In [1]:
```
class_names = ['Roses', 'Magnolias', 'Lilies', 'Sunflowers', 'Orchids',
               'Marigold', 'Hibiscus', 'Firebush', 'Pentas', 'Bougainvillea
```

In [2]:
```
import numpy as np
import numpy.random as npr
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('bmh')

# Loading Training Data
X_train = np.load('flower_species_classification/data_train.npy').T
t_train = np.load('flower_species_classification/labels_train.npy')

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

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

In [3]:
```
# Counting number samples per class
vals, counts = np.unique(t_train, return_counts=True)

plt.bar(vals, counts)
plt.xticks(range(10),range(10))
plt.xlabel('Classes',size=20)
plt.ylabel('# Samples per Class', size=20)
plt.title('Training Data (Total = '+str(X_train.shape[1])+' samples)',size=
```

In [5]:
```
!pip install tensorflow
```

```
Requirement already satisfied: tensorflow in /opt/anaconda3/lib/python3.1
2/site-packages (2.18.0)
Requirement already satisfied: absl-py>=1.0.0 in /opt/anaconda3/lib/python
3.12/site-packages (from tensorflow) (2.1.0)
Requirement already satisfied: astunparse>=1.6.0 in /opt/anaconda3/lib/pyt
hon3.12/site-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /opt/anaconda3/lib/
python3.12/site-packages (from tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /op
t/anaconda3/lib/python3.12/site-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in /opt/anaconda3/lib/p
ython3.12/site-packages (from tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in /opt/anaconda3/lib/pyth
on3.12/site-packages (from tensorflow) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in /opt/anaconda3/lib/pyt
hon3.12/site-packages (from tensorflow) (3.4.0)
Requirement already satisfied: packaging in /opt/anaconda3/lib/python3.12/
site-packages (from tensorflow) (24.1)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.
3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in /opt/anaconda3/lib/python3.12/si
te-packages (from tensorflow) (4.25.3)
Requirement already satisfied: requests<3,>=2.21.0 in /opt/anaconda3/lib/p
ython3.12/site-packages (from tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /opt/anaconda3/lib/python3.1
2/site-packages (from tensorflow) (75.1.0)
Requirement already satisfied: six>=1.12.0 in /opt/anaconda3/lib/python3.1
2/site-packages (from tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in /opt/anaconda3/lib/pyth
on3.12/site-packages (from tensorflow) (2.5.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /opt/anaconda3/
lib/python3.12/site-packages (from tensorflow) (4.11.0)
Requirement already satisfied: wrapt>=1.11.0 in /opt/anaconda3/lib/python
3.12/site-packages (from tensorflow) (1.14.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /opt/anaconda3/lib/p
ython3.12/site-packages (from tensorflow) (1.68.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in /opt/anaconda3/l
ib/python3.12/site-packages (from tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in /opt/anaconda3/lib/python3.
12/site-packages (from tensorflow) (3.7.0)
Requirement already satisfied: numpy<2.1.0,>=1.26.0 in /opt/anaconda3/lib/
python3.12/site-packages (from tensorflow) (1.26.4)
Requirement already satisfied: h5py>=3.11.0 in /opt/anaconda3/lib/python3.
12/site-packages (from tensorflow) (3.11.0)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in /opt/anaconda3/l
ib/python3.12/site-packages (from tensorflow) (0.4.1)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /opt/anaconda3/lib/py
thon3.12/site-packages (from astunparse>=1.6.0->tensorflow) (0.44.0)
Requirement already satisfied: rich in /opt/anaconda3/lib/python3.12/site-
packages (from keras>=3.5.0->tensorflow) (13.7.1)
Requirement already satisfied: namex in /opt/anaconda3/lib/python3.12/site
-packages (from keras>=3.5.0->tensorflow) (0.0.8)
Requirement already satisfied: optree in /opt/anaconda3/lib/python3.12/sit
e-packages (from keras>=3.5.0->tensorflow) (0.13.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /opt/anaconda3/
lib/python3.12/site-packages (from requests<3,>=2.21.0->tensorflow) (3.3.
2)
Requirement already satisfied: idna<4,>=2.5 in /opt/anaconda3/lib/python3.
12/site-packages (from requests<3,>=2.21.0->tensorflow) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /opt/anaconda3/lib/py
thon3.12/site-packages (from requests<3,>=2.21.0->tensorflow) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in /opt/anaconda3/lib/py
```

```
thon3.12/site-packages (from requests<3,>=2.21.0->tensorflow) (2024.8.30)
Requirement already satisfied: markdown>=2.6.8 in /opt/anaconda3/lib/pytho
n3.12/site-packages (from tensorboard<2.19,>=2.18->tensorflow) (3.4.1)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /o
pt/anaconda3/lib/python3.12/site-packages (from tensorboard<2.19,>=2.18->t
ensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in /opt/anaconda3/lib/pytho
n3.12/site-packages (from tensorboard<2.19,>=2.18->tensorflow) (3.0.3)
Requirement already satisfied: MarkupSafe>=2.1.1 in /opt/anaconda3/lib/pyt
hon3.12/site-packages (from werkzeug>=1.0.1->tensorboard<2.19,>=2.18->tens
orflow) (2.1.3)
Requirement already satisfied: markdown-it-py>=2.2.0 in /opt/anaconda3/li
b/python3.12/site-packages (from rich->keras>=3.5.0->tensorflow) (2.2.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /opt/anaconda3/l
ib/python3.12/site-packages (from rich->keras>=3.5.0->tensorflow) (2.15.1)
Requirement already satisfied: mdurl~=0.1 in /opt/anaconda3/lib/python3.1
2/site-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->tensorflo
w) (0.1.0)
```

In [6]:

```python
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical

# Normalize the data (scaling pixel values between 0 and 1)
X_train = X_train / 255.0

# One-hot encode the labels
t_train_onehot = to_categorical(t_train, num_classes=10)

# Split into training and validation sets (e.g., 80-20 split)
X_train_split, X_val, y_train_split, y_val = train_test_split(X_train, t_tr

# Reshape the data to (num_samples, 300, 300, 3)
X_train_split = X_train_split.reshape(-1, 300, 300, 3)
X_val = X_val.reshape(-1, 300, 300, 3)

print("Training set shape after reshaping:", X_train_split.shape)
print("Validation set shape after reshaping:", X_val.shape)
```

```
Training set shape after reshaping: (1326, 300, 300, 3)
Validation set shape after reshaping: (332, 300, 300, 3)
```

In [ ]:

```python

```

CNN

Hyperparameters set 1

In [9]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D
from tensorflow.keras.optimizers import Adam

# Define the CNN model
def model1(input_shape=(300, 300, 3), num_classes=10):
    model = Sequential([
        # First convolutional block
        Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=i
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.5),

        # Second convolutional block
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.5),

        # Third convolutional block
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D((2, 2)),
        Dropout(0.5),

        # Flatten and dense layers
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])
    return model

# Create the model
model = model1()

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

# Display the model summary
model.summary()
```

```
/opt/anaconda3/lib/python3.12/site-packages/keras/src/layers/convolutiona
l/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an `Input
(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 300, 300, 32)	896
batch_normalization (BatchNormalization)	(None, 300, 300, 32)	128
max_pooling2d (MaxPooling2D)	(None, 150, 150, 32)	0
dropout (Dropout)	(None, 150, 150, 32)	0
conv2d_1 (Conv2D)	(None, 150, 150, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 150, 150, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 75, 75, 64)	0
dropout_1 (Dropout)	(None, 75, 75, 64)	0
conv2d_2 (Conv2D)	(None, 75, 75, 64)	36,928
batch_normalization_2 (BatchNormalization)	(None, 75, 75, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 37, 37, 64)	0
dropout_2 (Dropout)	(None, 37, 37, 64)	0
flatten (Flatten)	(None, 87616)	0
dense (Dense)	(None, 128)	11,214,976
dropout_3 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1,290

Total params: 11,273,226 (43.00 MB)

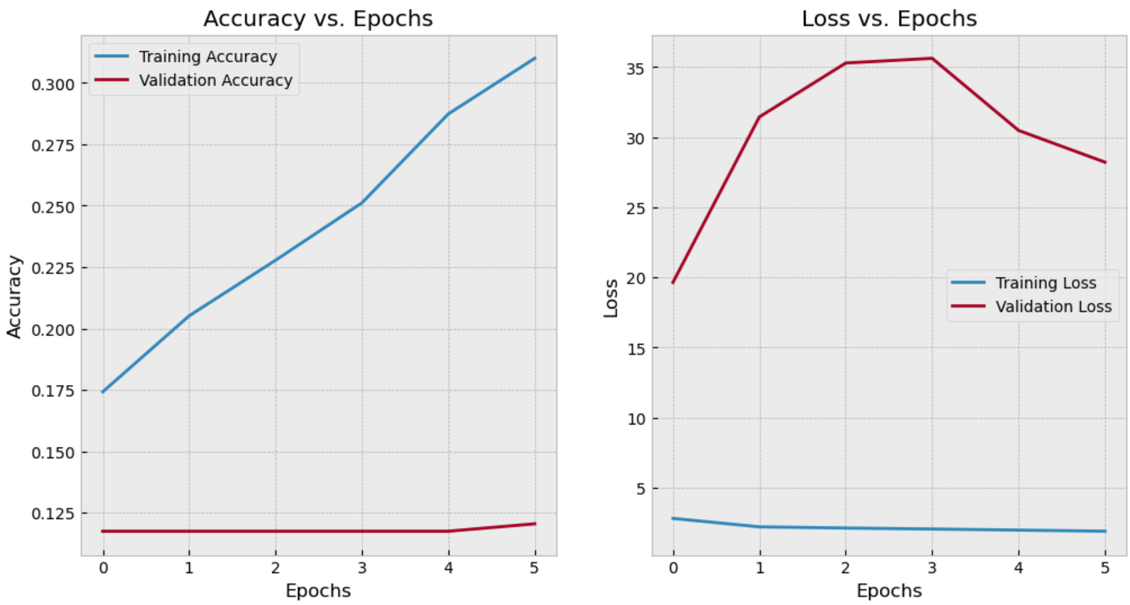
Trainable params: 11,272,906 (43.00 MB)

Non-trainable params: 320 (1.25 KB)

In [10]:
```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best
model_checkpoint = ModelCheckpoint('best_model.keras', save_best_only=True,

# Train the model
history = model.fit(X_train_split, y_train_split,
                    validation_data=(X_val, y_val),
                    epochs=30,
                    batch_size=16,
                    callbacks=[early_stopping, model_checkpoint])
```

```
Epoch 1/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 105s 1s/step - accuracy: 0.1501 - loss: 3.9907
- val_accuracy: 0.1175 - val_loss: 19.6511
Epoch 2/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 77s 916ms/step - accuracy: 0.1975 - loss: 2.258
7 - val_accuracy: 0.1175 - val_loss: 31.4438
Epoch 3/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 78s 939ms/step - accuracy: 0.2170 - loss: 2.121
7 - val_accuracy: 0.1175 - val_loss: 35.2888
Epoch 4/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 83s 1s/step - accuracy: 0.2612 - loss: 2.0860 -
val_accuracy: 0.1175 - val_loss: 35.6229
Epoch 5/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 94s 1s/step - accuracy: 0.2982 - loss: 1.9555 -
val_accuracy: 0.1175 - val_loss: 30.4803
Epoch 6/30
83/83 ━━━━━━━━━━━━━━━━━━━━ 101s 1s/step - accuracy: 0.3119 - loss: 1.9156
- val_accuracy: 0.1205 - val_loss: 28.2178
```

In [11]:
```
# Plot the learning curves
plt.figure(figsize=(12, 6))

# Plot accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy vs. Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Plot loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss vs. Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



In [12]:
```
# Evaluate on the validation set
val_loss, val_accuracy = model.evaluate(X_val, y_val)
print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Loss: {val_loss:.4f}")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 2s 179ms/step - accuracy: 0.1151 - loss: 19.836
6
Validation Accuracy: 0.1175
Validation Loss: 19.6511
```

Hyperparameter set 2

In [14]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D
from tensorflow.keras.optimizers import Adam

# Define the improved CNN model
def Model_second(input_shape=(300, 300, 3), num_classes=10):
    model = Sequential([
        # First convolutional block
        Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=i
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.3),

        # Second convolutional block
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.3),

        # Third convolutional block
        Conv2D(128, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.4),

        # Fourth convolutional block
        Conv2D(256, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.4),

        # Flatten and dense layers
        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])
    return model

# Create the improved model
model_2 = Model_second()

# Compile the model
model_2.compile(optimizer=Adam(learning_rate=0.00005),  # Reduced learning
                loss='categorical_crossentropy',
                metrics=['accuracy'])

# Display the model summary
model_2.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 300, 300, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 150, 150, 32)	0
batch_normalization_3 (BatchNormalization)	(None, 150, 150, 32)	128
dropout_4 (Dropout)	(None, 150, 150, 32)	0
conv2d_4 (Conv2D)	(None, 150, 150, 64)	18,496
max_pooling2d_4 (MaxPooling2D)	(None, 75, 75, 64)	0
batch_normalization_4 (BatchNormalization)	(None, 75, 75, 64)	256
dropout_5 (Dropout)	(None, 75, 75, 64)	0
conv2d_5 (Conv2D)	(None, 75, 75, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 37, 37, 128)	0
batch_normalization_5 (BatchNormalization)	(None, 37, 37, 128)	512
dropout_6 (Dropout)	(None, 37, 37, 128)	0
conv2d_6 (Conv2D)	(None, 37, 37, 256)	295,168
max_pooling2d_6 (MaxPooling2D)	(None, 18, 18, 256)	0
batch_normalization_6 (BatchNormalization)	(None, 18, 18, 256)	1,024
dropout_7 (Dropout)	(None, 18, 18, 256)	0
flatten_1 (Flatten)	(None, 82944)	0
dense_2 (Dense)	(None, 256)	21,233,920
dropout_8 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 10)	2,570

Total params: 21,626,826 (82.50 MB)

Trainable params: 21,625,866 (82.50 MB)

Non-trainable params: 960 (3.75 KB)

In [15]:
```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best
model_checkpoint = ModelCheckpoint('best_model_2.keras', save_best_only=Tru

# Train the improved model
history = model_2.fit(
    X_train_split, y_train_split,
    validation_data=(X_val, y_val),
    epochs=20,
    batch_size=32,
    callbacks=[early_stopping, model_checkpoint]
)

# Save the trained model in .keras and .h5 formats
# model_2.save('final_model_2.keras')  # Save in Keras format
model_2.save('final_model_flower2.h5')    # Save in HDF5 format

print("Model training complete and saved successfully!")
```

```
Epoch 1/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 92s 2s/step - accuracy: 0.2263 - loss: 3.2722 -
val_accuracy: 0.1145 - val_loss: 2.8181
Epoch 2/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 93s 2s/step - accuracy: 0.5248 - loss: 1.6954 -
val_accuracy: 0.1145 - val_loss: 3.2579
Epoch 3/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 85s 2s/step - accuracy: 0.5900 - loss: 1.3569 -
val_accuracy: 0.1145 - val_loss: 5.6933
Epoch 4/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 88s 2s/step - accuracy: 0.6551 - loss: 1.0182 -
val_accuracy: 0.1145 - val_loss: 6.0989
Epoch 5/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 88s 2s/step - accuracy: 0.7254 - loss: 0.8436 -
val_accuracy: 0.1145 - val_loss: 7.5747
Epoch 6/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 92s 2s/step - accuracy: 0.7880 - loss: 0.6262 -
val_accuracy: 0.1265 - val_loss: 8.5956

WARNING:absl:You are saving your model as an HDF5 file via `model.save()`
or `keras.saving.save_model(model)`. This file format is considered legac
y. We recommend using instead the native Keras format, e.g. `model.save('m
y_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Model training complete and saved successfully!
```

