In [1]:

```python
from PIL import Image
import cv2
import pandas as pd
import numpy as np
# import tensorflow_hub as hub
import numpy.random as npr
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('bmh')

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications.mobilenet import MobileNet
from tensorflow.keras.layers import Input
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, accuracy_score, confusion_matrix, classifi
```

```
2023-12-06 22:44:25.108228: E tensorflow/compiler/xla/stream_executor/cuda/cuda_d
nn.cc:9342] Unable to register cuDNN factory: Attempting to register factory for
plugin cuDNN when one has already been registered
2023-12-06 22:44:25.108286: E tensorflow/compiler/xla/stream_executor/cuda/cuda_f
ft.cc:609] Unable to register cuFFT factory: Attempting to register factory for p
lugin cuFFT when one has already been registered
2023-12-06 22:44:25.108292: E tensorflow/compiler/xla/stream_executor/cuda/cuda_b
las.cc:1518] Unable to register cuBLAS factory: Attempting to register factory fo
r plugin cuBLAS when one has already been registered
2023-12-06 22:44:25.113867: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in performa
nce-critical operations.
To enable the following instructions: SSE4.1 SSE4.2 AVX AVX2 FMA, in other operat
ions, rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:

```python
X_train = np.load('flower_species_classification/data_train.npy').T
t_train = np.load('flower_species_classification/labels_train.npy')

X_test = np.load('flower_species_classification/data_test.npy').T
t_test = np.load('flower_species_classification/labels_test.npy')

print(X_train.shape, t_train.shape)
```

```
(1658, 270000) (1658,)
```

In [3]:

```python
NEW_SIZE = (224,224)
INTERPOLATION = cv2.INTER_CUBIC
data = []

for i in range(1658):
    img = X_train[i,:].reshape(300,300,3)
    # img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    # img = tf.image.convert_image_dtype(img, tf.float32)
    # img = tf.image.resize(img, NEW_SIZE)
    img = cv2.resize(img, NEW_SIZE, interpolation=INTERPOLATION)
    img = np.array(img)
    data.append(img)

X_train_resized = np.array(data)
X_train_resized.shape
```

Out[3]: (1658, 224, 224, 3)

In [4]:
```
#Splitting data into training and validation
X_training, X_val, t_training, t_val = train_test_split(X_train_resized, t_train
```

In [5]:
```
# model = MobileNet(input_shape=(224,224,3), include_top=True)
# base_model = hub.load("https://tfhub.dev/google/tf2-preview/mobilenet_v2/class
# base_model = keras.applications.MobileNet(
#     input_shape=(224,224,3),
#     alpha=1.0,
#     depth_multiplier=1,
#     dropout=0.001,
#     include_top=True,
#     weights="imagenet",
#     pooling=None,
#     classes=1000,
#     classifier_activation="softmax",
# )

base_model = keras.applications.VGG19(
    include_top=False,
    weights="imagenet",
    input_tensor=Input(shape=(224, 224, 3)),
    input_shape=None,
    pooling=None,
    classes=1000,
    classifier_activation="softmax",
)

base_model.trainable = False
```

```
2023-12-06 22:44:39.526769: I tensorflow/core/common_runtime/gpu/gpu_device.cc:18
86] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 79087 MB mem
ory:  -> device: 0, name: NVIDIA A100-SXM4-80GB, pci bus id: 0000:47:00.0, comput
e capability: 8.0
2023-12-06 22:44:39.528561: I tensorflow/core/common_runtime/gpu/gpu_device.cc:18
86] Created device /job:localhost/replica:0/task:0/device:GPU:1 with 79087 MB mem
ory:  -> device: 1, name: NVIDIA A100-SXM4-80GB, pci bus id: 0000:4e:00.0, comput
e capability: 8.0
```

In [6]:
```
#Accuracy for 1 hidden layer = 55 %
#Accuracy for 2 hidden layers = 66 %
#Accuracy for 3 hidden layers =  % but val_loss higher  indicating overfitting
#Accuracy for 4 hidden layer =  %

model = keras.models.Sequential([
    base_model,
    keras.layers.Flatten(), # another option is to use the Global Average Poolin
    keras.layers.Dense(64, activation='relu'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])
```

In [7]:
```
# Learning rate = 0.001 - Accuracy = 65%
#Learning rate = 0.03 - Overfitting
loss = keras.losses.SparseCategoricalCrossentropy()
```

```python
optimizer = keras.optimizers.Adam(
    learning_rate=0.001,
    name="adam")

model.compile(optimizer= optimizer, loss=loss, metrics=['accuracy'])
```

In [8]:
```python
early_stopping_cb = keras.callbacks.EarlyStopping(patience=10,
                                                   monitor='val_loss',
                                                  restore_best_weights=True)



flowers = model.fit(X_training,t_training, epochs = 300,batch_size = 5, validati

model.save("Models/Flowers.h5")
```

```
Epoch 1/300
```

```
2023-12-06 22:44:55.051299: I tensorflow/compiler/xla/stream_executor/cuda/cuda_d
nn.cc:442] Loaded cuDNN version 8800
2023-12-06 22:44:57.186065: I tensorflow/compiler/xla/service/service.cc:168] XLA
service 0x1495b9c73310 initialized for platform CUDA (this does not guarantee tha
t XLA will be used). Devices:
2023-12-06 22:44:57.186111: I tensorflow/compiler/xla/service/service.cc:176]   S
treamExecutor device (0): NVIDIA A100-SXM4-80GB, Compute Capability 8.0
2023-12-06 22:44:57.186116: I tensorflow/compiler/xla/service/service.cc:176]   S
treamExecutor device (1): NVIDIA A100-SXM4-80GB, Compute Capability 8.0
2023-12-06 22:44:57.190505: I tensorflow/compiler/mlir/tensorflow/utils/dump_mlir
_util.cc:269] disabling MLIR crash reproducer, set env var `MLIR_CRASH_REPRODUCER
_DIRECTORY` to enable.
2023-12-06 22:44:57.279029: I ./tensorflow/compiler/jit/device_compiler.h:186] Co
mpiled cluster using XLA!  This line is logged at most once for the lifetime of t
he process.
```

