Driver drowsiness detection using CNN with resnet architecture

Importing drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Importing libraries

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from google.colab import drive
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.preprocessing.image import ImageDataGenerator as data_augment
```

Defining training and validation dataset

```
!unzip -uq "/content/drive/MyDrive/Driver_Drowsiness.zip"
!ls
```

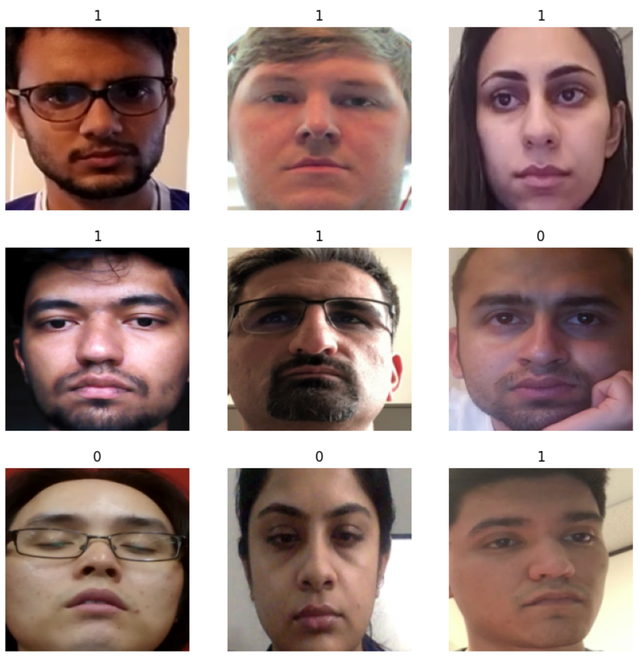
```
drive  'Driver Drowsiness Dataset (DDD)'   sample_data
```

```
image_size = (180, 180)
batch_size = 64

train_data = tf.keras.preprocessing.image_dataset_from_directory(
    "Driver Drowsiness Dataset (DDD)",
    validation_split=0.2,
    subset="training",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)
val_data = tf.keras.preprocessing.image_dataset_from_directory(
    "Driver Drowsiness Dataset (DDD)",
    validation_split=0.2,
    subset="validation",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)
```

```
Found 41788 files belonging to 2 classes.
Using 33431 files for training.
Found 41788 files belonging to 2 classes.
Using 8357 files for validation.
```

```
plt.figure(figsize=(10, 10))
for images, labels in train_data.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(int(labels[i]))
        plt.axis("off")
```



Data augmentation

```
data_augmentation = keras.Sequential(
    [
        layers.experimental.preprocessing.RandomFlip("horizontal"),
        layers.experimental.preprocessing.RandomRotation(0.1),
    ]
)
```

```
plt.figure(figsize=(10, 10))
for images, _ in train_data.take(1):
    for i in range(9):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[0].numpy().astype("uint8"))
        plt.axis("off")
```

```
train_data = train_data.prefetch(buffer_size=64)
val_data = val_data.prefetch(buffer_size=64)
```

Creating the model using Resnet architecture

```
base_model = keras.applications.ResNet152V2(weights="imagenet",input_shape=(180, 180, 3), include_top=False,)

base_model.trainable = True
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)



mean = np.array([127.5] * 3)
var = mean ** 2

norm_layer = keras.layers.experimental.preprocessing.Normalization(mean=mean, variance=var)
x = norm_layer(x)


x = base_model(x, training=False)
x = keras.layers.GlobalAveragePooling2D()(x)
x = keras.layers.Dropout(0.5)(x)


outputs = layers.Dense(1, activation='sigmoid')(x)
model = keras.Model(inputs, outputs)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet152v2_weights_tf_dim_ordering_tf_kernels_notop.h5
234545216/234545216 [==============================] - 1s 0us/step
```

Training the model

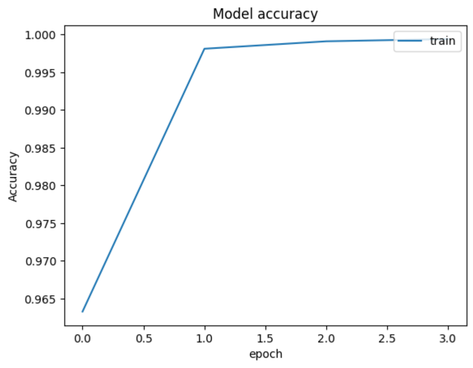
```
callbacks = [keras.callbacks.ModelCheckpoint("save_model_DDD.p1"),]
model.compile( optimizer=keras.optimizers.Adam(1e-5),loss="binary_crossentropy",metrics=["accuracy"],)
history=model.fit(train_data, epochs=4, callbacks=callbacks, validation_data=val_data,)
```

```
Epoch 1/4
523/523 [==============================] - ETA: 0s - loss: 0.0805 - accuracy: 0.9633WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 155). These functions will not be directly callable after loading.
523/523 [==============================] - 852s 1s/step - loss: 0.0805 - accuracy: 0.9633 - val_loss: 0.0030 - val_accuracy: 0.9992
Epoch 2/4
523/523 [==============================] - ETA: 0s - loss: 0.0059 - accuracy: 0.9981WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 155). These functions will not be directly callable after loading.
523/523 [==============================] - 733s 1s/step - loss: 0.0059 - accuracy: 0.9981 - val_loss: 0.0019 - val_accuracy: 0.9996
Epoch 3/4
523/523 [==============================] - ETA: 0s - loss: 0.0029 - accuracy: 0.9991WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 155). These functions will not be directly callable after loading.
523/523 [==============================] - 741s 1s/step - loss: 0.0029 - accuracy: 0.9991 - val_loss: 0.0044 - val_accuracy: 0.9983
Epoch 4/4
523/523 [==============================] - ETA: 0s - loss: 0.0017 - accuracy: 0.9994WARNING:absl:Found untraced functions such as _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op, _jit_compiled_convolution_op while saving (showing 5 of 155). These functions will not be directly callable after loading.
523/523 [==============================] - 689s 1s/step - loss: 0.0017 - accuracy: 0.9994 - val_loss: 3.9097e-04 - val_accuracy: 0.9999
```

PLotting epoch vs training accuracy

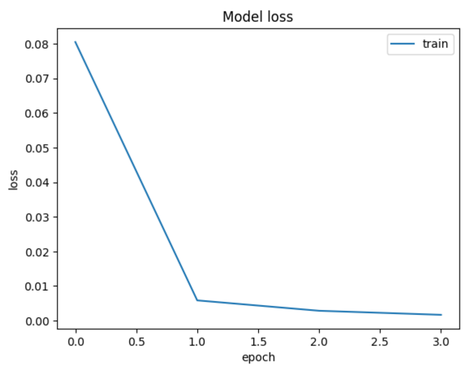
```
plt.plot(history.history['accuracy'])
plt.title('Model accuracy')
```

```
plt.ylabel('Accuracy')
plt.xlabel('epoch')
plt.legend(['train'],loc='upper right')
plt.show()
```



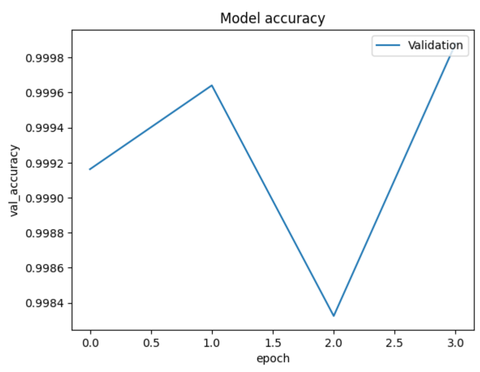
PLotting epoch vs training loss

```
plt.plot(history.history['loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train'],loc='upper right')
plt.show()
```



PLotting epoch vs tvalidation accuracy

```
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('val_accuracy')
plt.xlabel('epoch')
plt.legend(['Validation'],loc='upper right')
plt.show()
```



PLotting epoch vs validation loss

```
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('val_loss')
plt.xlabel('epoch')
plt.legend(['Validation'],loc='upper right')
plt.show()
```