In [16]:
```
import matplotlib.pyplot as plt

# Plot the learning curves
plt.figure(figsize=(14, 6))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy', marker='o'
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', mark
plt.title('Training and Validation Accuracy', fontsize=14)
plt.xlabel('Epochs', fontsize=12)
plt.ylabel('Accuracy', fontsize=12)
plt.legend(fontsize=12)
plt.grid(True)

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss', marker='o')
plt.plot(history.history['val_loss'], label='Validation Loss', marker='o')
plt.title('Training and Validation Loss', fontsize=14)
plt.xlabel('Epochs', fontsize=12)
plt.ylabel('Loss', fontsize=12)
plt.legend(fontsize=12)
plt.grid(True)

# Display the plots
plt.tight_layout()
plt.show()
```

In [17]:
```
# Evaluate the improved model on the validation set
val_loss, val_accuracy = model_2.evaluate(X_val, y_val, verbose=1)

# Print the results
print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Loss: {val_loss:.4f}")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 4s 345ms/step - accuracy: 0.1149 - loss: 2.8193
Validation Accuracy: 0.1145
Validation Loss: 2.8181
```

In [ ]:

```

```

Hyperparameter set 3

In [19]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D
from tensorflow.keras.optimizers import Adam

# Define the revised CNN model
def model_third(input_shape=(300, 300, 3), num_classes=10):
    model = Sequential([
        # First convolutional block
        Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=i
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.4),

        # Second convolutional block
        Conv2D(32, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.4),

        # Third convolutional block
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),
        BatchNormalization(),
        Dropout(0.5),

        # Flatten and dense layers
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(num_classes, activation='softmax')
    ])
    return model

# Create the improved model
model_3 = model_third()

# Compile the model with a lower learning rate
model_3.compile(optimizer=Adam(learning_rate=0.0001),
                loss='categorical_crossentropy',
                metrics=['accuracy'])

# Display the model summary
model_3.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 300, 300, 32)	896
max_pooling2d_7 (MaxPooling2D)	(None, 150, 150, 32)	0
batch_normalization_7 (BatchNormalization)	(None, 150, 150, 32)	128
dropout_9 (Dropout)	(None, 150, 150, 32)	0
conv2d_8 (Conv2D)	(None, 150, 150, 32)	9,248
max_pooling2d_8 (MaxPooling2D)	(None, 75, 75, 32)	0
batch_normalization_8 (BatchNormalization)	(None, 75, 75, 32)	128
dropout_10 (Dropout)	(None, 75, 75, 32)	0
conv2d_9 (Conv2D)	(None, 75, 75, 64)	18,496
max_pooling2d_9 (MaxPooling2D)	(None, 37, 37, 64)	0
batch_normalization_9 (BatchNormalization)	(None, 37, 37, 64)	256
dropout_11 (Dropout)	(None, 37, 37, 64)	0
flatten_2 (Flatten)	(None, 87616)	0
dense_4 (Dense)	(None, 128)	11,214,976
dropout_12 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 10)	1,290

Total params: 11,245,418 (42.90 MB)

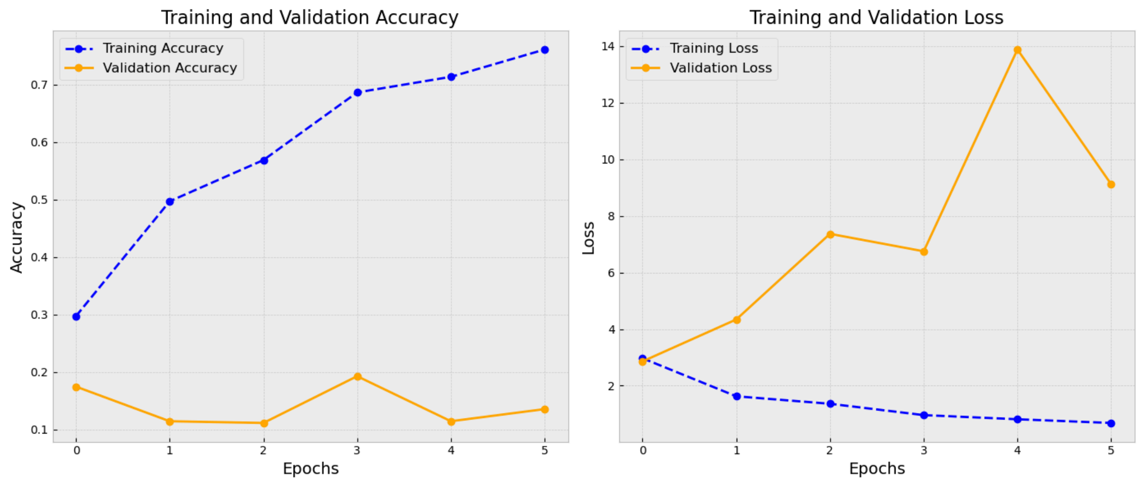
Trainable params: 11,245,162 (42.90 MB)

Non-trainable params: 256 (1.00 KB)

In [20]:
```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best
model_checkpoint = ModelCheckpoint('best_model_3.keras', save_best_only=Tru

# Train the improved model
history = model_3.fit(
    X_train_split, y_train_split,
    validation_data=(X_val, y_val),
    epochs=20,
    batch_size=32,
    callbacks=[early_stopping, model_checkpoint]
)

# Save the trained model in .keras and .h5 formats
# model_3.save('final_model_3.keras')  # Save in Keras format
model_3.save('final_model_flower3.h5')    # Save in HDF5 format

print("Model training complete and saved successfully!")
```

```
Epoch 1/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 56s 1s/step - accuracy: 0.2280 - loss: 3.4224 -
val_accuracy: 0.1747 - val_loss: 2.8583
Epoch 2/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 43s 996ms/step - accuracy: 0.5107 - loss: 1.587
4 - val_accuracy: 0.1145 - val_loss: 4.3398
Epoch 3/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 52s 1s/step - accuracy: 0.5708 - loss: 1.2813 -
val_accuracy: 0.1114 - val_loss: 7.3672
Epoch 4/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 46s 1s/step - accuracy: 0.6841 - loss: 0.9508 -
val_accuracy: 0.1928 - val_loss: 6.7498
Epoch 5/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 52s 1s/step - accuracy: 0.7283 - loss: 0.7642 -
val_accuracy: 0.1145 - val_loss: 13.8814
Epoch 6/20
42/42 ━━━━━━━━━━━━━━━━━━━━ 45s 1s/step - accuracy: 0.7686 - loss: 0.6549 -
val_accuracy: 0.1355 - val_loss: 9.1189

WARNING:absl:You are saving your model as an HDF5 file via `model.save()`
or `keras.saving.save_model(model)`. This file format is considered legac
y. We recommend using instead the native Keras format, e.g. `model.save('m
y_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Model training complete and saved successfully!
```

In [21]:
```
import matplotlib.pyplot as plt

# Plot the learning curves
plt.figure(figsize=(14, 6))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy', marker='o'
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', mark
plt.title('Training and Validation Accuracy', fontsize=16)
plt.xlabel('Epochs', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True, linestyle='--', alpha=0.6)

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss', marker='o', linest
plt.plot(history.history['val_loss'], label='Validation Loss', marker='o',
plt.title('Training and Validation Loss', fontsize=16)
plt.xlabel('Epochs', fontsize=14)
plt.ylabel('Loss', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True, linestyle='--', alpha=0.6)

# Display the plots
plt.tight_layout()
plt.show()
```



In [22]:
```
# Evaluate the improved model on the validation set
val_loss, val_accuracy = model_3.evaluate(X_val, y_val, verbose=1)

# Print the results
print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Loss: {val_loss:.4f}")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 2s 176ms/step - accuracy: 0.1697 - loss: 2.7839
Validation Accuracy: 0.1747
Validation Loss: 2.8583
```

