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(An Autonomous Institute affiliated to VTU, Approved by AICTE & ISO 9001:2008 Certified)

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Assignment

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A Report on

Driver activity detection on the basis of CNN Using Sequential Model

Machine Learning Assignment

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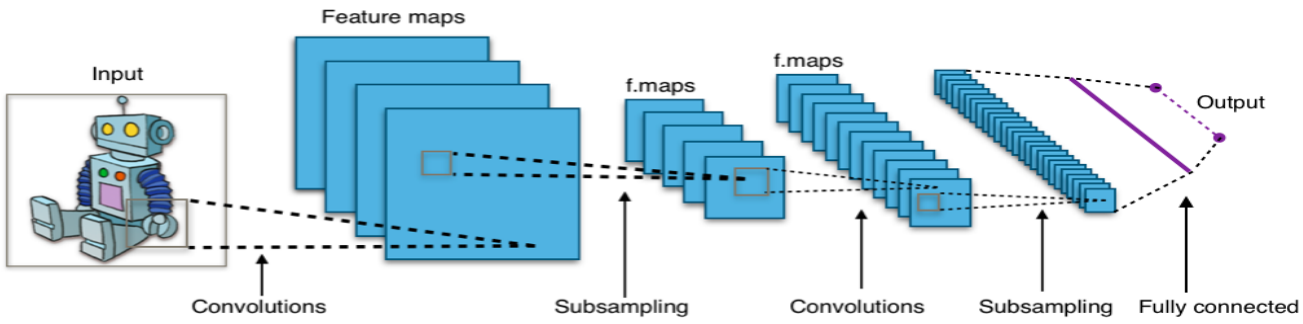
INTRODUCTION

The increasing prevalence of advanced driver assistance systems (ADAS) has led to the development of models capable of recognizing driver actions to improve road safety. CNNs, a type of deep learning model, are particularly effective for image-based tasks, making them suitable for driver action detection.

Objective:

The primary goal of this project is to create a CNN-based model that can accurately identify driver actions by processing sequential input data, such as video frames.



The presented report discusses the implementation and evaluation of a Convolutional Neural Network (CNN) designed for detecting driver actions, with a particular emphasis on utilizing a sequential model architecture. The main objective of the project is to enhance driver safety by accurately identifying various actions performed by the driver through the analysis of sequential input data, such as video frames.

The methodology involves training the CNN on a labeled dataset containing video sequences that capture diverse driver actions, including turning, braking, and accelerating. The model architecture follows a sequential design, incorporating convolutional layers to extract spatial features and recurrent layers to capture temporal dependencies in the sequence of frames. The training process includes optimizing the model's parameters and utilizing techniques like data augmentation and dropout to improve generalization.

Results are evaluated using standard performance metrics such as accuracy, precision, recall, and F1 score, with the confusion matrix providing insights into the model's classification capabilities. The report highlights potential challenges, including variations in lighting conditions, occlusions, and the presence of multiple drivers in the scene, and suggests strategies such as attention mechanisms to address these issues.

In conclusion, the CNN with a sequential model architecture shows promising results in detecting driver actions, especially by considering the temporal aspect of the input data. The report suggests further refinement and optimization to address specific challenges and improve real-world applicability. Future directions include fine-tuning on larger datasets, incorporating additional sensor inputs, and exploring real-time implementation for on-board applications in collaboration with automotive industry stakeholders.

Algorithm:

1. Import necessary libraries and frameworks
2. Define the Sequential CNN model
3. Compile the model
4. Train the model
5. Evaluate the model
6. Make predictions
7. Post-process and analyze results