```
232/232 [==============================] - 6s 11ms/step - loss: 1.6780 - accurac
y: 0.4362 - val_loss: 0.8935 - val_accuracy: 0.7349
Epoch 2/300
232/232 [==============================] - 2s 8ms/step - loss: 1.1244 - accuracy:
0.6500 - val_loss: 0.5862 - val_accuracy: 0.8273
Epoch 3/300
232/232 [==============================] - 2s 8ms/step - loss: 0.7499 - accuracy:
0.7603 - val_loss: 0.4977 - val_accuracy: 0.8574
Epoch 4/300
232/232 [==============================] - 2s 8ms/step - loss: 0.6255 - accuracy:
0.8078 - val_loss: 0.4111 - val_accuracy: 0.8735
Epoch 5/300
232/232 [==============================] - 2s 9ms/step - loss: 0.5152 - accuracy:
0.8353 - val_loss: 0.4054 - val_accuracy: 0.8735
Epoch 6/300
232/232 [==============================] - 2s 8ms/step - loss: 0.5446 - accuracy:
0.8233 - val_loss: 0.3746 - val_accuracy: 0.8755
Epoch 7/300
232/232 [==============================] - 2s 8ms/step - loss: 0.4264 - accuracy:
0.8560 - val_loss: 0.3963 - val_accuracy: 0.8655
Epoch 8/300
232/232 [==============================] - 2s 8ms/step - loss: 0.4855 - accuracy:
0.8431 - val_loss: 0.3701 - val_accuracy: 0.8735
Epoch 9/300
232/232 [==============================] - 2s 8ms/step - loss: 0.3790 - accuracy:
0.8767 - val_loss: 0.3253 - val_accuracy: 0.8936
Epoch 10/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2943 - accuracy:
0.9052 - val_loss: 0.3218 - val_accuracy: 0.8876
Epoch 11/300
232/232 [==============================] - 2s 8ms/step - loss: 0.3049 - accuracy:
0.8991 - val_loss: 0.3734 - val_accuracy: 0.8735
Epoch 12/300
232/232 [==============================] - 2s 8ms/step - loss: 0.3451 - accuracy:
0.8931 - val_loss: 0.3059 - val_accuracy: 0.8996
Epoch 13/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2654 - accuracy:
0.9086 - val_loss: 0.3084 - val_accuracy: 0.8956
Epoch 14/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2449 - accuracy:
0.9155 - val_loss: 0.3237 - val_accuracy: 0.8896
Epoch 15/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2817 - accuracy:
0.9017 - val_loss: 0.3163 - val_accuracy: 0.9036
Epoch 16/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2629 - accuracy:
0.9086 - val_loss: 0.3209 - val_accuracy: 0.8996
Epoch 17/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2626 - accuracy:
0.9224 - val_loss: 0.3346 - val_accuracy: 0.8956
Epoch 18/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2414 - accuracy:
0.9233 - val_loss: 0.3497 - val_accuracy: 0.8956
Epoch 19/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2314 - accuracy:
0.9284 - val_loss: 0.3490 - val_accuracy: 0.8835
Epoch 20/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2431 - accuracy:
0.9224 - val_loss: 0.3472 - val_accuracy: 0.8956
Epoch 21/300
```

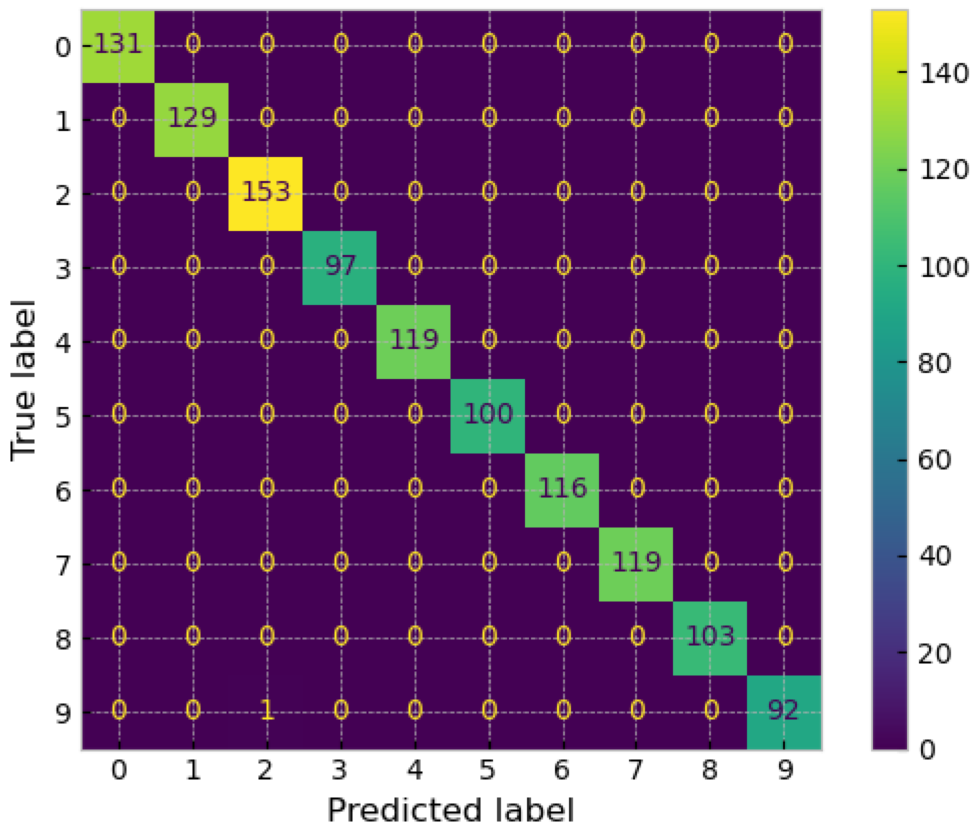
```
232/232 [==============================] - 2s 8ms/step - loss: 0.2333 - accuracy:
0.9284 - val_loss: 0.3480 - val_accuracy: 0.8916
Epoch 22/300
232/232 [==============================] - 2s 8ms/step - loss: 0.2283 - accuracy:
0.9276 - val_loss: 0.4188 - val_accuracy: 0.8635
```

```
/apps/tensorflow/2.14/lib/python3.11/site-packages/keras/src/engine/training.py:3
079: UserWarning: You are saving your model as an HDF5 file via `model.save()`. T
his file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

