CNN model for Accident Detection based on the MobileNetV2 archtecture

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Set up and Definintion

This section covers all set ups, installations and definitions of tools for the project

Importing required packages/librarise for this project

`numpy` for mathematical operations

`PIL` for visualizing image data

`pathlib` provides an easy way to access files in various directories

`matplotlib.pyplot` for data visualization

`tensorflow` is the deep learning framework which we use to develop and train the model

`tensorflow_hub` is the source of the MobileNetV2 pretrained model archtecture

```
import numpy as np
import PIL
import pathlib
import matplotlib.pyplot as plt
import PIL.Image
import tensorflow as tf
import tensorflow_hub as hub
```

:::

Defining the `train_test_validation_dataset` function

This function is to help us extract image datasets for training, testing and validation respectively.

It takes in the paths to the corresponding image collections and returns the 3 datasets in `tf.keras.dataset` format

```
def train_test_validation_dataset(train_directory, test_directory, validation_directory):
    train_data = tf.keras.utils.image_dataset_from_directory(
      train_directory,
      labels='inferred',
      label_mode='int',
      class_names=None,
      color_mode='rgb',
      batch_size=batch_size,
      image_size=image_size,
      shuffle=True,
      seed=333,
      validation_split=None,
      subset=None,
      interpolation='bilinear',
      follow_links=False,
      crop_to_aspect_ratio=False,
    )

    test_data = tf.keras.utils.image_dataset_from_directory(
      test_dir,
      labels='inferred',
      label_mode='int',
      class_names=None,
      color_mode='rgb',
      batch_size=batch_size,
      image_size=image_size,
      shuffle=True,
      seed=333,
      validation_split=None,
      subset=None,
      interpolation='bilinear',
      follow_links=False,
      crop_to_aspect_ratio=False,
    )
```

```
    val_data = tf.keras.utils.image_dataset_from_directory(
      val_dir,
      labels='inferred',
      label_mode='int',
      class_names=None,
      color_mode='rgb',
      batch_size=batch_size,
      image_size=image_size,
      shuffle=True,
      seed=333,
      validation_split=None,
      subset=None,
      interpolation='bilinear',
      follow_links=False,
      crop_to_aspect_ratio=False,
    )

    return (train_data, test_data, val_data)
```

Defining `sample_images` function

This function is intended to help us sample and view images from any of the dataset.

It takes in a `tf.keras.dataset` and displays sampled images from it

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

Defining the `show_distribution_function`

This is to be used to visualize the distribution of classes in the datasets

```
def show_distribution(dataset):
    # Extract class names and counts
    class_names = dataset.class_names
    class_counts = np.zeros(len(class_names), dtype=np.int32)
    for images, labels in dataset:
        for label in labels:
            class_counts[label] += 1

    # Plot the distribution
    plt.bar(class_names, class_counts)
    plt.title('Image class distribution')
    plt.show()
```

This function will standardize values to be in the `[0, 1]` range by using `tf.keras.layers.Rescaling`

```
def normalize(dataset):
  normalization_layer = tf.keras.layers.Rescaling(1./255)
  normalized_dataset = dataset.map(lambda x, y: (normalization_layer(x), y))
  return normalized_dataset
```

Definition of the `graph_accuracy_loss` function

This function is intended to help us create plots of the loss and accuracy on the training and validation sets

```
def graph_accuracy_loss(history, epochs):
  accuracy = history.history['accuracy']
  validation_accuracy = history.history['val_accuracy']
  loss = history.history["loss"]
  validation_loss = history.history['val_loss']

  epochs_range = range(epochs)

  plt.figure(figsize = (8,8))

  plt.subplot(1, 2, 1)
  plt.plot(epochs_range, accuracy, label = "Training Accuracy")
  plt.plot(epochs_range, validation_accuracy, label= "Validation Accuracy")
```

```
plt.legend(loc = "lower right")
plt.title("Training and Validation Accuracy")

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label = "Training Loss")
plt.plot(epochs_range, validation_loss, label= "Validation Loss")
plt.legend(loc = "upper right")
plt.title("Training and Validation loss")

plt.show()
```

External Resources

This part contains paths and links to external resources relevant to the project

Loading Google Drive

The images dataset was stored in the google drive for easy access via the Google Colabotory IDE

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

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

Setting the paths to the datsets

Paths are set relative to the google drive root system

```
train_dir = "/content/drive/MyDrive/Data sets/Accident_Detection_From_CCTV_Footage/data/tr
test_dir = "/content/drive/MyDrive/Data sets/Accident_Detection_From_CCTV_Footage/data/tes
val_dir = "/content/drive/MyDrive/Data sets/Accident_Detection_From_CCTV_Footage/data/val"
```

The `feature_extractor_model`

The feature extractor of the pretrained MobileNetV2 archtecture from tensorflow hub

```
feature_extractor_model = "https://tfhub.dev/google/tf2-preview/mobilenet_v2/feature_vecto
```

Loading Datasets and converting them to ‘`tf.keras.Dataset`

This is done using the already defined `train_test_validation_dataset` function

Defining Parameters

Useful parameters while loading images and designing the model archtecture and training later

```
batch_size = 32
image_size = (224, 224)
```

Loading the datasets

```
train_dataset, test_dataset, val_dataset = train_test_validation_dataset(
    train_dir, test_dir, val_dir
)
class_names = train_dataset.class_names
```

```
Found 791 files belonging to 2 classes.
Found 100 files belonging to 2 classes.
Found 98 files belonging to 2 classes.
```

Noramlizing the train, test and validation datasets

```
normalized_train_dataset, normalized_test_dataset, normalized_val_dataset = normalize(
    train_dataset), normalize(test_dataset), normalize(val_dataset)
```

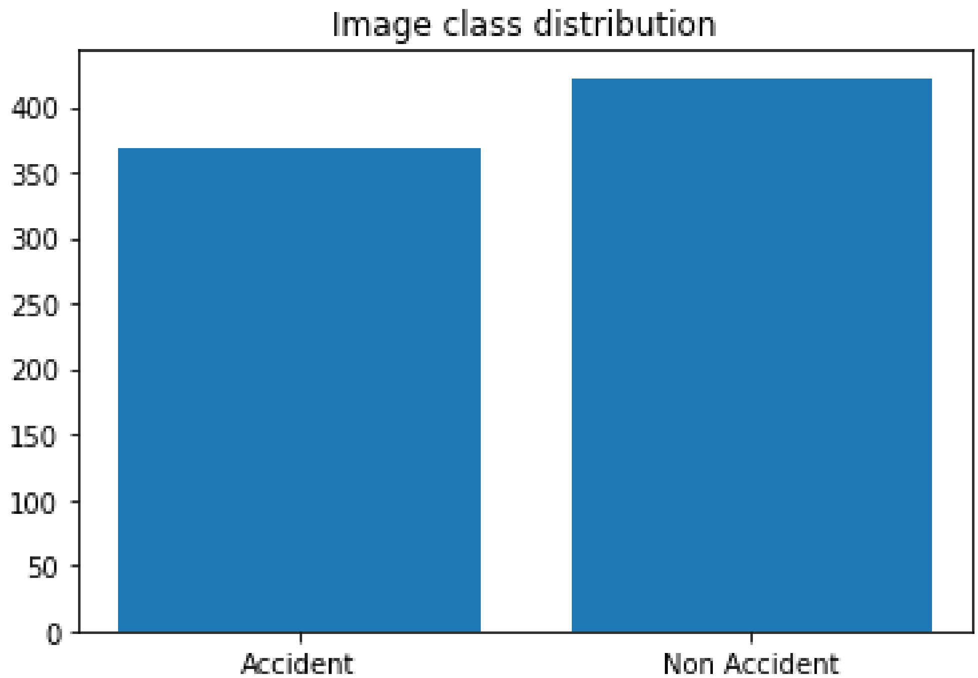
Data Visualization

Sampling images from the training set

```
sample_images(train_dataset)
```

Visualizing class distribution in the train dataset

```
show_distribution(train_dataset)
```



Model Development and Training

This part is where model in implemented

Defining useful model parameters

Some parameter and hyper-parameters for the model to achieve desired performence

```
epochs = 30
activation = "relu"
optimizer = "adam"
metrics = ["accuracy"]
```

Defining the pre-trained model

This is loaded without the top layer and its parameter are set to not trainable so as to avoid adjusting the already good weights

```
pretrained_model_without_top_layer = hub.KerasLayer(
    feature_extractor_model, input_shape=(224, 224, 3),
    trainable=False)
```

Model set up

A sequential model is used so we can easily add layers to the pretrained model to fine tune it to the problem at hand

```
model = tf.keras.Sequential([
  pretrained_model_without_top_layer,
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(128, activation = activation, kernel_regularizer = tf.keras.regula
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(len(class_names))
])

model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer (KerasLayer)    (None, 1280)              2257984

 dropout_6 (Dropout)         (None, 1280)              0

 dense_6 (Dense)             (None, 128)               163968

 dropout_7 (Dropout)         (None, 128)               0

 dense_7 (Dense)             (None, 2)                 258

=================================================================
Total params: 2,422,210
Trainable params: 164,226
Non-trainable params: 2,257,984
_________________________________________________________________
```

Compiling the model

We set up the model to use Adam as optimizer and monitor accuracy and loss

The training will stop early when overfitting is detected

```
model.compile(
  optimizer=optimizer,
  loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
  metrics=metrics)

early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=3,
    restore_best_weights=True)
```

Training the model

Training the model to fit the normalized train dataset while validating on normalized validation datase

```
hist = model.fit(
    normalized_train_dataset,
    validation_data = normalized_val_dataset,
    epochs=epochs,
    callbacks = [early_stopping])
```

```
Epoch 1/30
25/25 [==============================] - 9s 243ms/step - loss: 0.9910 - accuracy: 0.6169 - va
Epoch 2/30
25/25 [==============================] - 5s 167ms/step - loss: 0.7220 - accuracy: 0.7244 - va
Epoch 3/30
25/25 [==============================] - 7s 240ms/step - loss: 0.6000 - accuracy: 0.8217 - va
Epoch 4/30
25/25 [==============================] - 5s 161ms/step - loss: 0.5533 - accuracy: 0.8521 - va
Epoch 5/30
25/25 [==============================] - 7s 216ms/step - loss: 0.5382 - accuracy: 0.8293 - va
Epoch 6/30
25/25 [==============================] - 5s 163ms/step - loss: 0.4635 - accuracy: 0.8748 - va
Epoch 7/30
25/25 [==============================] - 6s 168ms/step - loss: 0.4455 - accuracy: 0.8824 - va
```

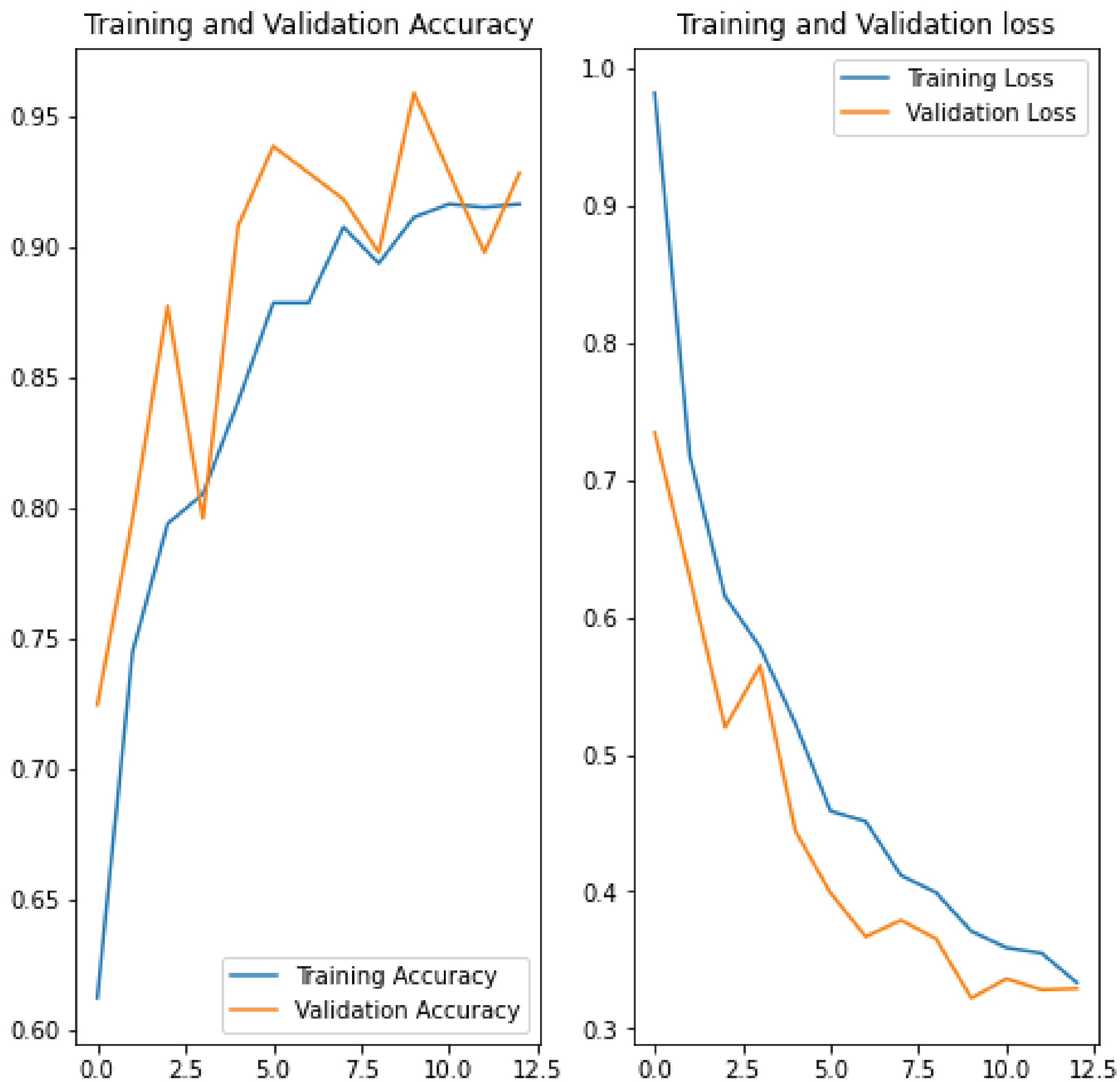
```
Epoch 8/30
25/25 [==============================] - 6s 195ms/step - loss: 0.4338 - accuracy: 0.8774 - va
Epoch 9/30
25/25 [==============================] - 5s 165ms/step - loss: 0.3976 - accuracy: 0.9039 - va
Epoch 10/30
25/25 [==============================] - 7s 237ms/step - loss: 0.3773 - accuracy: 0.9140 - va
Epoch 11/30
25/25 [==============================] - 5s 165ms/step - loss: 0.3882 - accuracy: 0.9001 - va
Epoch 12/30
25/25 [==============================] - 7s 224ms/step - loss: 0.3514 - accuracy: 0.9254 - va
Epoch 13/30
25/25 [==============================] - 6s 197ms/step - loss: 0.3491 - accuracy: 0.9229 - va
Epoch 14/30
25/25 [==============================] - 8s 249ms/step - loss: 0.3386 - accuracy: 0.9305 - va
Epoch 15/30
25/25 [==============================] - 6s 192ms/step - loss: 0.3269 - accuracy: 0.9317 - va
Epoch 16/30
25/25 [==============================] - 6s 168ms/step - loss: 0.3098 - accuracy: 0.9393 - va
Epoch 17/30
25/25 [==============================] - 6s 168ms/step - loss: 0.3064 - accuracy: 0.9343 - va
Epoch 18/30
25/25 [==============================] - 5s 165ms/step - loss: 0.3188 - accuracy: 0.9279 - va
Epoch 19/30
25/25 [==============================] - 7s 224ms/step - loss: 0.3397 - accuracy: 0.9191 - va
Epoch 20/30
25/25 [==============================] - 6s 199ms/step - loss: 0.3084 - accuracy: 0.9355 - va
```

Model Evaluation

Visualizing model performance

See changes in loss and accuracy for training and validation sets over the epochs

```
graph_accuracy_loss(hist, epochs)
```



Evaluation of test dataset

```
model.evaluate(normalized_test_dataset)
```

```
4/4 [==============================] - 39s 141ms/step - loss: 0.2888 - accuracy: 0.9700
```

```
[0.28882908821105957, 0.9700000286102295]
```

Saving the model to the drive

```
model.save("/content/drive/MyDrive/Colab Notebooks/Accident Detection/acc_modelv3.h5",)
```