Program:

```
#Import the Libraries
import os
from glob import glob
import random
import time
import tensorflow
import datetime
os.environ['KERAS_BACKEND'] = 'tensorflow'
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3' # 3 = INFO, WARNING, and ERROR messages are not printed
from tqdm import tqdm

import numpy as np
import pandas as pd
```

```
from IPython.display import FileLink
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
%matplotlib inline
from IPython.display import display, Image
import matplotlib.image as mpimg
import cv2

from sklearn.model_selection import train_test_split
from sklearn.datasets import load_files
from keras.utils import np_utils
from sklearn.utils import shuffle
from sklearn.metrics import log_loss

from keras.models import Sequential, Model
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, BatchNormalization, GlobalAveragePooling2D
from keras.preprocessing.image import ImageDataGenerator
from keras.preprocessing import image
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras.applications.vgg16 import VGG16

#Import the Datasets
dataset = pd.read_csv('/kaggle/input/imageslist/driver_imgs_list.csv')
dataset.head(5)

#Import Driver Dataset
by_drivers = dataset.groupby('subject')
unique_drivers = by_drivers.groups.keys()
print(unique_drivers)
```

```
# Load the dataset previously downloaded from Kaggle
NUMBER_CLASSES = 10
# Col1 or type: 1- grey, 3 - rgb
def get_cv2_image(path, img_rows, img_cols, color_type=3):
    # Loading as Grayscale image
    if color_type == 1:
        img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)
    elif color_type == 3:
        img = cv2.imread(path, cv2.IMREAD_COLOR)
    # Reduce size
    img = cv2.resize(img, (img_rows, img_cols))
    return img

# Training
def load_train(img_rows, img_cols, color_type=3):
    start_time = time.time()
    train_images = []
    train_labels = []
    # Loop over the training folder
    for classed in tqdm(range(NUMBER_CLASSES)):
    #     /kaggle/input/state-farm-distracted-driver-detection/imgs/train
        print(f'Loading directory c{classed}')
        class_path = os.path.join('/kaggle/input/state-farm-distracted-driver-detection/imgs/train', f'c{classed}')

        # Check if the directory exists
        if not os.path.exists(class_path):
            print(f"Directory c{classed} does not exist.")
            continue

        files = glob(os.path.join(class_path, '*.jpg'))
```

```
#        print('Loading directory c{}'.format(classed))
#            files = glob(os.path.join('..','kaggle', 'input', 'state-farm-distracted-driver-detection','imgs','train', 'c' + str(classed), '*.jpg'))
#        files = glob(os.path.join(class_path, '*.jpg'))

        for file in files:
            img = get_cv2_image(file, img_rows, img_cols, color_type)
            train_images.append(img)
            train_labels.append(classed)
    print("Data Loaded in {} second".format(time.time() - start_time))
    return train_images, train_labels

def read_and_normalize_train_data(img_rows, img_cols, color_type):
    X, labels = load_train(img_rows, img_cols, color_type)
    y = np_utils.to_categorical(labels, 10)   #Binary Matrix  (2,10)  [0 0 1 0 0 0 0 0 0 0 ]
#     print(X)
#     print(y)

#     X, labels = load_train(img_rows, img_cols, color_type)
#     y = np_utils.to_categorical(labels, 10)
#     print("Number of samples:", len(X))
#     print("Number of labels:", len(labels))
#     print(y)

    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, train_size=0.8, random_state=42, shuffle=True)



    x_train = np.array(x_train, dtype=np.uint8).reshape(-1,img_rows,img_cols,color_type)
    x_test = np.array(x_test, dtype=np.uint8).reshape(-1,img_rows,img_cols,color_type)
```

```
    return x_train, x_test, y_train, y_test



# Validation
def load_test(size=200000, img_rows=64, img_cols=64, color_type=3):
    path = '/kaggle/input/state-farm-distracted-driver-detection/imgs/test/*.jpg'
    files = sorted(glob(path))
    X_test, X_test_id = [], []
    total = 0
    files_size = len(files)
    for file in tqdm(files):
        if total >= size or total >= files_size:
            break
        file_base = os.path.basename(file)
        img = get_cv2_image(file, img_rows, img_cols, color_type)
        X_test.append(img)
        X_test_id.append(file_base)
        total += 1
    return X_test, X_test_id

def read_and_normalize_sampled_test_data(size, img_rows, img_cols, color_type=3):
    test_data, test_ids = load_test(size, img_rows, img_cols, color_type)

    test_data = np.array(test_data, dtype=np.uint8)
    test_data = test_data.reshape(-1,img_rows,img_cols,color_type)

    return test_data, test_ids

img_rows = 64
img_cols = 64
color_type = 1
```

```
x_train, x_test, y_train, y_test = read_and_normalize_train_data(img_rows, img_cols, color_type)

print('Train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')



nb_test_samples = 200
test_files, test_targets = read_and_normalize_sampled_test_data(nb_test_samples, img_rows, img_cols, color_type)
print('Test shape:', test_files.shape)
print(test_files.shape[0], 'Test samples')

# Assuming x_train, x_test, and x_validation are your loaded datasets

# Statistics
# Load the list of names
names = [item[17:19] for item in sorted(glob("/kaggle/input/state-farm-distracted-driver-detection/imgs/train/*/"))]
test_files_size = len(np.array(glob(os.path.join('/kaggle/input/state-farm-distracted-driver-detection/imgs/test', '*.jpg'))))
x_train_size = len(x_train)
categories_size = len(names)
x_test_size = len(x_test)
print('There are %s total images.\n' % (test_files_size + x_train_size + x_test_size))
print('There are %d training images.' % x_train_size)
print('There are %d total training categories.' % categories_size)
print('There are %d validation images.' % x_test_size)
print('There are %d test images.' % test_files_size)

# Plot figure size
```

```
plt.figure(figsize = (10,10))
# Count the number of images per category
sns.countplot(x = 'classname', data = dataset)
# Change the Axis names
plt.ylabel('Count')
plt.title('Categories Distribution')
# Show plot
plt.show()
# Find the frequency of images per driver
drivers_id = pd.DataFrame((dataset['subject'].value_counts()).reset_index())
drivers_id.columns = ['driver_id', 'Counts']
drivers_id

# Plotting class distribution
dataset['class_type'] = dataset['classname'].str.extract('(\d)',expand=False).astype(np.float)
plt.figure(figsize = (20,20))
dataset.hist('class_type', alpha=0.5, layout=(1,1), bins=10)
plt.title('Class distribution')
plt.show()

activity_map = {'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=(12, 20))
```

```
BASE_URL = '/kaggle/input/state-farm-distracted-driver-detection/imgs/train/'
image_count = 1