In [ ]:

In [ ]:

Transfer Learning

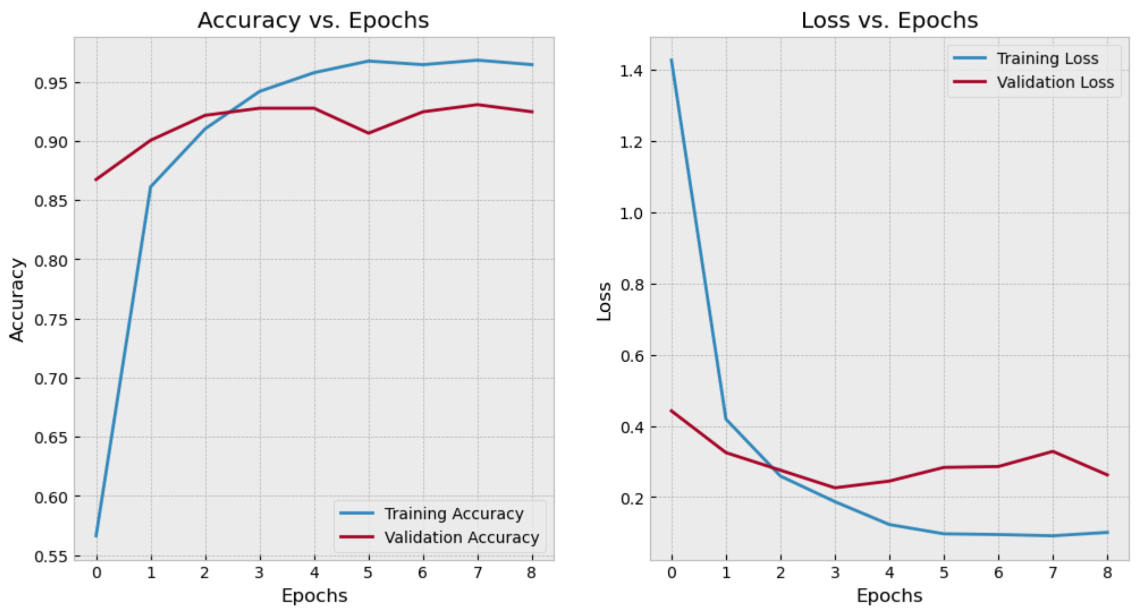
In [ ]:

In [24]:
```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Model

# Load the pre-trained MobileNetV2 model
base_model = MobileNetV2(input_shape=(300, 300, 3), include_top=False, weig

# Freeze the base model layers
base_model.trainable = False

# Add custom layers on top
model_pt = Sequential([
    base_model,
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])

# Compile the model
model_pt.compile(optimizer=Adam(learning_rate=0.0001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model_pt.fit(X_train_split, y_train_split,
                    validation_data=(X_val, y_val),
                    epochs=30,
                    batch_size=32,
                    callbacks=[early_stopping, model_checkpoint])
```

```
/var/folders/_7/5njfsggn3j538cj0dd_22b680000gn/T/ipykernel_63782/373832373
7.py:5: UserWarning: `input_shape` is undefined or non-square, or `rows` i
s not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will
be loaded as the default.
  base_model = MobileNetV2(input_shape=(300, 300, 3), include_top=False, w
eights='imagenet',classes=10)
```

```
Epoch 1/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 52s 1s/step - accuracy: 0.4155 - loss: 2.1350 -
val_accuracy: 0.8675 - val_loss: 0.4421
Epoch 2/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 27s 634ms/step - accuracy: 0.8576 - loss: 0.419
1 - val_accuracy: 0.9006 - val_loss: 0.3250
Epoch 3/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 34s 820ms/step - accuracy: 0.9193 - loss: 0.250
0 - val_accuracy: 0.9217 - val_loss: 0.2756
Epoch 4/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 31s 732ms/step - accuracy: 0.9460 - loss: 0.194
6 - val_accuracy: 0.9277 - val_loss: 0.2261
Epoch 5/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 29s 691ms/step - accuracy: 0.9591 - loss: 0.123
8 - val_accuracy: 0.9277 - val_loss: 0.2450
Epoch 6/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 36s 866ms/step - accuracy: 0.9716 - loss: 0.086
8 - val_accuracy: 0.9066 - val_loss: 0.2835
Epoch 7/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 35s 805ms/step - accuracy: 0.9657 - loss: 0.095
6 - val_accuracy: 0.9247 - val_loss: 0.2860
Epoch 8/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 29s 669ms/step - accuracy: 0.9755 - loss: 0.065
6 - val_accuracy: 0.9307 - val_loss: 0.3285
Epoch 9/30
42/42 ━━━━━━━━━━━━━━━━━━━━ 31s 754ms/step - accuracy: 0.9586 - loss: 0.114
1 - val_accuracy: 0.9247 - val_loss: 0.2624
```

In [25]:
```
# Plot learning curves
plt.figure(figsize=(12, 6))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy vs. Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss vs. Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



In [26]:
```
val_loss, val_accuracy = model_pt.evaluate(X_val, y_val)
print(f"Validation Accuracy: {val_accuracy:.4f}")
print(f"Validation Loss: {val_loss:.4f}")
```

```
11/11 ━━━━━━━━━━━━━━━━━━━━ 6s 566ms/step - accuracy: 0.9192 - loss: 0.2414
Validation Accuracy: 0.9277
Validation Loss: 0.2261
```

In [27]:
```
# Save the trained model in HDF5 format
model_pt.save('mobilenetv2_model_flower.h5')  # Save the entire model
print("Model saved successfully as 'mobilenetv2_model.h5'")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Model saved successfully as 'mobilenetv2_model.h5'
```

In [ ]:

In [ ]:

Dataset 2: Car Detection Dataset

In [30]:
```
!pip install opencv-python

from PIL import Image
import cv2 # install opencv, if you don't already have it (https://pypi.org
import pandas as pd
```

```
Requirement already satisfied: opencv-python in /opt/anaconda3/lib/python3.12/site-packages (4.10.0.84)
Requirement already satisfied: numpy>=1.21.2 in /opt/anaconda3/lib/python3.12/site-packages (from opencv-python) (1.26.4)
```

In [31]:
```
bbox = pd.read_csv('car_detection_dataset/train_bounding_boxes.csv')
bbox
```

Out[31]:

	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 [32]:
```
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]

    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)

X_train.shape, t_train.shape
```

Out[32]: ((559, 770640), (559, 4))

In [33]:
```
# size of each RGB image
(Nx,Ny,Nz) = image.shape

Nx, Ny, Nz
```

Out[33]: (380, 676, 3)

In [34]:
```
# Example of object visualization using opencv rectangle function
idx=N-1
x= image

plt.imshow(x)
cv2.rectangle(x, (t_train[idx,0], t_train[idx,1]),
              (t_train[idx,2], t_train[idx,3]),
              (255, 0, 0), 2);
```

In [ ]:

In [35]:
```
from sklearn.model_selection import train_test_split

X_train, X_val, t_train, t_val = train_test_split(X_train, t_train, test_si
```

In [56]:
```
X_train = X_train / 255.0
X_val = X_val / 255.0

# Ensure bounding box coordinates are float before normalization
t_train = t_train.astype(float)
t_val = t_val.astype(float)

# Normalize bounding box coordinates (relative to image dimensions)
t_train[:, [0, 2]] /= 676  # Normalize x_min and x_max by width
t_train[:, [1, 3]] /= 380  # Normalize y_min and y_max by height

t_val[:, [0, 2]] /= 676  # Normalize x_min and x_max by width
t_val[:, [1, 3]] /= 380  # Normalize y_min and y_max by height
```

In [57]:
```
X_train = X_train.reshape(-1, 380, 676, 3)
X_val = X_val.reshape(-1, 380, 676, 3)
```

In [58]:
```
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, GlobalAveragePooling2D,
from tensorflow.keras.optimizers import Adam