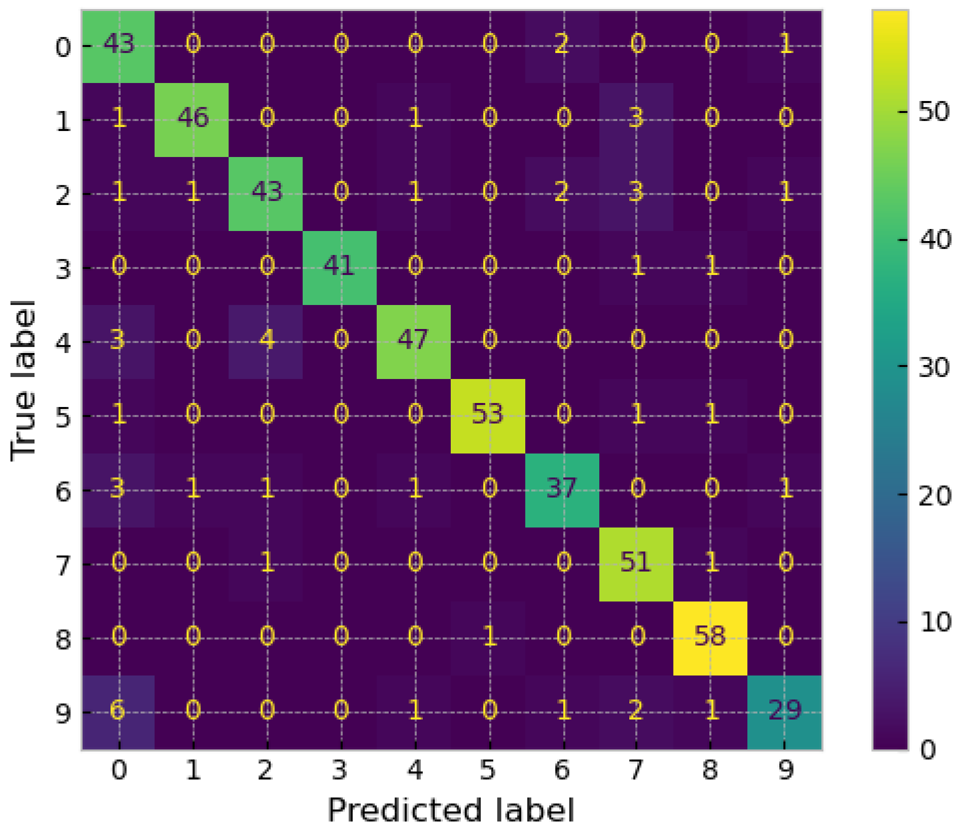
In [10]:

```
class_names = ['Roses', 'Magnolias', 'Lilies', 'Sunflowers', 'Orchids',
               'Marigold', 'Hibiscus', 'Firebush', 'Pentas', 'Bougainvillea']

#Printing the training and validation scores
y_train = np.argmax(model.predict(X_training), axis = 1)
y_valid = np.argmax(model.predict(X_val), axis = 1)


print("Classification Report for Training set:\n", classification_report(t_train
disp = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(t_training, y_tr
disp.plot()
plt.figure(figsize = (50,10))
plt.show()
# print(r2_score(t_val, y_valid))
print("Classification Report for Validation set:\n", classification_report(t_val
disp = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(t_val, y_valid))
disp.plot()
plt.figure(figsize = (10,7))
plt.show()
```

```
37/37 [==============================] - 1s 21ms/step
16/16 [==============================] - 0s 20ms/step
Classification Report for Training set:
               precision    recall  f1-score   support

         0.0       1.00      1.00      1.00       131
         1.0       1.00      1.00      1.00       129
         2.0       0.99      1.00      1.00       153
         3.0       1.00      1.00      1.00        97
         4.0       1.00      1.00      1.00       119
         5.0       1.00      1.00      1.00       100
         6.0       1.00      1.00      1.00       116
         7.0       1.00      1.00      1.00       119
         8.0       1.00      1.00      1.00       103
         9.0       1.00      0.99      0.99        93

    accuracy                           1.00      1160
   macro avg       1.00      1.00      1.00      1160
weighted avg       1.00      1.00      1.00      1160
```




```
<Figure size 5000x1000 with 0 Axes>
Classification Report for Validation set:
              precision    recall  f1-score   support

         0.0       0.74      0.93      0.83        46
         1.0       0.96      0.90      0.93        51
         2.0       0.88      0.83      0.85        52
         3.0       1.00      0.95      0.98        43
         4.0       0.92      0.87      0.90        54
         5.0       0.98      0.95      0.96        56
         6.0       0.88      0.84      0.86        44
         7.0       0.84      0.96      0.89        53
         8.0       0.94      0.98      0.96        59
         9.0       0.91      0.72      0.81        40

    accuracy                           0.90       498
   macro avg       0.90      0.89      0.90       498
weighted avg       0.91      0.90      0.90       498
```




```
<Figure size 1000x700 with 0 Axes>
```

In [11]:

```python
NEW_SIZE = (224,224)
INTERPOLATION = cv2.INTER_CUBIC
data = []

for i in range(415):
    img = X_test[i,:].reshape(300,300,3)
    # img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    # img = tf.image.convert_image_dtype(img, tf.float32)
    # img = tf.image.resize(img, NEW_SIZE)
    img = cv2.resize(img, NEW_SIZE, interpolation=INTERPOLATION)
    img = np.array(img)
    data.append(img)

X_test_resized = np.array(data)

model.evaluate(X_test_resized, t_test)
```

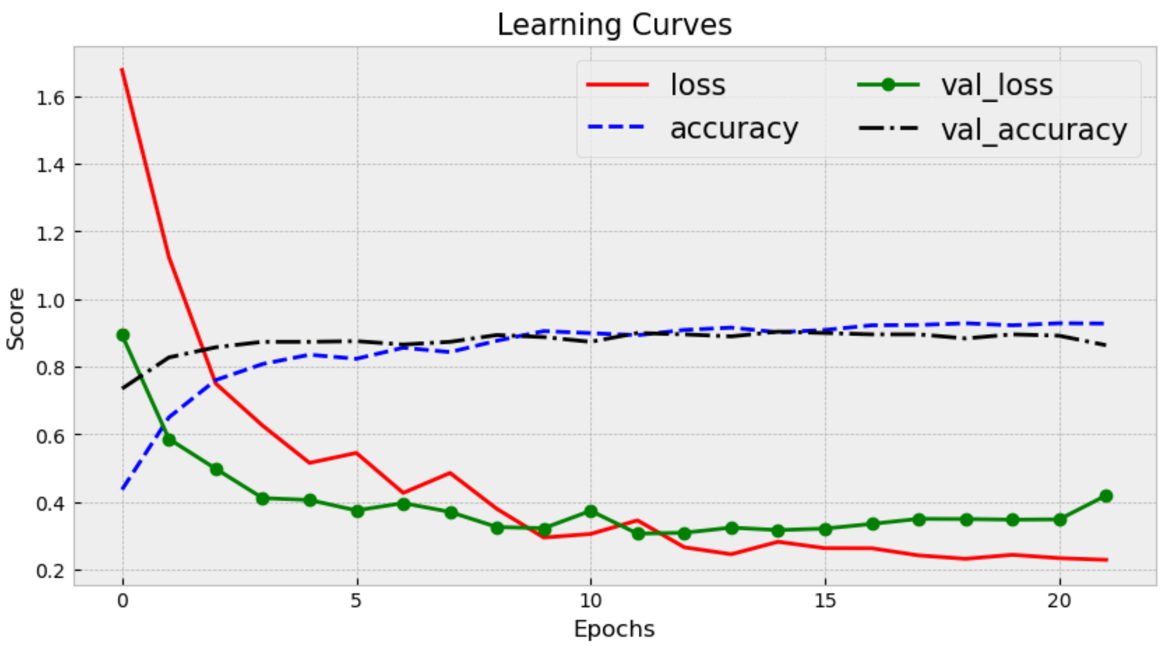
```
13/13 [==============================] - 1s 82ms/step - loss: 0.6127 - accuracy:
0.8554
```

Out[11]:

```
[0.612656831741333, 0.8554216623306274]
```

In [12]:

```python
key_names = list(flowers.history.keys())
colors = ['-r','--b','-og','-.k']

plt.figure(figsize=(10,5))
for i in range(len(key_names)):
    plt.plot(flowers.history[key_names[i]], colors[i], label=key_names[i])
plt.legend(fontsize=15,ncol=2)
plt.title('Learning Curves', size=15);
plt.xlabel('Epochs');
plt.ylabel('Score');
```



In [ ]:

2. Car detection

In [13]:
```
bbox = pd.read_csv('car_detection_dataset/train_bounding_boxes.csv')
bbox
```

Out[13]:

	image	xmin	ymin	xmax	ymax
0	vid_4_1000.jpg	281.259045	187.035071	327.727931	223.225547
1	vid_4_10000.jpg	15.163531	187.035071	120.329957	236.430180
2	vid_4_10040.jpg	239.192475	176.764801	361.968162	236.430180
3	vid_4_10020.jpg	496.483358	172.363256	630.020260	231.539575
4	vid_4_10060.jpg	16.630970	186.546010	132.558611	238.386422
...	...	...	...	...	...
554	vid_4_9860.jpg	0.000000	198.321729	49.235251	236.223284
555	vid_4_9880.jpg	329.876184	156.482351	536.664239	250.497895
556	vid_4_9900.jpg	0.000000	168.295823	141.797524	239.176652
557	vid_4_9960.jpg	487.428988	172.233646	616.917699	228.839864
558	vid_4_9980.jpg	221.558631	182.570434	348.585579	238.192196

559 rows × 5 columns

In [14]:
```
N = len(bbox) # no. of training samples

# Create a numpy array with all images
for i in range(N):
    filename='car_detection_dataset/training_images/'+bbox['image'][i]
    image = np.array(Image.open(filename))
    image_col = image.ravel()[:,np.newaxis]
```

```
    (h, w) = image.shape[:2]

    if i==0:
        X_train = image_col
    else:
        X_train = np.hstack((X_train, image_col))

# Training feature matrices
X_train = X_train.T

# Training labels
t_train = bbox.drop('image', axis=1).round().to_numpy().astype(int)

t_train = t_train.astype(float)

t_train[:, [0, 2]] /= w
t_train[:, [1, 3]] /= h

X_train.shape, t_train.shape
```

Out[14]: ((559, 770640), (559, 4))

In [15]:

```
# NEW_SIZE = (224,224)
# INTERPOLATION = cv2.INTER_CUBIC
data = []

for i in range(559):
    img = X_train[i,:].reshape(380,676,3)
    # img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    # img = tf.image.convert_image_dtype(img, tf.float32)
    # img = tf.image.resize(img, NEW_SIZE)
    # img = cv2.resize(img, NEW_SIZE, interpolation=INTERPOLATION)
    img = np.array(img)
    data.append(img)

X_train_resized = np.array(data)
X_train_resized.shape

#Splitting data into training and validation
X_training, X_val, t_training, t_val = train_test_split(X_train_resized, t_train
```

In [16]:

```
base_model = keras.applications.VGG19(
    include_top=False,
    weights="imagenet",
    input_shape=None,
    pooling=None,
    classes=1000,
    classifier_activation="softmax",
    input_tensor=Input(shape=(380, 676, 3))
)

base_model.trainable = False
```

In [17]:

```
#Relu activation function was giving bad results, use sigmoid since I have norma
# The Relu activation function was giving 0 accuracy as it was having vanishing
model = keras.models.Sequential([
    base_model,
    keras.layers.Flatten(),
    keras.layers.BatchNormalization(),
```

```
    keras.layers.Dense(128, activation='relu'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(4, activation='sigmoid') #without normalization
])
```

In [18]:
```
loss = keras.losses.MeanSquaredError(name="mean_squared_error"
)

optimizer = keras.optimizers.Adam(
    learning_rate=0.001,
    name="adam")

model.compile(optimizer= optimizer, loss=loss, metrics=keras.metrics.MeanSquared
```

In [33]:
```
early_stopping_cb = keras.callbacks.EarlyStopping(patience=20,
                                                   monitor='val_loss',
                                                  restore_best_weights=True)



cars = model.fit(X_training,t_training, epochs = 300,batch_size = 10, validation

# model.save("Models/Car_detection.h5")
```