# Assuming you have an activity_map dictionary defined
activity_map = {'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'}

for directory in os.listdir(BASE_URL):
    if directory[0] != '.':
        files_path = os.path.join(BASE_URL, directory)
        files = os.listdir(files_path)
        for i, file in enumerate(files):
            if i == 1:
                break
            else:
                plt.subplot(5, 2, image_count)
                image_count += 1
                image_path = os.path.join(files_path, file)
                image = mpimg.imread(image_path)
                plt.imshow(image)
                plt.title(activity_map.get(directory, directory))

plt.show()

def create_submission(predictions, test_id, info):
    result = pd.DataFrame(predictions, columns=['c0', 'c1', 'c2', 'c3', 'c4', 'c5', 'c6', 'c7', 'c8', 'c9'])
    result.loc[:, 'img'] = pd.Series(test_id, index=result.index)

    now = datetime.datetime.now()
```

```
    if not os.path.isdir('kaggle_submissions'):
        os.mkdir('kaggle_submissions')

    suffix = "{}_{}".format(info,str(now.strftime("%Y-%m-%d-%H-%M")))
    sub_file = os.path.join('kaggle_submissions', 'submission_' + suffix + '.csv')

    result.to_csv(sub_file, index=False)

    return sub_file
batch_size = 40
nb_epoch = 10

!rm -f saved_models/weights_best_vanilla.hdf5  #Removing the file from s_m



models_dir = "saved_models"
if not os.path.exists(models_dir):
    os.makedirs(models_dir)

checkpointer = ModelCheckpoint(filepath='saved_models/weights_best_vanilla.hdf5',
                               monitor='val_loss', mode='min',
                               verbose=1, save_best_only=True)
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=2)
callbacks = [checkpointer, es]

def create_model_v1():
    # Vanilla CNN model
    model = Sequential()

    model.add(Conv2D(filters = 64, kernel_size = 3, padding='same', activation = 'relu', input_shape=(img_rows,
img_cols, color_type)))
    model.add(MaxPooling2D(pool_size = 2))
```

```
    model.add(Conv2D(filters = 128, padding='same', kernel_size = 3, activation = 'relu'))
    model.add(MaxPooling2D(pool_size = 2))

    model.add(Conv2D(filters = 256, padding='same', kernel_size = 3, activation = 'relu'))
    model.add(MaxPooling2D(pool_size = 2))

    model.add(Conv2D(filters = 512, padding='same', kernel_size = 3, activation = 'relu'))
    model.add(MaxPooling2D(pool_size = 2))

    model.add(Dropout(0.5))

    model.add(Flatten())

    model.add(Dense(500, activation = 'relu'))
    model.add(Dropout(0.5))
    model.add(Dense(10, activation = 'softmax'))

    return model

model_v1 = create_model_v1()

# More details about the layers
model_v1.summary()

# Compiling the model
model_v1.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
#  Root Mean Square Propagation

# Training the Vanilla Model version 1
history_v1 = model_v1.fit(x_train, y_train,
        validation_data=(x_test, y_test),
```

```
        callbacks=callbacks,
        epochs=nb_epoch, batch_size=batch_size, verbose=1)

model_v1.load_weights('saved_models/weights_best_vanilla.hdf5')

def plot_train_history(history):
    # Summarize history for accuracy
    plt.plot(history.history['acc'])
    plt.plot(history.history['val_acc'])
    plt.title('Model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    # Summarize history for loss
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

plot_train_history(history_v1)

def plot_test_class(model, test_files, image_number, color_type=1):
    img_brute = test_files[image_number]
    img_brute = cv2.resize(img_brute,(img_rows,img_cols))
    plt.imshow(img_brute, cmap='gray')

    new_img = img_brute.reshape(-1,img_rows,img_cols,color_type)
```

```
    y_prediction = model.predict(new_img, batch_size=batch_size, verbose=1)
    print('Y prediction: {}'.format(y_prediction))
    print('Predicted: {}'.format(activity_map.get('c{}'.format(np.argmax(y_prediction)))))

    plt.show()

score = model_v1.evaluate(x_test, y_test, verbose=1)
print('Score: ', score)

plot_test_class(model_v1, test_files, 20)

!rm -f saved_models/weights_best_vanilla.hdf5

def create_model_v2():
    # Optimised Vanilla CNN model
    model = Sequential()

    ## CNN 1
    model.add(Conv2D(32,(3,3),activation='relu',input_shape=(img_rows, img_cols, color_type)))
    model.add(BatchNormalization())
    model.add(Conv2D(32,(3,3),activation='relu',padding='same'))
    model.add(BatchNormalization(axis = 3))
    model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
    model.add(Dropout(0.3))

    ## CNN 2
    model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
    model.add(BatchNormalization())
    model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
    model.add(BatchNormalization(axis = 3))
    model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
```

```
    model.add(Dropout(0.3))

    ## CNN 3
    model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
    model.add(BatchNormalization())
    model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
    model.add(BatchNormalization(axis = 3))
    model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
    model.add(Dropout(0.5))

    ## Output
    model.add(Flatten())
    model.add(Dense(512,activation='relu'))
    model.add(BatchNormalization())
    model.add(Dropout(0.5))
    model.add(Dense(128,activation='relu'))
    model.add(Dropout(0.25))
    model.add(Dense(10,activation='softmax'))

    return model

model_v2 = create_model_v2()

# More details about the layers
model_v2.summary()

# Compiling the model
model_v2.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

# Training the Vanilla Model
history_v2 = model_v2.fit(x_train, y_train,
        validation_data=(x_test, y_test),
```

```
        callbacks=callbacks,
        epochs=nb_epoch, batch_size=batch_size, verbose=1)

plot_train_history(history_v2)

model_v2.load_weights('saved_models/weights_best_vanilla.hdf5')

score = model_v2.evaluate(x_test, y_test, verbose=1)
print('Score: ', score)

y_pred = model_v2.predict(x_test, batch_size=batch_size, verbose=1)
score = log_loss(y_test, y_pred)  #Entropy loss
print('Score log loss:', score)

plot_test_class(model_v2, test_files, 101) # The model really performs badly

plot_test_class(model_v2, test_files, 1) # The model really performs badly

plot_test_class(model_v2, test_files, 143)

!rm -f saved_models/weights_best_vanilla.hdf5

# Prepare data augmentation configuration
train_datagen = ImageDataGenerator(rescale = 1.0/255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True,
                                   validation_split = 0.2)

test_datagen = ImageDataGenerator(rescale=1.0/ 255, validation_split = 0.2)

nb_train_samples = x_train.shape[0]
```

