)
model.summary()
predict_and_write_results(model, test_images, files,␣
 ↪'kaggle_self_trained_third_model.csv')
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_22 (Conv2D)	(None, 64, 64, 64)	832
max_pooling2d_22 (MaxPooling2D)	(None, 32, 32, 64)	0
conv2d_23 (Conv2D)	(None, 32, 32, 128)	32,896
max_pooling2d_23 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_24 (Conv2D)	(None, 16, 16, 256)	131,328
max_pooling2d_24 (MaxPooling2D)	(None, 8, 8, 256)	0

```
conv2d_25 (Conv2D)              (None, 8, 8, 512)          524,800

max_pooling2d_25 (MaxPooling2D)  (None, 4, 4, 512)               0

conv2d_26 (Conv2D)              (None, 4, 4, 1024)       2,098,176

max_pooling2d_26 (MaxPooling2D)  (None, 2, 2, 1024)              0

dropout_10 (Dropout)            (None, 2, 2, 1024)               0

flatten_5 (Flatten)             (None, 4096)                     0

dense_10 (Dense)                (None, 500)              2,048,500

dropout_11 (Dropout)            (None, 500)                      0

dense_11 (Dense)                (None, 10)                   5,010


Total params: 14,524,628 (55.41 MB)

Trainable params: 4,841,542 (18.47 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 9,683,086 (36.94 MB)

  54/2492            7s 3ms/step
W0000 00:00:1714043305.647168      88 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
2492/2492            9s 3ms/step
W0000 00:00:1714043314.027145      89 graph_launch.cc:671] Fallback to op-by-op
mode because memset node breaks graph update
/tmp/ipykernel_34/950582733.py:18: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  df = pd.concat([df, pd.DataFrame([new_row])], ignore_index=True)
```

Submission and Description	Private Score	Public Score	Selected
kaggle_self_trained_third_model.csv Complete (after deadline) · now	1.10784	1.30779	

This model performed better than the last 2 models after the hyper parameter tuning

	accuracy	loss	val_accuracy	val_loss	Kaggle Private Score	Kaggle Public Score
Model 1	0.4512	1.6058	0.7946	0.7764	2.24537	2.46848
Model 2	0.4960	1.4666	0.5859	1.5672	1.62022	1.71969
Model 3	0.6715	0.9381	0.6579	1.2424	1.10784	1.30779

1.7 Results Comparision

Apart from the self trained models, I have tried transfer learning using Mobilenet and Resnet models. I am not adding those details in this notebook file since it will increase the size of this notebook.

The corresponding Jupyter notebooks are available on github: https://github.com/krishnakuruvadi/5511_Final

Comparision between the best models is given below

	accuracy	loss	val_accuracy	val_loss	Kaggle Private Score	Kaggle Public Score
Self trained	0.6715	0.9381	0.6579	1.2424	1.10784	1.30779
Mobilenet	0.8816	0.3670	0.8621	0.4850	0.41831	0.60318
Resnet	0.7843	0.6402	0.8602	0.4452	0.41789	0.52613

1.8 Findings From Results

Mobilenet and Resnet achieved almost same results and the results are better then the self trained model. When we compare the self trained models with these pre-trained models, we see the number of layers and parameters are more. Also the weights in the pre-trained models are set based on a lot of training data.

1.9 Conclusion

- Pre-trained models work well for such usecase when compared to a general self trained model
- We could take the pre-trained models and add more layers or use the pre-trained models as reference to come up with a better self trained model
- Training takes more time and without GPUs working on this kind of tasks is very time consuming

What I would like to try:

- I would try to use other recent image processing pre-trained models like YOLO
- Fine tune the hyper parameters further
- Change image size/resolution to 224 instead of 64

1.10 Deliverables

Github: https://github.com/krishnakuruvadi/5511_Final

Presentation: https://github.com/krishnakuruvadi/5511_Final

Kaggle scores of all models tried (including the ones not available on github):

Submission and Description	Private Score	Public Score	Selected
kaggle_self_trained_second_model.csv Complete (after deadline) · 27m ago	1.62022	1.71969	☐
kaggle_self_trained_first_model.csv Complete (after deadline) · 1h ago	2.24537	2.46848	☐
self_trained_test_result_4.csv Complete (after deadline) · 12h ago	1.72830	1.75492	☐
self_trained_test_result_3.csv Complete (after deadline) · 18h ago	2.01536	2.81197	☐
resnet_sgd_1.csv Complete (after deadline) · 1d ago	0.41789	0.52613	☐
mobilenet_sgd_1.csv Complete (after deadline) · 3d ago	0.41831	0.60318	☐
self_trained_test_result_2.csv Complete (after deadline) · 4d ago	1.94104	1.38854	☐

Probable leaderboard place based on best model results (Resnet) is ~271/1439:

270	▾ 21	FromChn	0.41577	2	8y
271	▾ 19	TeamD	0.41922	21	8y

1.11 References

- RESNET: https://en.wikipedia.org/wiki/Residual_neural_network
- Mobilenet: https://keras.io/api/applications/mobilenet/
- State Farm Kaggle competition: https://www.kaggle.com/competitions/state-farm-distracted-driver-detection