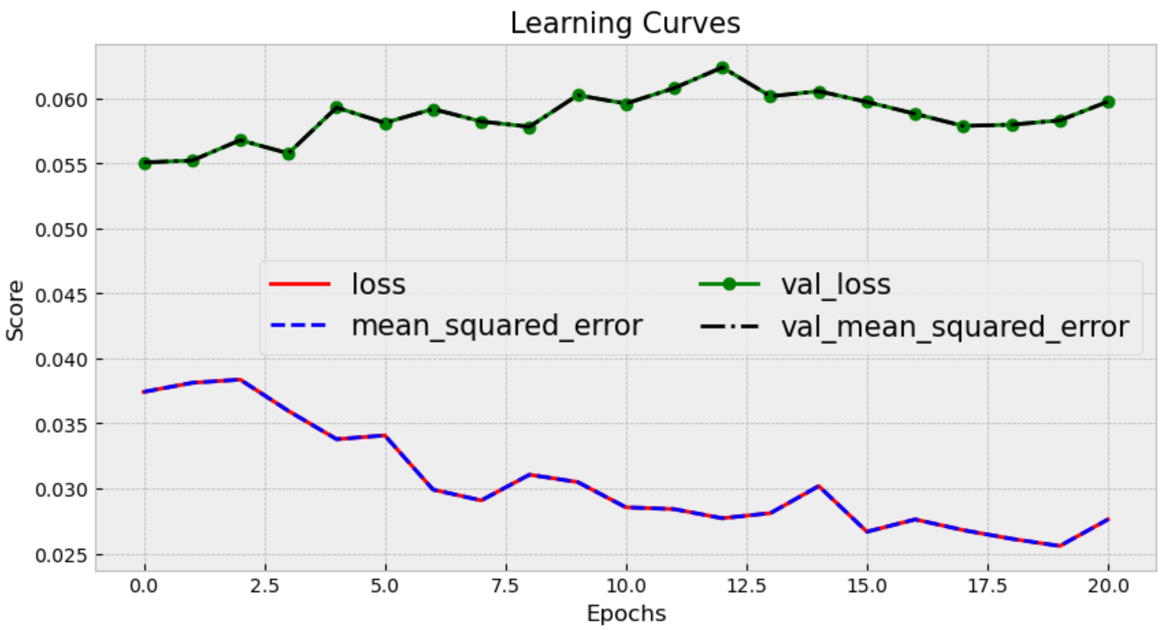
```
Epoch 1/300
40/40 [==============================] - 2s 58ms/step - loss: 0.0374 - mean_squar
ed_error: 0.0374 - val_loss: 0.0551 - val_mean_squared_error: 0.0551
Epoch 2/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0381 - mean_squar
ed_error: 0.0381 - val_loss: 0.0552 - val_mean_squared_error: 0.0552
Epoch 3/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0384 - mean_squar
ed_error: 0.0384 - val_loss: 0.0568 - val_mean_squared_error: 0.0568
Epoch 4/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0360 - mean_squar
ed_error: 0.0360 - val_loss: 0.0558 - val_mean_squared_error: 0.0558
Epoch 5/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0338 - mean_squar
ed_error: 0.0338 - val_loss: 0.0593 - val_mean_squared_error: 0.0593
Epoch 6/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0341 - mean_squar
ed_error: 0.0341 - val_loss: 0.0581 - val_mean_squared_error: 0.0581
Epoch 7/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0299 - mean_squar
ed_error: 0.0299 - val_loss: 0.0592 - val_mean_squared_error: 0.0592
Epoch 8/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0291 - mean_squar
ed_error: 0.0291 - val_loss: 0.0582 - val_mean_squared_error: 0.0582
Epoch 9/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0311 - mean_squar
ed_error: 0.0311 - val_loss: 0.0578 - val_mean_squared_error: 0.0578
Epoch 10/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0305 - mean_squar
ed_error: 0.0305 - val_loss: 0.0603 - val_mean_squared_error: 0.0603
Epoch 11/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0285 - mean_squar
ed_error: 0.0285 - val_loss: 0.0596 - val_mean_squared_error: 0.0596
Epoch 12/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0284 - mean_squar
ed_error: 0.0284 - val_loss: 0.0608 - val_mean_squared_error: 0.0608
Epoch 13/300
40/40 [==============================] - 2s 52ms/step - loss: 0.0277 - mean_squar
ed_error: 0.0277 - val_loss: 0.0624 - val_mean_squared_error: 0.0624
Epoch 14/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0281 - mean_squar
ed_error: 0.0281 - val_loss: 0.0602 - val_mean_squared_error: 0.0602
Epoch 15/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0302 - mean_squar
ed_error: 0.0302 - val_loss: 0.0606 - val_mean_squared_error: 0.0606
Epoch 16/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0267 - mean_squar
ed_error: 0.0267 - val_loss: 0.0597 - val_mean_squared_error: 0.0597
Epoch 17/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0276 - mean_squar
ed_error: 0.0276 - val_loss: 0.0588 - val_mean_squared_error: 0.0588
Epoch 18/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0268 - mean_squar
ed_error: 0.0268 - val_loss: 0.0579 - val_mean_squared_error: 0.0579
Epoch 19/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0261 - mean_squar
ed_error: 0.0261 - val_loss: 0.0580 - val_mean_squared_error: 0.0580
Epoch 20/300
40/40 [==============================] - 2s 51ms/step - loss: 0.0256 - mean_squar
ed_error: 0.0256 - val_loss: 0.0583 - val_mean_squared_error: 0.0583
```

```
Epoch 21/300
40/40 [==============================] - 2s 53ms/step - loss: 0.0276 - mean_squar
ed_error: 0.0276 - val_loss: 0.0598 - val_mean_squared_error: 0.0598
```