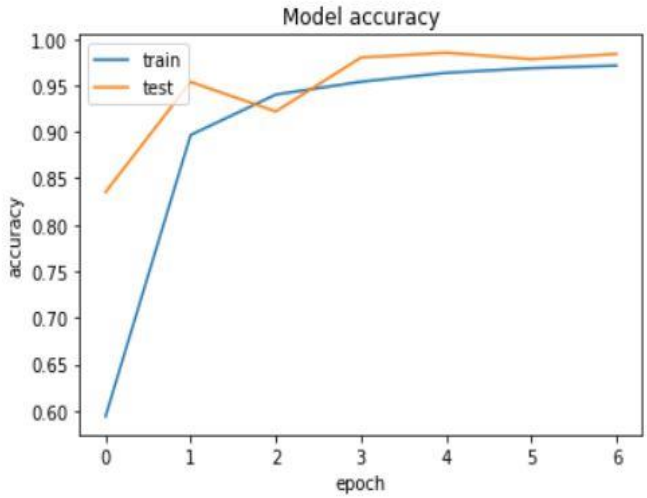
```
nb_validation_samples = x_test.shape[0]
print(nb_train_samples)
print(nb_validation_samples)
training_generator = train_datagen.flow(x_train, y_train, batch_size=batch_size)
validation_generator = test_datagen.flow(x_test, y_test, batch_size=batch_size)  #Applies the specified no of set at a time

checkpoint = ModelCheckpoint('saved_models/weights_best_vanilla.hdf5', monitor='val_acc', verbose=1, save_best_only=True, mode='max')
history_v3 = model_v2.fit_generator(training_generator,
                    steps_per_epoch = nb_train_samples // batch_size,
                    epochs = 5,
                    callbacks=[es, checkpoint],
                    verbose = 1,
                    validation_data = validation_generator,
                    validation_steps = nb_validation_samples // batch_size)

model_v2.load_weights('saved_models/weights_best_vanilla.hdf5')

plot_train_history(history_v3)

# Evaluate the performance of the new model
score = model_v2.evaluate_generator(validation_generator, nb_validation_samples // batch_size)
print("Test Score:", score[0])
print("Test Accuracy:", score[1])

plot_test_class(model_v2, test_files, 101)

plot_test_class(model_v2, test_files, 1)

plot_test_class(model_v2, test_files, 145)
```

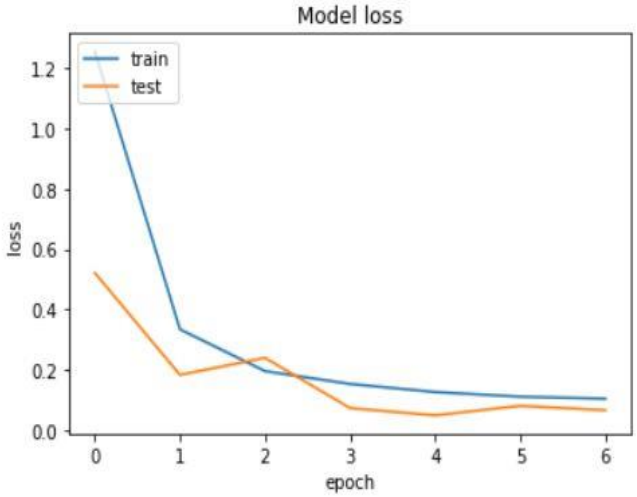
```
plot_test_class(model_v2, test_files, 143)

predictions = model_v2.predict(test_files, batch_size=batch_size)
FileLink(create_submission(predictions, test_targets, score[0]))

!rm -f saved_models/weights_best_vanilla.hdf5

def vgg_std16_model(img_rows, img_cols, color_type=3):
    nb_classes = 10
    # Remove fully connected layer and replace
    # with softmax for classifying 10 classes
    vgg16_model = VGG16(weights="imagenet", include_top=False)

    # Freeze all layers of the pre-trained model
    for layer in vgg16_model.layers:
        layer.trainable = False

    x = vgg16_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dense(1024, activation='relu')(x)
    predictions = Dense(nb_classes, activation = 'softmax')(x)

    model = Model(input = vgg16_model.input, output = predictions)

    return model

# Load the VGG16 network
print("Loading network...")
model_vgg16 = vgg_std16_model(img_rows, img_cols)

model_vgg16.summary()
```

```
model_vgg16.compile(loss='categorical_crossentropy',
                    optimizer='rmsprop',
                    metrics=['accuracy'])

training_generator = train_datagen.flow_from_directory('/kaggle/input/state-farm-distracted-driver-detection/imgs/train',
                                    target_size = (img_rows, img_cols),
                                    batch_size = batch_size,
                                    shuffle=True,
                                    class_mode='categorical', subset="training")

validation_generator=test_datagen.flow_from_directory('/kaggle/input/state-farm-distracted-driver-detection/imgs/train',
                                     target_size = (img_rows, img_cols),
                                     batch_size = batch_size,
                                     shuffle=False,
                                     class_mode='categorical', subset="validation")
nb_train_samples = 17943
nb_validation_samples = 4481

!rm -f saved_models/weights_best_vgg16.hdf5

# Training the Vanilla Model
checkpoint = ModelCheckpoint('saved_models/weights_best_vgg16.hdf5', monitor='val_acc', verbose=1, save_best_only=True, mode='max')
history_v4 = model_vgg16.fit_generator(training_generator,
                    steps_per_epoch = nb_train_samples // batch_size,
                    epochs = 5,
                    callbacks=[es, checkpoint],
                    verbose = 1,
                    class_weight='auto',
                    validation_data = validation_generator,
```