# Load the pre-trained ResNet50 model without the top layer
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(3

# Freeze the base model layers to retain pre-trained features
for layer in base_model.layers:
    layer.trainable = False
```

In [59]:
```
# Define custom layers
input_layer = Input(shape=(380, 676, 3))
x = base_model(input_layer)
x = GlobalAveragePooling2D()(x)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.3)(x)
output_layer = Dense(4, activation='linear')(x)  # Output layer for boundin

# Create the complete model
model = Model(inputs=input_layer, outputs=output_layer)

# Compile the model
model.compile(optimizer=Adam(learning_rate=1e-4), loss='mse', metrics=['mae

# Display model summary
model.summary()
```

Model: "functional_4"

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 380, 676, 3)	0
resnet50 (Functional)	(None, 12, 22, 2048)	23,587,712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense_8 (Dense)	(None, 256)	524,544
dropout_14 (Dropout)	(None, 256)	0
dense_9 (Dense)	(None, 128)	32,896
dropout_15 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 4)	516

Total params: 24,145,668 (92.11 MB)

Trainable params: 557,956 (2.13 MB)

Non-trainable params: 23,587,712 (89.98 MB)

In [60]:
```python
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

callbacks = [
    EarlyStopping(patience=10, restore_best_weights=True),
    ModelCheckpoint('pretrained_car_detection.keras', save_best_only=True)
]

# Train the custom layers
history = model.fit(
    X_train, t_train,
    validation_data=(X_val, t_val),
    epochs=20,
    batch_size=16,
    callbacks=callbacks
)
```

```
Epoch 1/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 114s 4s/step - loss: 3.1961 - mae: 1.3675 - val
_loss: 0.3096 - val_mae: 0.5066
Epoch 2/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 107s 4s/step - loss: 0.6509 - mae: 0.6450 - val
_loss: 0.3360 - val_mae: 0.5352
Epoch 3/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 109s 4s/step - loss: 0.2183 - mae: 0.3625 - val
_loss: 0.2988 - val_mae: 0.5032
Epoch 4/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 103s 4s/step - loss: 0.0724 - mae: 0.2123 - val
_loss: 0.3131 - val_mae: 0.5160
Epoch 5/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 118s 4s/step - loss: 0.0245 - mae: 0.1225 - val
_loss: 0.3101 - val_mae: 0.5140
Epoch 6/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 103s 4s/step - loss: 0.0105 - mae: 0.0817 - val
_loss: 0.3185 - val_mae: 0.5209
Epoch 7/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 112s 4s/step - loss: 0.0037 - mae: 0.0488 - val
_loss: 0.3264 - val_mae: 0.5287
Epoch 8/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 98s 4s/step - loss: 0.0014 - mae: 0.0294 - val_
loss: 0.3311 - val_mae: 0.5324
Epoch 9/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 97s 3s/step - loss: 4.6279e-04 - mae: 0.0165 -
val_loss: 0.3311 - val_mae: 0.5325
Epoch 10/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 91s 3s/step - loss: 1.4393e-04 - mae: 0.0094 -
val_loss: 0.3321 - val_mae: 0.5332
Epoch 11/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 107s 4s/step - loss: 4.4884e-05 - mae: 0.0053 -
val_loss: 0.3324 - val_mae: 0.5335
Epoch 12/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 95s 3s/step - loss: 1.5753e-05 - mae: 0.0031 -
val_loss: 0.3328 - val_mae: 0.5337
Epoch 13/20
28/28 ━━━━━━━━━━━━━━━━━━━━ 101s 4s/step - loss: 5.7915e-06 - mae: 0.0019 -
val_loss: 0.3333 - val_mae: 0.5342
```

In [61]:
```
# Unfreeze the last few layers of the pre-trained model
for layer in base_model.layers[-10:]:
    layer.trainable = True

# Compile the model with a lower learning rate for fine-tuning
model.compile(optimizer=Adam(learning_rate=1e-5), loss='mse', metrics=['mae

# Fine-tune the model
fine_tune_history = model.fit(
    X_train, t_train,
    validation_data=(X_val, t_val),
    epochs=10,
    batch_size=16,
    callbacks=callbacks
)
```

```
Epoch 1/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 122s 4s/step - loss: 0.0756 - mae: 0.2172 - val
_loss: 0.3314 - val_mae: 0.5307
Epoch 2/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 100s 4s/step - loss: 0.0175 - mae: 0.1035 - val
_loss: 0.3752 - val_mae: 0.5686
Epoch 3/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 121s 4s/step - loss: 0.0034 - mae: 0.0460 - val
_loss: 0.4016 - val_mae: 0.5913
Epoch 4/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 110s 4s/step - loss: 4.9023e-04 - mae: 0.0171 -
val_loss: 0.4041 - val_mae: 0.5902
Epoch 5/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 110s 4s/step - loss: 5.3091e-05 - mae: 0.0056 -
val_loss: 0.3940 - val_mae: 0.5815
Epoch 6/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 111s 4s/step - loss: 3.4533e-06 - mae: 0.0015 -
val_loss: 0.3796 - val_mae: 0.5704
Epoch 7/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 117s 4s/step - loss: 9.4639e-07 - mae: 7.7987e-
04 - val_loss: 0.3709 - val_mae: 0.5642
Epoch 8/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 108s 4s/step - loss: 6.0786e-07 - mae: 6.2760e-
04 - val_loss: 0.3630 - val_mae: 0.5583
Epoch 9/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 109s 4s/step - loss: 5.1534e-07 - mae: 5.7867e-
04 - val_loss: 0.3527 - val_mae: 0.5501
Epoch 10/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 108s 4s/step - loss: 4.7617e-07 - mae: 5.6058e-
04 - val_loss: 0.3454 - val_mae: 0.5440
```

In [62]:
```
model.save('resnet50_car_detection_model.keras')
```

Hyperparameter set 1

In [68]:
```
import os
import numpy as np
import pandas as pd
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint


def preprocess_train_data(images_dir, annotations_file):

    # Load annotations
    annotations = pd.read_csv(annotations_file)

    X_train = []
    y_train = []

    for _, row in annotations.iterrows():
        # Load and preprocess image
        image_path = os.path.join(images_dir, row['image'])
        image = Image.open(image_path).resize((676, 380))  # Resize to (wid
        X_train.append(np.array(image) / 255.0)  # Normalize pixel values t

        # Normalize bounding box
        bbox = [
            row['xmin'] / 676,  # Normalize x_min
            row['ymin'] / 380,  # Normalize y_min
            row['xmax'] / 676,  # Normalize x_max
            row['ymax'] / 380   # Normalize y_max
        ]
        y_train.append(bbox)

    return np.array(X_train), np.array(y_train)
```

In [69]:
```
# Path to the training images and annotations
images_dir = "car_detection_dataset/training_images"
annotations_file = "car_detection_dataset/train_bounding_boxes.csv"

# Preprocess the training data
X, y = preprocess_train_data(images_dir, annotations_file)

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, rand

print(f"Training data shape: {X_train.shape}")
print(f"Validation data shape: {X_val.shape}")
```

```
Training data shape: (447, 380, 676, 3)
Validation data shape: (112, 380, 676, 3)
```

In [70]:

```
# --- Step 2: Define the Model ---
def create_model():
    """
    Define a CNN model for bounding box regression.
    """
    model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(380, 676, 3)),
        MaxPooling2D(pool_size=(2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Conv2D(128, (3, 3), activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.5),
        Dense(4, activation='linear')  # Bounding box regression
    ])

    model.compile(optimizer='adam', loss='mse', metrics=['mae'])
    return model

model = create_model()
model.summary()
```

```
/opt/anaconda3/lib/python3.12/site-packages/keras/src/layers/convolutiona
l/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an `Input
(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 378, 674, 32)	896
max_pooling2d_10 (MaxPooling2D)	(None, 189, 337, 32)	0
conv2d_11 (Conv2D)	(None, 187, 335, 64)	18,496
max_pooling2d_11 (MaxPooling2D)	(None, 93, 167, 64)	0
conv2d_12 (Conv2D)	(None, 91, 165, 128)	73,856
max_pooling2d_12 (MaxPooling2D)	(None, 45, 82, 128)	0
flatten_4 (Flatten)	(None, 472320)	0
dense_11 (Dense)	(None, 256)	120,914,176
dropout_16 (Dropout)	(None, 256)	0
dense_12 (Dense)	(None, 4)	1,028

Total params: 121,008,452 (461.61 MB)

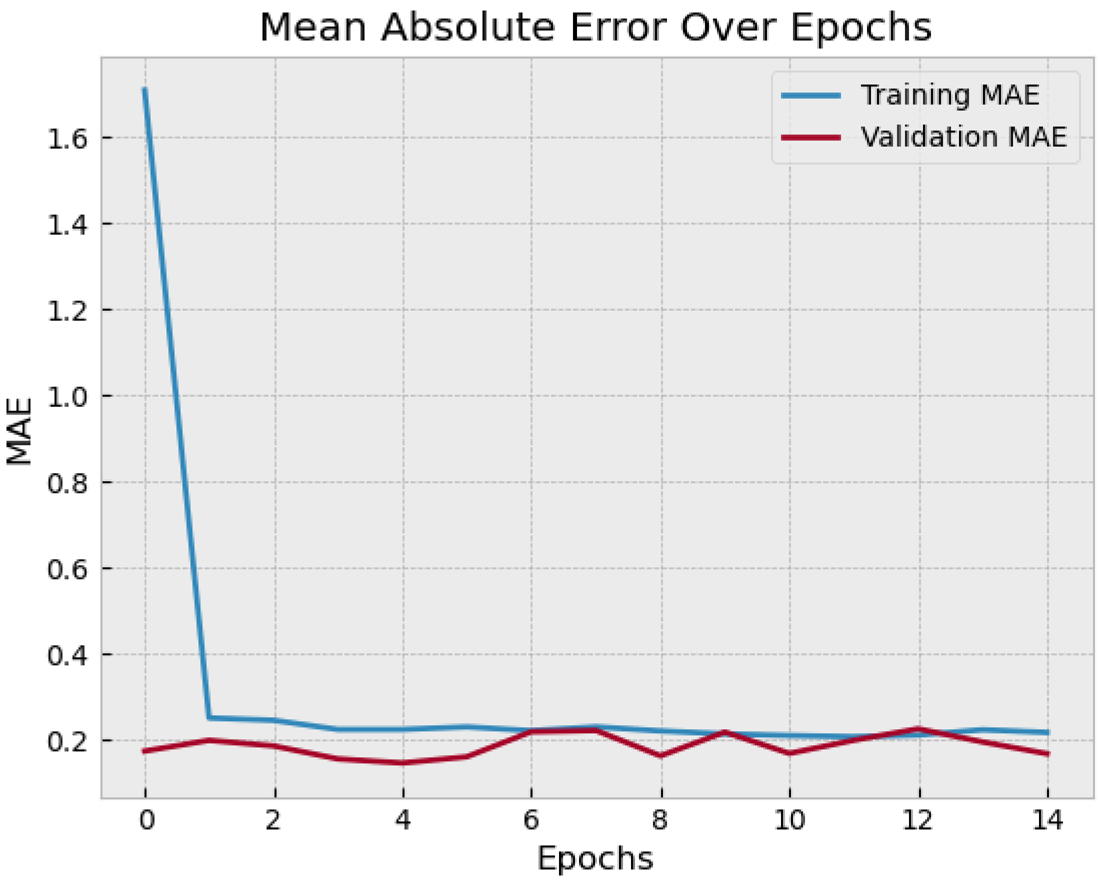
Trainable params: 121,008,452 (461.61 MB)

Non-trainable params: 0 (0.00 B)

In [71]:
```
# --- Step 3: Train the Model ---
# Define callbacks
callbacks = [
    EarlyStopping(patience=10, restore_best_weights=True),
    ModelCheckpoint("best_car_detection_model.keras", save_best_only=True)
]

# Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=50,
    batch_size=16,
    callbacks=callbacks
)

# Save the final model
model.save("car_detection_model_1.keras")
```

```
Epoch 1/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 131s 5s/step - loss: 111.3679 - mae: 4.0717 - v
al_loss: 0.0568 - val_mae: 0.1750
Epoch 2/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 91s 3s/step - loss: 0.1045 - mae: 0.2512 - val_
loss: 0.0651 - val_mae: 0.1999
Epoch 3/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 94s 3s/step - loss: 0.1014 - mae: 0.2550 - val_
loss: 0.0669 - val_mae: 0.1870
Epoch 4/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 77s 3s/step - loss: 0.0876 - mae: 0.2286 - val_
loss: 0.0502 - val_mae: 0.1568
Epoch 5/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 100s 3s/step - loss: 0.0782 - mae: 0.2163 - val
_loss: 0.0446 - val_mae: 0.1474
Epoch 6/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 87s 3s/step - loss: 0.0883 - mae: 0.2325 - val_
loss: 0.0537 - val_mae: 0.1617
Epoch 7/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 89s 3s/step - loss: 0.0736 - mae: 0.2155 - val_
loss: 0.0725 - val_mae: 0.2198
Epoch 8/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 78s 3s/step - loss: 0.0877 - mae: 0.2322 - val_
loss: 0.0807 - val_mae: 0.2228
Epoch 9/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 81s 3s/step - loss: 0.0782 - mae: 0.2219 - val_
loss: 0.0532 - val_mae: 0.1640
Epoch 10/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 80s 3s/step - loss: 0.0692 - mae: 0.2076 - val_
loss: 0.0744 - val_mae: 0.2190
Epoch 11/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 97s 3s/step - loss: 0.0664 - mae: 0.2044 - val_
loss: 0.0564 - val_mae: 0.1696
Epoch 12/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 82s 3s/step - loss: 0.0648 - mae: 0.2014 - val_
loss: 0.0679 - val_mae: 0.2001
Epoch 13/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 95s 3s/step - loss: 0.0762 - mae: 0.2170 - val_
loss: 0.0755 - val_mae: 0.2266
Epoch 14/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 73s 3s/step - loss: 0.0793 - mae: 0.2260 - val_
loss: 0.0652 - val_mae: 0.1963
Epoch 15/50
28/28 ━━━━━━━━━━━━━━━━━━━━ 47s 2s/step - loss: 0.0728 - mae: 0.2132 - val_
loss: 0.0561 - val_mae: 0.1689
```

In [72]:
```
# --- Step 4: Plot Training History ---
import matplotlib.pyplot as plt

# Plot loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Over Epochs')
plt.show()

# Plot MAE
plt.plot(history.history['mae'], label='Training MAE')
plt.plot(history.history['val_mae'], label='Validation MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.title('Mean Absolute Error Over Epochs')
plt.show()
```



In [ ]:

Hyperparameter set2

In [3]:
```
import os
import numpy as np
import pandas as pd
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,Reduc

def preprocess_train_data(images_dir, annotations_file):
    """
    Preprocess training images and labels.
    Args:
        images_dir: Directory containing training images.
        annotations_file: CSV file with bounding box annotations.
    Returns:
        X_train: Preprocessed images (num_samples, height, width, channels)
        y_train: Normalized bounding box coordinates (num_samples, 4).
    """
    # Load annotations
    annotations = pd.read_csv(annotations_file)

    X_train = []
    y_train = []

    for _, row in annotations.iterrows():
        # Load and preprocess image
        image_path = os.path.join(images_dir, row['image'])
        image = Image.open(image_path).resize((676, 380))  # Resize to (wid
        X_train.append(np.array(image) / 255.0)  # Normalize pixel values t

        # Normalize bounding box
        bbox = [
            row['xmin'] / 676,  # Normalize x_min
            row['ymin'] / 380,  # Normalize y_min
            row['xmax'] / 676,  # Normalize x_max
            row['ymax'] / 380   # Normalize y_max
        ]
        y_train.append(bbox)

    return np.array(X_train), np.array(y_train)

# Path to the training images and annotations
images_dir = "car_detection_dataset/training_images"
annotations_file = "car_detection_dataset/train_bounding_boxes.csv"

# Preprocess the training data
X, y = preprocess_train_data(images_dir, annotations_file)

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, rand

print(f"Training data shape: {X_train.shape}")
print(f"Validation data shape: {X_val.shape}")
```

```
Training data shape: (447, 380, 676, 3)
Validation data shape: (112, 380, 676, 3)
```

In [4]:
```
# --- Step 2: Define the Model ---
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, D

def car_model_2():
    """
    Define an improved CNN model for bounding box regression.
    """
    model = Sequential([
        # First Convolutional Block
        Conv2D(64, (3, 3), activation='relu', padding='same', input_shape=(
        BatchNormalization(),
        MaxPooling2D(pool_size=(2, 2)),

        # Second Convolutional Block
        Conv2D(128, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D(pool_size=(2, 2)),

        # Third Convolutional Block
        Conv2D(256, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D(pool_size=(2, 2)),

        # Fully Connected Layers
        Flatten(),
        Dense(512, activation='relu'),
        Dropout(0.3),
        Dense(256, activation='relu'),
        Dropout(0.3),

        # Output Layer
        Dense(4, activation='linear')  # Bounding box regression
    ])

    # Compile the model
    model.compile(
        optimizer=tf.keras.optimizers.RMSprop(learning_rate=0.0001),
        loss='mse',
        metrics=['mae']
    )
    return model

model = car_model_2()
model.summary()
```

```
/opt/anaconda3/lib/python3.12/site-packages/keras/src/layers/convolutiona
l/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an `Input
(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 380, 676, 64)	1,792
batch_normalization (BatchNormalization)	(None, 380, 676, 64)	256
max_pooling2d (MaxPooling2D)	(None, 190, 338, 64)	0
conv2d_1 (Conv2D)	(None, 190, 338, 128)	73,856
batch_normalization_1 (BatchNormalization)	(None, 190, 338, 128)	512
max_pooling2d_1 (MaxPooling2D)	(None, 95, 169, 128)	0
conv2d_2 (Conv2D)	(None, 95, 169, 256)	295,168
batch_normalization_2 (BatchNormalization)	(None, 95, 169, 256)	1,024
max_pooling2d_2 (MaxPooling2D)	(None, 47, 84, 256)	0
flatten (Flatten)	(None, 1010688)	0
dense (Dense)	(None, 512)	517,472,768
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 4)	1,028

Total params: 517,977,732 (1.93 GB)

Trainable params: 517,976,836 (1.93 GB)

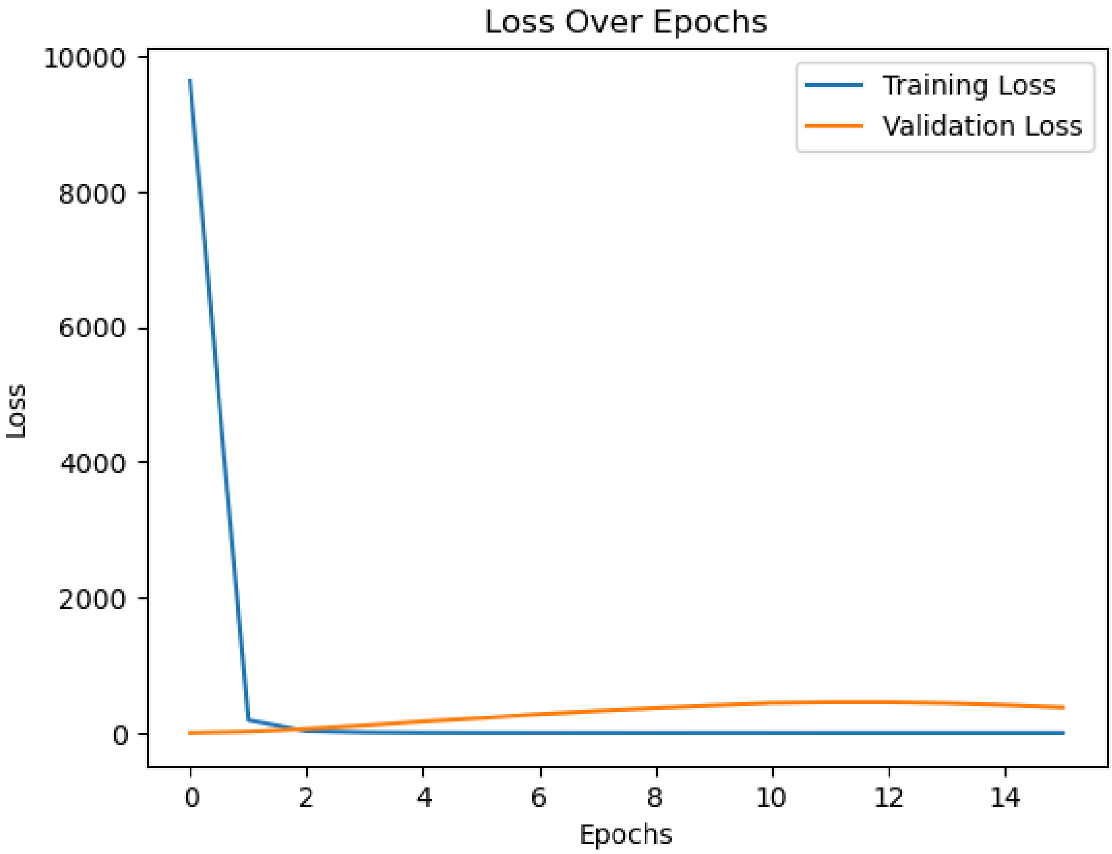
Non-trainable params: 896 (3.50 KB)

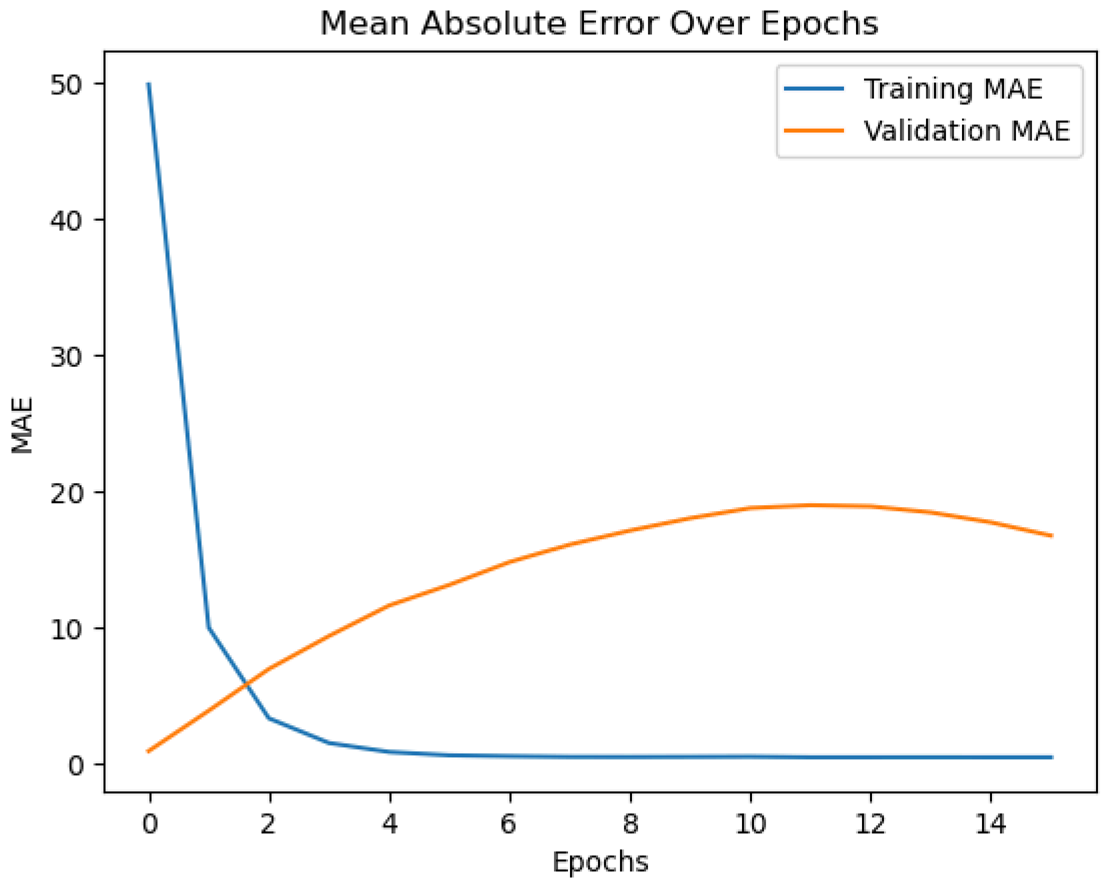
In [5]:
```
callbacks = [
    EarlyStopping(patience=15, restore_best_weights=True),  # Stop if no im
    ModelCheckpoint("best_improved_car_detection_model.keras", save_best_on
    ReduceLROnPlateau(factor=0.1, patience=5, verbose=1)  # Reduce learning
]

# Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=20,  # Allow more epochs for better convergence
    batch_size=32,  # Larger batch size for stable training
    callbacks=callbacks
)
# Save the final model
model.save("car_detection_model_2.keras")
```

```
Epoch 1/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 481s 33s/step - loss: 18071.3086 - mae: 70.2672
- val_loss: 1.6370 - val_mae: 0.9677 - learning_rate: 1.0000e-04
Epoch 2/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 435s 31s/step - loss: 265.0457 - mae: 12.1959 -
val_loss: 20.9436 - val_mae: 3.9339 - learning_rate: 1.0000e-04
Epoch 3/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 443s 31s/step - loss: 38.0897 - mae: 4.0481 - v
al_loss: 61.7995 - val_mae: 6.9937 - learning_rate: 1.0000e-04
Epoch 4/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 419s 30s/step - loss: 12.9602 - mae: 1.9659 - v
al_loss: 111.4070 - val_mae: 9.4109 - learning_rate: 1.0000e-04
Epoch 5/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 403s 29s/step - loss: 4.4339 - mae: 1.0111 - va
l_loss: 169.4540 - val_mae: 11.6515 - learning_rate: 1.0000e-04
Epoch 6/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 29s/step - loss: 2.9151 - mae: 0.6935
Epoch 6: ReduceLROnPlateau reducing learning rate to 9.999999747378752e-0
6.
14/14 ━━━━━━━━━━━━━━━━━━━━ 422s 30s/step - loss: 2.8548 - mae: 0.6911 - va
l_loss: 220.4771 - val_mae: 13.1619 - learning_rate: 1.0000e-04
Epoch 7/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 402s 28s/step - loss: 1.0110 - mae: 0.5614 - va
l_loss: 278.1497 - val_mae: 14.8344 - learning_rate: 1.0000e-05
Epoch 8/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 393s 27s/step - loss: 1.7124 - mae: 0.5827 - va
l_loss: 327.1138 - val_mae: 16.1233 - learning_rate: 1.0000e-05
Epoch 9/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 416s 30s/step - loss: 0.5198 - mae: 0.5278 - va
l_loss: 370.1486 - val_mae: 17.1530 - learning_rate: 1.0000e-05
Epoch 10/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 409s 29s/step - loss: 0.7531 - mae: 0.5355 - va
l_loss: 410.2597 - val_mae: 18.0572 - learning_rate: 1.0000e-05
Epoch 11/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 27s/step - loss: 1.1903 - mae: 0.5930
Epoch 11: ReduceLROnPlateau reducing learning rate to 9.999999747378752e-0
7.
14/14 ━━━━━━━━━━━━━━━━━━━━ 398s 28s/step - loss: 1.1620 - mae: 0.5907 - va
l_loss: 446.1713 - val_mae: 18.8007 - learning_rate: 1.0000e-05
Epoch 12/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 388s 28s/step - loss: 0.3606 - mae: 0.5121 - va
l_loss: 458.6282 - val_mae: 19.0121 - learning_rate: 1.0000e-06
Epoch 13/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 398s 28s/step - loss: 0.3896 - mae: 0.5136 - va
l_loss: 458.4925 - val_mae: 18.9270 - learning_rate: 1.0000e-06
Epoch 14/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 399s 28s/step - loss: 0.4222 - mae: 0.5153 - va
l_loss: 443.0068 - val_mae: 18.4844 - learning_rate: 1.0000e-06
Epoch 15/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 442s 32s/step - loss: 0.3578 - mae: 0.5100 - va
l_loss: 416.0252 - val_mae: 17.7550 - learning_rate: 1.0000e-06
Epoch 16/20
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 29s/step - loss: 0.3866 - mae: 0.5160
Epoch 16: ReduceLROnPlateau reducing learning rate to 9.999999974752428e-0
8.
14/14 ━━━━━━━━━━━━━━━━━━━━ 441s 30s/step - loss: 0.3862 - mae: 0.5158 - va
l_loss: 379.5549 - val_mae: 16.7785 - learning_rate: 1.0000e-06
```

In [6]:

```
# --- Step 4: Plot Training History ---
import matplotlib.pyplot as plt

# Plot Loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Over Epochs')
plt.show()

# Plot MAE
plt.plot(history.history['mae'], label='Training MAE')
plt.plot(history.history['val_mae'], label='Validation MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.title('Mean Absolute Error Over Epochs')
plt.show()
```





In [ ]:

3. Validating Performance in the Test Set Without Target Labels

1. Visual Inspection

- Overlay predicted bounding boxes on the test images.
- Assess visually if the bounding boxes align with cars in the images.
- This qualitative method helps identify obvious mispredictions but lacks a quantitative metric.

---

2. Annotate a Subset of the Test Set

- Use tools like **MakeSenseAI** to manually annotate a small subset of the test set.
- Export these annotations and use them as ground truth for performance evaluation.
- This allows for a more quantitative evaluation using metrics like Intersection over Union (IoU).

---

3. Metrics for Quantitative Evaluation

Intersection over Union (IoU)

- IoU measures the overlap between the predicted bounding box and the ground truth bounding box.
- **Formula**: [IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}]
- Define an IoU threshold (e.g., IoU > 0.5) to classify predictions as acceptable.

Accuracy for No-Car Images

- For images without cars, the predicted bounding box should be `[0, 0, 0, 0]`.
- Compute the proportion of correctly identified no-car images: [\text{No-Car Accuracy} = \frac{\text{Correct No-Car Predictions}}{\text{Total No-Car Images}}]

---

4. Handling Images Without Cars

Training

- Include images without cars in the training dataset.
- Assign these images a fixed bounding box of `[0, 0, 0, 0]`.

Post-Processing

- Define a threshold to identify no-car predictions. For instance, if the predicted bounding box is close to `[0, 0, 0, 0]` within a tolerance, classify it as a no-car prediction.

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5. Overlapping Region of Interest (ROI)

- The exact bounding box may not always be the target. Small deviations in predictions are acceptable.
- Use IoU as a measure of acceptable overlap:
  - IoU > 0.5: Prediction is acceptable.
  - IoU ≤ 0.5: Prediction is inaccurate.

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6. Using MakeSenseAI

- Manually annotate a subset of test images:
  - Label images with cars using bounding boxes.
  - Leave images without cars blank or label them as "No Car."
- Export the annotations and use them for validation:
  - Compute IoU for images with cars.
  - Measure no-car accuracy for images without cars.

Conclusion

1. **For images with cars**:

- Validate using IoU and report the proportion of predictions with IoU above a defined threshold.

2. **For images without cars**:

   - Include them in training and validation with fixed labels `[0, 0, 0, 0]`

In [ ]: