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## **Title:TRAFFIC MANAGEMENT**

### **TEAM MEMBERS:**

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### **PHASE 3:**

#### **DEVELOPMENT PART 1**

This Traffic Management System will not only optimize traffic flow but also contribute to a safer and more sustainable urban environment.

By harnessing the power of Python and its extensive libraries, we aim to create a cutting-edge solution that addresses the challenges of modern urban transportation.

#### **1. Obtain the Dataset:**

- You can find datasets for traffic management from various sources, including government agencies, research institutions, or online data repositories. Make sure the dataset is relevant to your specific problem (e.g., traffic prediction, congestion analysis, etc.).

## 2. Read and Understand the Data:

- Load the dataset into a suitable data structure (e.g., pandas DataFrame in Python). Understand the features (columns) and the meaning of each variable.
- 

## 3. Data Cleaning:

- Handle missing values: Depending on the dataset, you may encounter missing data. Decide whether to impute missing values or remove the corresponding entries.
- Handle duplicates: Check for and remove duplicate records if they exist.
- Handle outliers: Identify and decide whether to remove or transform outliers.
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## 4. Data Exploration and Visualization:

- Understand the distribution of variables, correlations, and any interesting patterns in the data. Visualization tools like matplotlib or seaborn in Python can be helpful.
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## 5. Feature Engineering:

- Create new features if necessary. For example, you might extract time-related information (hour, day of the week, etc.) from timestamps, or derive additional features from existing ones.
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## 6. Data Transformation:

- Convert categorical variables into numerical format (e.g., one-hot encoding or label encoding).
- Standardize or normalize numerical features if necessary.
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## 7. Splitting the Data:

- Divide the dataset into training, validation, and test sets. The training set is used to train the model, the validation set is used for hyperparameter tuning, and the test set is used for evaluating the final model.
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#### 8. **Scaling:**

- Depending on the algorithm you plan to use, you might need to scale the features (e.g., using StandardScaler in scikit-learn) to ensure they have similar magnitudes.

#### 9. **Save Preprocessed Data:**

- Once you've completed the preprocessing steps, it's a good practice to save the preprocessed data so you can easily load it for future analyses without repeating the entire process.

#### 10. **Model Building:**

- Use the preprocessed data to train a model for your specific traffic management task. This could be a regression model for traffic prediction, a classification model for congestion analysis, or any other relevant machine learning approach.

### **Importing Libraries**

- [Pandas](#) – Use to load the data frame in a 2D array format.
- [NumPy](#) – NumPy arrays are very fast and can perform large computations in a very short time.
- [Matplotlib](#) – This library is used to draw visualizations.
- Sklearn – It contains multiple libraries having pre-implemented functions of model development and evaluation.
- [OpenCV](#) – This library mainly focused on image processing and handling.
- [Tensorflow](#) – It provides a range of functions to achieve complex functionalities with single lines of code.

### **PYTHON CODE:**

```
import matplotlib.image as mpimg  
import os
```

```
from tensorflow.keras.callbacks import EarlyStopping  
from tensorflow.keras.preprocessing import image_dataset_from_directory  
from tensorflow.keras.preprocessing.image import ImageDataGenerator,  
load_img
```

```
from keras.utils.np_utils import to_categorical  
from tensorflow.keras.utils import image_dataset_from_directory  
from tensorflow.keras.optimizers import Adam  
from tensorflow.keras.layers import Conv2D, MaxPooling2D  
from tensorflow.keras.layers import Activation, Dropout, Flatten, Dense  
from tensorflow.keras.models import Sequential  
from keras import layers  
from tensorflow import keras  
from tensorflow.keras.layers.experimental.preprocessing import Rescaling  
from sklearn.model_selection import train_test_split  
  
import matplotlib.pyplot as plt  
import tensorflow as tf  
import pandas as pd  
import numpy as np  
from glob import glob  
import cv2  
  
import warnings  
warnings.filterwarnings('ignore')
```

## **Loading and Extracting the Dataset:**

The dataset has 58 classes of Traffic Signs and a label.csv file. The folder is in zip format. To unzip the dataset, we will run the code below.

### **PYTHON CODE:**

```
# Extracting the compressed dataset.  
from zipfile import ZipFile data_path  
    = '/content/traffic-sign-dataset-classification.zip' with  
    ZipFile(data_path, 'r') as zip  
    : zip.extractall()
```

## **Data Visualization**

[Data visualization](#) means the visualization of data to understand the key features of the dataset.

### PYTHON CODE:

```
# path to the folder containing our dataset
dataset = '../content/traffic_Data/DATA'

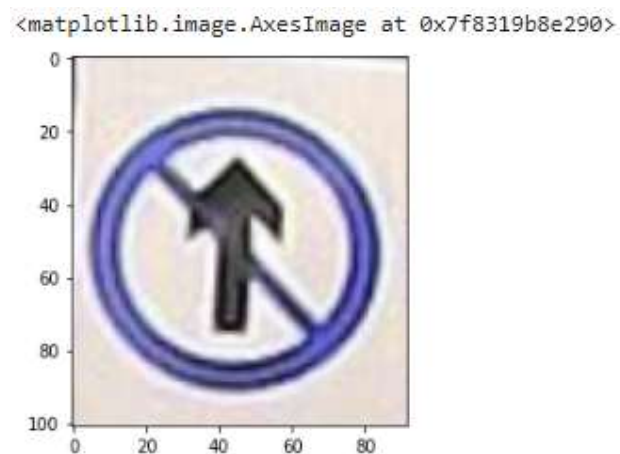
# path of label file
labelfile = pd.read_csv('labels.csv')
```

Once we load the dataset, now let's visualize some random images from the different folders. For that, we will use plt.imshow() command.

### PYTHON CODE:

```
# Visualize some images from the dataset
img = cv2.imread("/content/traffic_Data/DATA/10/010_0011.png")
plt.imshow(img)
```

### Output :



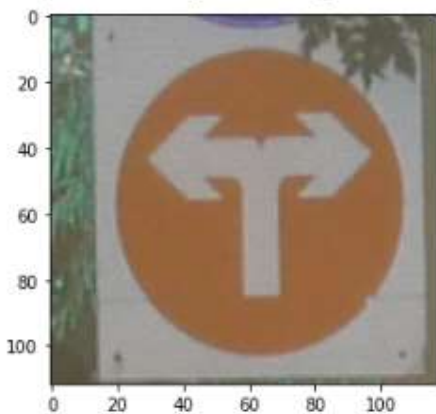
### ONE MORE IMAGE AS EXAMPLE:

### PYTHON CODE:

```
img = cv2.imread("/content/traffic_Data/DATA/23/023_0001.png")
plt.imshow(img)
```

### Output :

```
<matplotlib.image.AxesImage at 0x7f8319b2a1d0>
```



### Label File –

This file includes the 58 rows and 2 columns. The columns contains the class id and the name of the symbol. And the rows depicts the 58 different classes id and names.

### PYTHON CODE:

```
labelfile.head()
```

### Output:

	ClassId	Name
0	0	Speed limit (5km/h)
1	1	Speed limit (15km/h)
2	2	Speed limit (30km/h)
3	3	Speed limit (40km/h)
4	4	Speed limit (50km/h)

### Data Preparation for Training

In this section, we will split the dataset into train and val set. Train set will be used to train the model and val set will be use to evaluate the performance of our model.

### PYTHON CODE”:

```

train_ds = tf.keras.preprocessing.image_dataset_from_directory(dataset,
validation_split=0.2,
subset='training',
image_size=(224, 224),
seed=123,
batch_size=32)
val_ds = tf.keras.preprocessing.image_dataset_from_directory(dataset,
validation_split=0.2,
subset='validation',
image_size=(224, 224),
seed=123,
batch_size=32)

```

### Output:

Found 4170 files belonging to 58 classes.

Using 3336 files for training.

Found 4170 files belonging to 58 classes.

Using 834 files for validation.

Once we split the dataset, Let's create the list of the class names and print few images along with their class names.

### PYTHON CODE:

```

class_numbers = train_ds.class_names
class_names = []
for i in class_numbers:
    class_names.append(labelfile['Name'][int(i)])

```

Let's visualize the train dataset and print 25 images from the dataset.

### PYTHON CODE:

```
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(25):
        ax = plt.subplot(5, 5, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")

plt.show()
```

### Output:



### Data Augmentation:

Sometimes the data is limited and we the model is not performing well with limited data. For this method, we use [Data Augmentation](#). It is the method to increase the amount and diversity in data. We do not collect new data, rather we transform the already present data.

### PYTHON CODE:

```
data_augmentation = tf.keras.Sequential(
```



```
[
    tf.keras.layers.experimental.preprocessing.RandomFlip(
        "horizontal", input_shape=(224, 224, 3)),
    tf.keras.layers.experimental.preprocessing.RandomRotation(0.1),
    tf.keras.layers.experimental.preprocessing.RandomZoom(0.2),
    tf.keras.layers.experimental.preprocessing.RandomFlip(
        mode="horizontal_and_vertical")
]
```

## Model Architecture:

The model will contain the following Layers:

- Four [Convolutional](#) Layers followed by [MaxPooling](#) Layers.
- The [Flatten](#) layer to flatten the output of the convolutional layer.
- Then we will have three fully connected Dense layers followed by the output of the of [Softmax](#) activation function.

## PYTHON CODE:

```
model = Sequential()
model.add(data_augmentation)
model.add(Rescaling(1./255))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(256, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(128, activation='relu'))
model.add(Dense(1000, activation='softmax'))
```

Let's print the summary of the model.

## PYTHON CODE:

```
model.summary()
```

## Output :

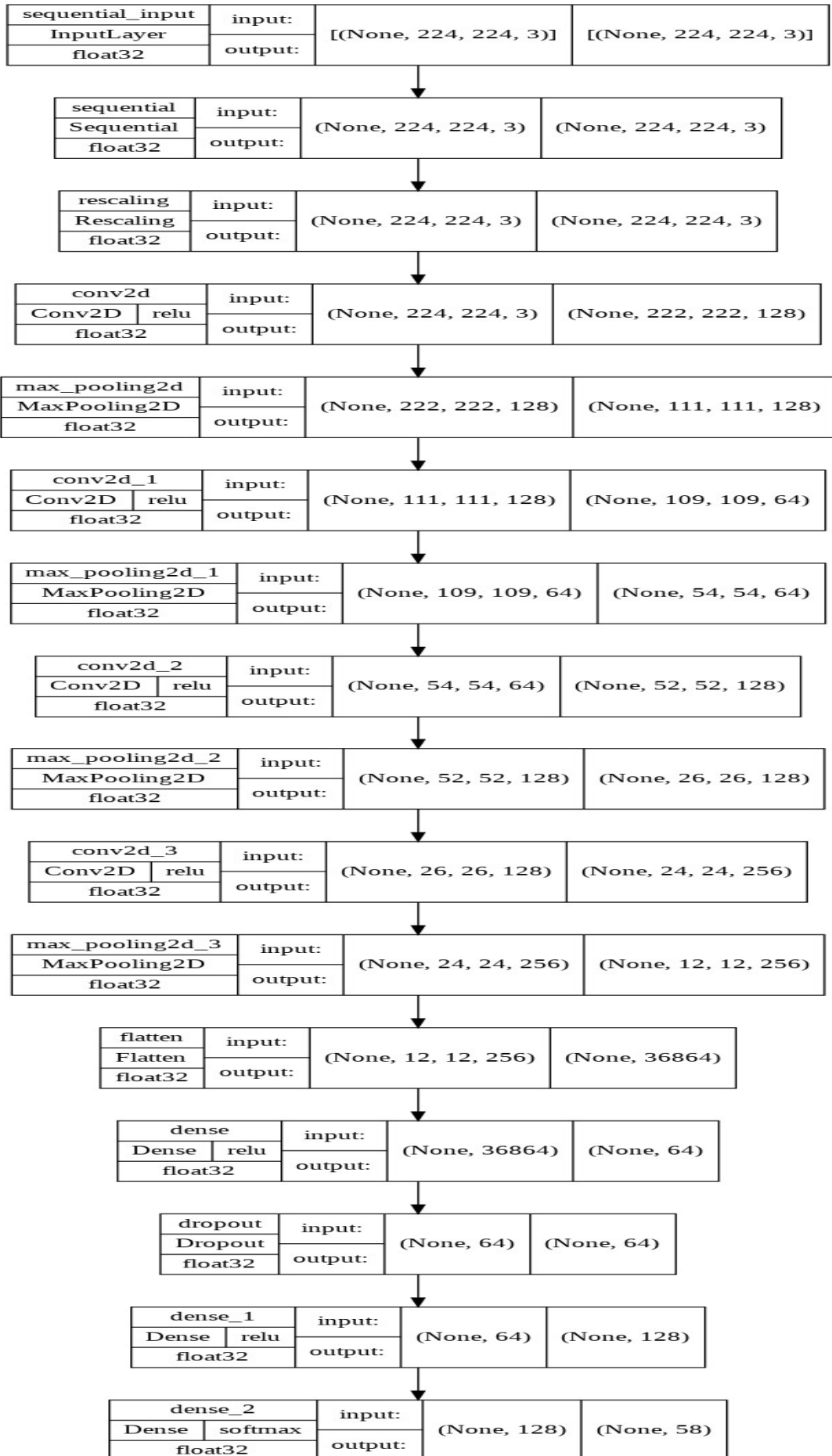
```
Model: "sequential_5"
Layer (type)                 Output Shape                 Param #
-----
sequential_2 (Sequential)    (None, 224, 224, 3)         0
rescaling_1 (Rescaling)      (None, 224, 224, 3)         0
conv2d_14 (Conv2D)           (None, 222, 222, 128)       3584
max_pooling2d_12 (MaxPoolin  (None, 111, 111, 128)       0
g2D)
conv2d_15 (Conv2D)           (None, 109, 109, 64)        73792
max_pooling2d_13 (MaxPoolin  (None, 54, 54, 64)          0
g2D)
conv2d_16 (Conv2D)           (None, 52, 52, 128)         73856
max_pooling2d_14 (MaxPoolin  (None, 26, 26, 128)         0
g2D)
conv2d_17 (Conv2D)           (None, 24, 24, 256)         295168
max_pooling2d_15 (MaxPoolin  (None, 12, 12, 256)         0
g2D)
flatten_3 (Flatten)          (None, 36864)               0
dense_9 (Dense)              (None, 64)                  2359360
dropout_5 (Dropout)          (None, 64)                  0
dense_10 (Dense)             (None, 128)                 8320
dense_11 (Dense)             (None, 58)                  7482
Total params: 2,821,562
Trainable params: 2,821,562
Non-trainable params: 0
```

To understand the huge number of parameters and complexity of the model which helps us to achieve a high-performance model let's see the plot\_model.

## PYTHON CODE:

```
keras.utils.plot_model(
    model,
    show_shapes=True,
    show_dtype=True,
    show_layer_activations=True )
```

## Output :



### PYTHON CODE:

```
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              optimizer='adam',
              metrics=['accuracy'])
```

## Model Training

Now we will train our model, the model is working fine on epochs = 50, but you can perform hyperparameter tuning for better results.

We can also use **callback** function for early stopping the model training.

### PYTHON CODE:

```
# Set callback functions to early stop training

mycallbacks = [EarlyStopping(monitor='val_loss', patience=5)]
history = model.fit(train_ds,
                    validation_data=val_ds,
                    epochs=50,
                    callbacks=mycallbacks)
```

### Output:

```
Epoch 34/50
105/105 [=====] - 16s 149ms/step - loss: 0.4358 - accuracy: 0.8558 - val_loss: 0.2030 - val_accuracy: 0.9365
Epoch 35/50
105/105 [=====] - 16s 150ms/step - loss: 0.4203 - accuracy: 0.8582 - val_loss: 0.2974 - val_accuracy: 0.9053
Epoch 36/50
105/105 [=====] - 16s 148ms/step - loss: 0.4097 - accuracy: 0.8594 - val_loss: 0.1873 - val_accuracy: 0.9388
Epoch 37/50
105/105 [=====] - 16s 148ms/step - loss: 0.4145 - accuracy: 0.8636 - val_loss: 0.1513 - val_accuracy: 0.9472
Epoch 38/50
105/105 [=====] - 16s 148ms/step - loss: 0.3831 - accuracy: 0.8690 - val_loss: 0.1681 - val_accuracy: 0.9448
Epoch 39/50
105/105 [=====] - 16s 149ms/step - loss: 0.3658 - accuracy: 0.8723 - val_loss: 0.1826 - val_accuracy: 0.9424
Epoch 40/50
105/105 [=====] - 16s 149ms/step - loss: 0.4035 - accuracy: 0.8636 - val_loss: 0.1965 - val_accuracy: 0.9448
Epoch 41/50
105/105 [=====] - 16s 148ms/step - loss: 0.3976 - accuracy: 0.8675 - val_loss: 0.1687 - val_accuracy: 0.9556
Epoch 42/50
105/105 [=====] - 16s 149ms/step - loss: 0.3395 - accuracy: 0.8807 - val_loss: 0.1791 - val_accuracy: 0.9376
```

The above image shows the last epochs of the model.

## Model Evaluation:

Let's visualize the training and validation accuracy with each epoch.

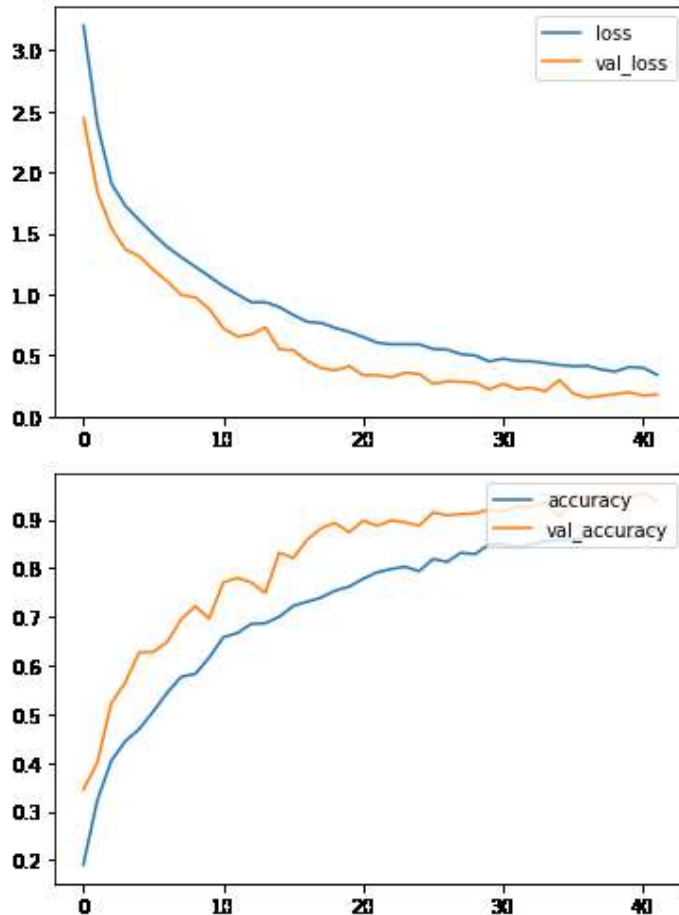
### PYTHON CODE:

```
# Loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['loss', 'val_loss'], loc='upper right')
```

```
# Accuracy
```

```
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.legend(['accuracy', 'val_accuracy'], loc='upper right')
```

### Output :



### Conclusion:

CNN model is performing very well with these layers. Further we can include more traffic and danger sign to warn the drivers.