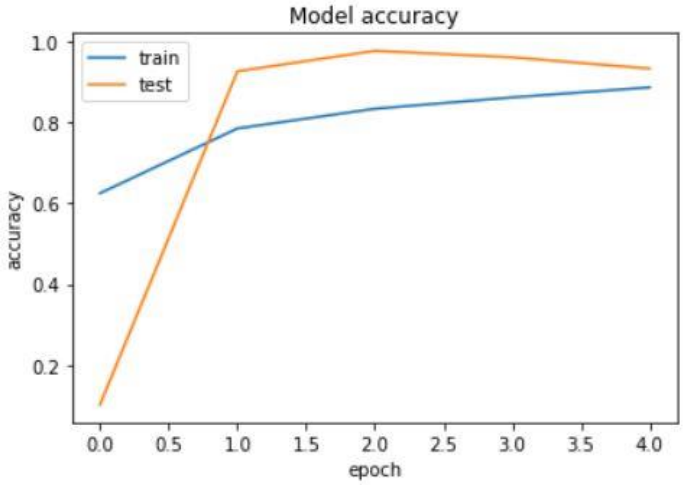
```
                    validation_steps = nb_validation_samples // batch_size)

model_vgg16.load_weights('saved_models/weights_best_vgg16.hdf5')

plot_train_history(history_v4)

def plot_vgg16_test_class(model, test_files, image_number):
    img_brute = test_files[image_number]

    im =cv2.resize(cv2.cvtColor(img_brute, cv2.COLOR_BGR2RGB), (img_rows,img_cols)).astype(np.float32)
/ 255.0
    im = np.expand_dims(im, axis =0)
    img_display = cv2.resize(img_brute,(img_rows,img_cols))
    plt.imshow(img_display, cmap='gray')
    y_preds = model.predict(im, batch_size=batch_size, verbose=1)
    print(y_preds)
    y_prediction = np.argmax(y_preds)
    print('Y Prediction: {}'.format(y_prediction))
    print('Predicted as: {}'.format(activity_map.get('c{}'.format(y_prediction))))

    plt.show()

plot_vgg16_test_class(model_vgg16, test_files, 133) # Texting left
plot_vgg16_test_class(model_vgg16, test_files, 29) # Texting left
plot_vgg16_test_class(model_vgg16, test_files, 82) # Hair

# Evaluate the performance of the new model
score = model_vgg16.evaluate_generator(validation_generator, nb_validation_samples // batch_size, verbose =
1)
print("Test Score:", score[0])
print("Test Accuracy:", score[1])
```

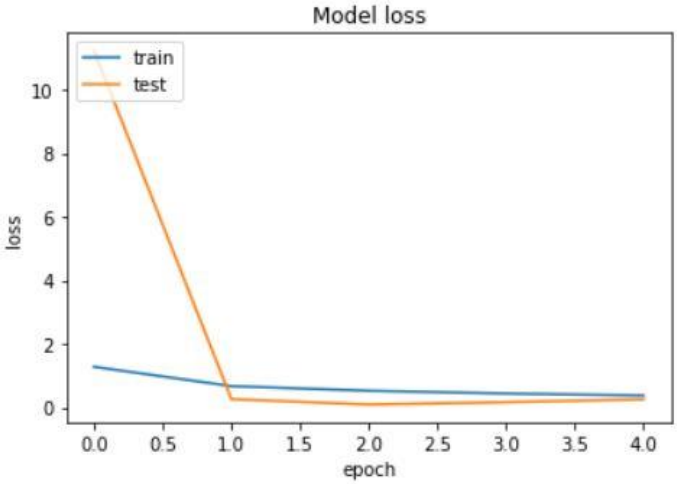
Result:





Accuracy and loss graph of the model

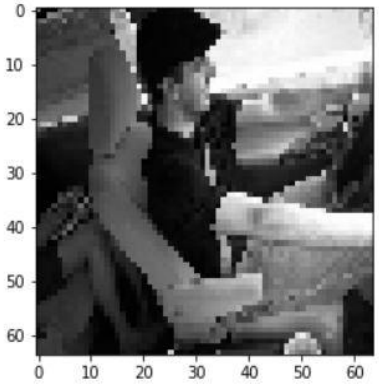




Accuracy and loss graph of the Optimized model

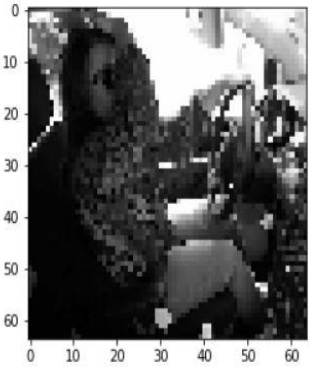
- Output shows the activity done by the driver, the prediction list is raised to 1 for the detected event/action.

```
1/1 [==============================] - 0s 4ms/step
Y prediction: [[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]]
Predicted: Operating the radio
```



```
1/1 [==============================] - 0s 4ms/step
Y prediction: [[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]]
Predicted: Texting - left
```

```
1/1 [==============================] - 0s 4ms/step
[[8.7794047e-03 2.9838075e-05 1.7809985e-03 6.1610097e-04 8.6737804e-02
  1.8839471e-01 4.4392377e-02 4.4116559e-03 4.9298564e-01 1.7187145e-01]]
Y Prediction: 8
Predicted as: Hair and makeup
```



```
1/1 [==============================] - 0s 4ms/step
[[1.74136704e-03 6.12906806e-05 4.68631368e-03 2.16858815e-02
  9.48548466e-02 2.57794345e-05 1.10980014e-04 3.46482921e-05
  2.76343455e-03 8.74035478e-01]]
Y Prediction: 9
Predicted as: Talking to passenger
```

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