In [48]:
```python
model.save("Models/Car_detection_380.h5")
```

```
/apps/tensorflow/2.14/lib/python3.11/site-packages/keras/src/engine/training.py:3
079: UserWarning: You are saving your model as an HDF5 file via `model.save()`. T
his file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

In [34]:
```python
key_names = list(cars.history.keys())
colors = ['-r','--b','-og','-.k']

plt.figure(figsize=(10,5))
for i in range(len(key_names)):
    plt.plot(cars.history[key_names[i]], colors[i], label=key_names[i])
plt.legend(fontsize=15,ncol=2)
plt.title('Learning Curves', size=15);
plt.xlabel('Epochs');
plt.ylabel('Score');
```

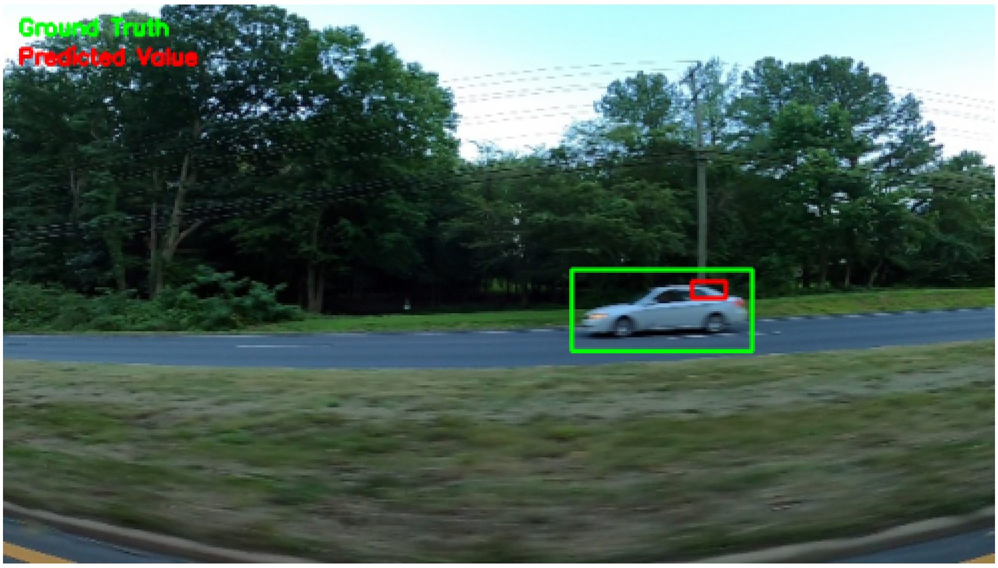


In [35]:
```python
#Function to compute Intersection over union.
def IOU(box1, box2):
    x1, y1, w1, h1 = box1
    x2, y2, w2, h2 = box2

    w_intersection = min(x1 + w1, x2 + w2) - max(x1, x2)
    h_intersection = min(y1 + h1, y2 + h2) - max(y1, y2)

    if w_intersection <= 0 or h_intersection <= 0:
        return 0

    Intersection = w_intersection * h_intersection
    Union = w1 * h1 + w2 * h2 - Intersection
    return Intersection / Union
```

In [49]:
```python
images = ['vid_4_9820.jpg', 'vid_4_9740.jpg', 'vid_4_10040.jpg']
indexes = []
```

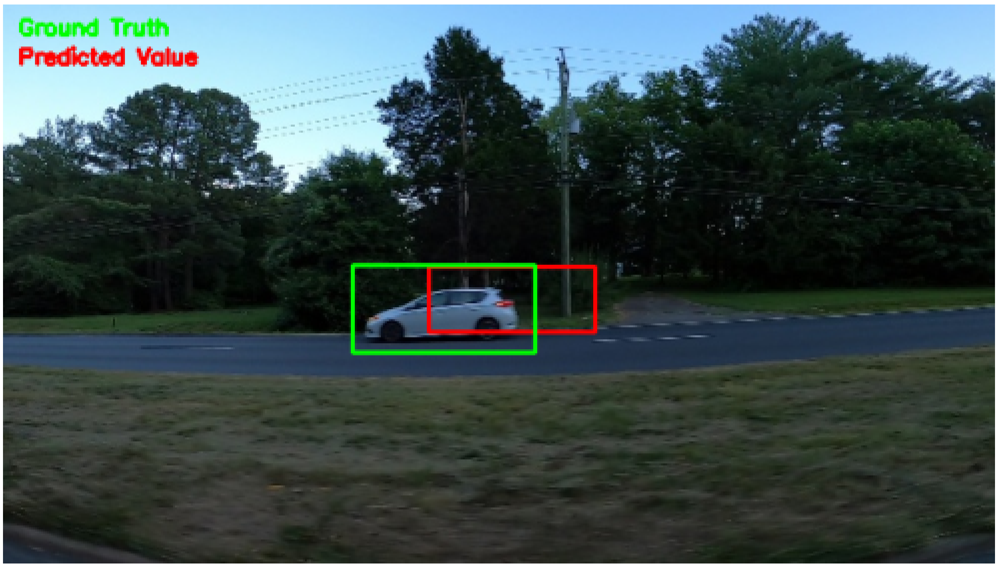
```
i = 1

for image in images:
    filename='car_detection_dataset/training_images/'+image
    img = np.array(Image.open(filename))
    (h,w,c) = img.shape
    img = np.array(img)
    index = (bbox.index[bbox['image']==image][0])
    predicted_bbox = model.predict(np.expand_dims(img, axis=0))
    ground_truth = t_train[index]*(w,h,w,h)
    ground_truth = ground_truth.astype(int)

    predicted_bbox = predicted_bbox*(w,h,w,h)
    predicted_bbox = predicted_bbox.astype(int)

    cv2.putText(img, f"Ground Truth", (10, 20), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (
    cv2.putText(img, f"Predicted Value", (10, 40), cv2.FONT_HERSHEY_SIMPLEX, 0.5

    cv2.rectangle(img, (predicted_bbox[0][0],  predicted_bbox[0][1]),
              ( predicted_bbox[0][2],  predicted_bbox[0][3]),
              (255, 0, 0), 2);

    cv2.rectangle(img, (ground_truth[0],  ground_truth[1]),
              (ground_truth[2],  ground_truth[3]),
              (0, 255, 0), 2);

    # Display the image on the corresponding subplot
    plt.imshow(img)
    plt.axis('off')

    plt.show()


    i = i+1

    # Show the plot
    # plt.show()

    iou = IOU(ground_truth, predicted_bbox[0])
    print('IOU for image' +image+': ', iou)
```

```
1/1 [==============================] - 0s 31ms/step
```



```
IOU for imagevid_4_9820.jpg:  0.6423905993091277
1/1 [==============================] - 0s 25ms/step
```


```
IOU for imagevid_4_9740.jpg:  0.12191064215939218
1/1 [==============================] - 0s 32ms/step
```




```
IOU for imagevid_4_10040.jpg:  0.6487678877806897
```

3. Adding the case when there are no cars in the image.

In [50]:

```
#Appending samples with [0,0,0,0] in which the cars are not present.
bbox = pd.read_csv('car_detection_dataset/train_bounding_boxes_nocars.csv')

data = []
N = len(bbox) # no. of training samples

# Create a numpy array with all images
for i in range(N):
    filename='car_detection_dataset/training_images/'+bbox['image'][i]
    image = np.array(Image.open(filename))
    image_col = image.ravel()[:,np.newaxis]
    (h, w) = image.shape[:2]

    if i==0:
        X_train = image_col
```

```
    else:
        X_train = np.hstack((X_train, image_col))

# Training feature matrices
X_train = X_train.T

# Training labels
t_train = bbox.drop('image', axis=1).round().to_numpy().astype(int)

t_train = t_train.astype(float)

t_train[:, [0, 2]] /= w
t_train[:, [1, 3]] /= h

X_train.shape, t_train.shape

#Reshaping data
for i in range(578):
    img = X_train[i,:].reshape(380,676,3)
    img = np.array(img)
    data.append(img)

training_nocars = np.array(data)

X_train_nocars, X_val_nocars, t_train_nocars, t_val_nocars = train_test_split(tr
```

In [54]:

```
base_model = keras.applications.VGG19(
    include_top=False,
    weights="imagenet",
    input_shape=None,
    pooling=None,
    classes=1000,
    classifier_activation="softmax",
    input_tensor=Input(shape=(380, 676, 3))
)

base_model.trainable = False


model_nocars = keras.models.Sequential([
    base_model,
    keras.layers.Flatten(),
    keras.layers.BatchNormalization(),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(4, activation='sigmoid') #without normalization
])


#Learnign rate =0.01 - Gradient is not converging, my guess is its bouncing acro

loss = keras.losses.MeanSquaredError(name="mean_squared_error"
)

optimizer = keras.optimizers.Adam(
```

```
    learning_rate=0.001,
    name="adam")

model_nocars.compile(optimizer= optimizer, loss=loss, metrics=keras.metrics.Mean

early_stopping_cb = keras.callbacks.EarlyStopping(patience=20,
                                                  monitor='val_loss', restore_be
```

In [55]:
```
nocars = model_nocars.fit(X_train_nocars,t_train_nocars, epochs = 300,batch_size
```

```
Epoch 1/300
41/41 [==============================] - 4s 63ms/step - loss: 0.1155 - mean_squar
ed_error: 0.1155 - val_loss: 0.2094 - val_mean_squared_error: 0.2094
Epoch 2/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0805 - mean_squar
ed_error: 0.0805 - val_loss: 0.0954 - val_mean_squared_error: 0.0954
Epoch 3/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0775 - mean_squar
ed_error: 0.0775 - val_loss: 0.0720 - val_mean_squared_error: 0.0720
Epoch 4/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0687 - mean_squar
ed_error: 0.0687 - val_loss: 0.0639 - val_mean_squared_error: 0.0639
Epoch 5/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0608 - mean_squar
ed_error: 0.0608 - val_loss: 0.0609 - val_mean_squared_error: 0.0609
Epoch 6/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0583 - mean_squar
ed_error: 0.0583 - val_loss: 0.0616 - val_mean_squared_error: 0.0616
Epoch 7/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0542 - mean_squar
ed_error: 0.0542 - val_loss: 0.0633 - val_mean_squared_error: 0.0633
Epoch 8/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0478 - mean_squar
ed_error: 0.0478 - val_loss: 0.0651 - val_mean_squared_error: 0.0651
Epoch 9/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0476 - mean_squar
ed_error: 0.0476 - val_loss: 0.0645 - val_mean_squared_error: 0.0645
Epoch 10/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0441 - mean_squar
ed_error: 0.0441 - val_loss: 0.0659 - val_mean_squared_error: 0.0659
Epoch 11/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0455 - mean_squar
ed_error: 0.0455 - val_loss: 0.0655 - val_mean_squared_error: 0.0655
Epoch 12/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0378 - mean_squar
ed_error: 0.0378 - val_loss: 0.0695 - val_mean_squared_error: 0.0695
Epoch 13/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0383 - mean_squar
ed_error: 0.0383 - val_loss: 0.0691 - val_mean_squared_error: 0.0691
Epoch 14/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0375 - mean_squar
ed_error: 0.0375 - val_loss: 0.0703 - val_mean_squared_error: 0.0703
Epoch 15/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0384 - mean_squar
ed_error: 0.0384 - val_loss: 0.0708 - val_mean_squared_error: 0.0708
Epoch 16/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0377 - mean_squar
ed_error: 0.0377 - val_loss: 0.0708 - val_mean_squared_error: 0.0708
Epoch 17/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0334 - mean_squar
ed_error: 0.0334 - val_loss: 0.0719 - val_mean_squared_error: 0.0719
Epoch 18/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0353 - mean_squar
ed_error: 0.0353 - val_loss: 0.0737 - val_mean_squared_error: 0.0737
Epoch 19/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0327 - mean_squar
ed_error: 0.0327 - val_loss: 0.0726 - val_mean_squared_error: 0.0726
Epoch 20/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0339 - mean_squar
ed_error: 0.0339 - val_loss: 0.0745 - val_mean_squared_error: 0.0745
```

```
Epoch 21/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0330 - mean_squar
ed_error: 0.0330 - val_loss: 0.0737 - val_mean_squared_error: 0.0737
Epoch 22/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0293 - mean_squar
ed_error: 0.0293 - val_loss: 0.0735 - val_mean_squared_error: 0.0735
Epoch 23/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0296 - mean_squar
ed_error: 0.0296 - val_loss: 0.0742 - val_mean_squared_error: 0.0742
Epoch 24/300
41/41 [==============================] - 2s 52ms/step - loss: 0.0280 - mean_squar
ed_error: 0.0280 - val_loss: 0.0752 - val_mean_squared_error: 0.0752
Epoch 25/300
41/41 [==============================] - 2s 53ms/step - loss: 0.0337 - mean_squar
ed_error: 0.0337 - val_loss: 0.0747 - val_mean_squared_error: 0.0747
```

In [ ]:

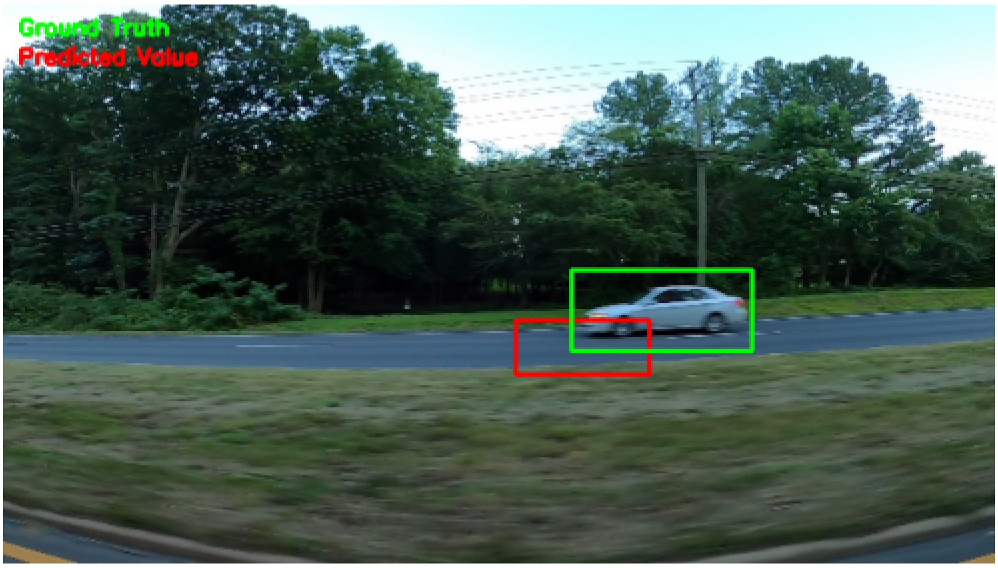
In [56]:

```
#Printing IOU for Region of Interest

images = ['vid_4_9980.jpg','vid_4_9820.jpg', 'vid_4_9740.jpg', 'vid_4_10040.jpg'
indexes = []
i = 1

for image in images:
    filename='car_detection_dataset/training_images/'+image
    img = np.array(Image.open(filename))
    (h,w,c) = img.shape
    img = np.array(img)
    index = (bbox.index[bbox['image']==image][0])
    predicted_bbox = model_nocars.predict(np.expand_dims(img, axis=0))
    ground_truth = t_train[index]*(w,h,w,h)
    ground_truth = ground_truth.astype(int)

    predicted_bbox = predicted_bbox*(w,h,w,h)
    predicted_bbox = predicted_bbox.astype(int)

    cv2.putText(img, f"Ground Truth", (10, 20), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (
    cv2.putText(img, f"Predicted Value", (10, 40), cv2.FONT_HERSHEY_SIMPLEX, 0.5

    cv2.rectangle(img, (predicted_bbox[0][0],  predicted_bbox[0][1]),
              ( predicted_bbox[0][2],  predicted_bbox[0][3]),
              (255, 0, 0), 2);

    cv2.rectangle(img, (ground_truth[0],  ground_truth[1]),
              (ground_truth[2],  ground_truth[3]),
              (0, 255, 0), 2);

    # Display the image on the corresponding subplot
    plt.imshow(img)
    plt.axis('off')
    # plt.label()


    plt.show()


    i = i+1

    # Show the plot
```

```
    # plt.show()

    iou = IOU(ground_truth, predicted_bbox[0])
    print('IOU for image' +image+': ', iou)
```

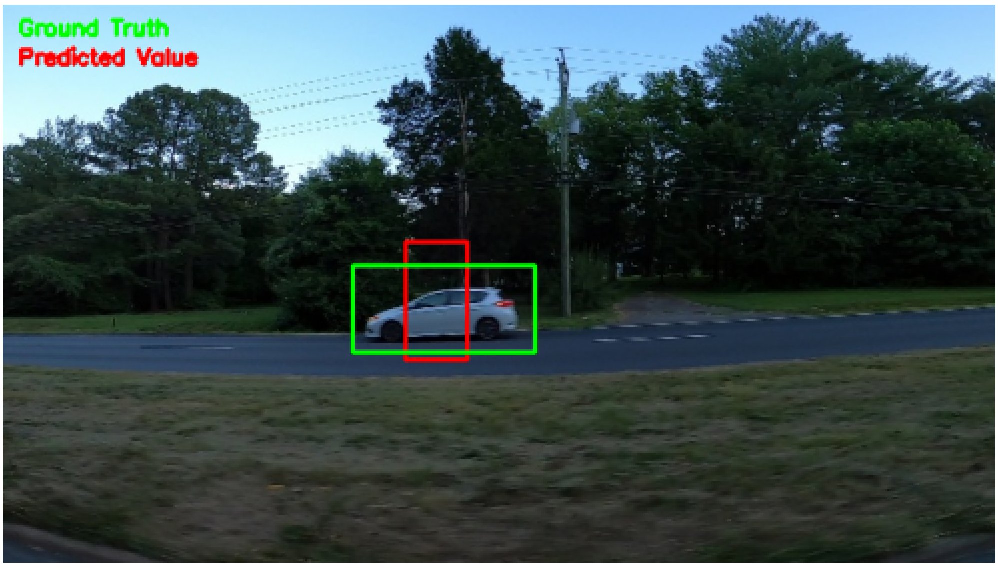
1/1 [==============================] - 0s 174ms/step

IOU for imagevid_4_9980.jpg: 0.7882091818854406
1/1 [==============================] - 0s 30ms/step



IOU for imagevid_4_9820.jpg: 0.5405249919725998
1/1 [==============================] - 0s 29ms/step


```
IOU for imagevid_4_9740.jpg:  0.29504447268106737
1/1 [==============================] - 0s 25ms/step
```




```
IOU for imagevid_4_10040.jpg:  0.7857395455751038
```

In [ ]: