In [3]:
```
%%shell
jupyter nbconvert --to html /content/Student_performance.ipynb
```

Problem Statement

You are a data scientist working for a school

You are asked to predict the GPA of the current students based on the following provided data:

0 StudentID int64

1 Age int64

2 Gender int64

3 Ethnicity int64

4 ParentalEducation int64

5 StudyTimeWeekly float64 6 Absences int64

7 Tutoring int64

8 ParentalSupport int64

9 Extracurricular int64

10 Sports int64

11 Music int64

12 Volunteering int64

13 GPA float64 14 GradeClass float64

The GPA is the Grade Point Average, typically ranges from 0.0 to 4.0 in most educational systems, with 4.0 representing an 'A' or excellent performance.

The minimum passing GPA can vary by institution, but it's often around 2.0. This usually corresponds to a 'C' grade, which is considered satisfactory.

You need to create a Deep Learning model capable to predict the GPA of a Student based on a set of provided features. The data provided represents 2,392 students.

In this excersice you will be requested to create a total of three models and select the most performant one.

1) Import Libraries

First let's import the following libraries, if there is any library that you need and is not in the list bellow feel free to include it

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
```

```
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten
from tensorflow.keras.regularizers import l2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

2) Load Data

- You will be provided with a cvs (comma separated value) file.
- You will need to add that file into a pandas dataframe, you can use the following code as reference
- The file will be available in canvas

In [5]:
```
data = pd.read_csv("Student_performance_data _.csv")
data
```

Out[5]:

	StudentID	Age	Gender	Ethnicity	ParentalEducation	StudyTimeWeekly	Absences	Tutoring	I
0	1001	17	1	0	2	19.833723	7	1	
1	1002	18	0	0	1	15.408756	0	0	
2	1003	15	0	2	3	4.210570	26	0	
3	1004	17	1	0	3	10.028829	14	0	
4	1005	17	1	0	2	4.672495	17	1	
...	...	...	...	...	...	...	...	...	
2387	3388	18	1	0	3	10.680555	2	0	
2388	3389	17	0	0	1	7.583217	4	1	
2389	3390	16	1	0	2	6.805500	20	0	
2390	3391	16	1	1	0	12.416653	17	0	
2391	3392	16	1	0	2	17.819907	13	0	

2392 rows × 15 columns

3) Review you data:

Make sure you review your data. Place special attention of null or empty values.

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   StudentID          2392 non-null   int64  
 1   Age                2392 non-null   int64  
 2   Gender             2392 non-null   int64  
 3   Ethnicity          2392 non-null   int64  
 4   ParentalEducation  2392 non-null   int64  
 5   StudyTimeWeekly    2392 non-null   float64
 6   Absences           2392 non-null   int64  
 7   Tutoring           2392 non-null   int64  
 8   ParentalSupport    2392 non-null   int64  
 9   Extracurricular    2392 non-null   int64  
 10  Sports             2392 non-null   int64  
 11  Music              2392 non-null   int64  
 12  Volunteering       2392 non-null   int64  
 13  GPA                2392 non-null   float64
 14  GradeClass         2392 non-null   float64
dtypes: float64(3), int64(12)
memory usage: 280.4 KB
```

4. Remove the columns not needed for Student performance prediction

- Choose only the columns you consider to be valuable for your model training.
- For example, StudentID might not be a good feature for your model, and thus should be removed from your main dataset, which other columns should also be removed?
- You can name that final dataset as 'dataset'

In [7]:

```
columns_to_remove = ['StudentID']
dataset = data.drop(columns=columns_to_remove)

dataset.head()
```

Out[7]:

	Age	Gender	Ethnicity	ParentalEducation	StudyTimeWeekly	Absences	Tutoring	ParentalSupport
0	17	1	0	2	19.833723	7	1	2
1	18	0	0	1	15.408756	0	0	1
2	15	0	2	3	4.210570	26	0	2
3	17	1	0	3	10.028829	14	0	3
4	17	1	0	2	4.672495	17	1	3

In [8]:

```
final_dataset = dataset.drop(columns=['Gender', 'Ethnicity','Volunteering'])

final_dataset.head()
```

Out[8]:

	Age	ParentalEducation	StudyTimeWeekly	Absences	Tutoring	ParentalSupport	Extracurricular	S
0	17	2	19.833723	7	1	2	0	
1	18	1	15.408756	0	0	1	0	
2	15	3	4.210570	26	0	2	0	
3	17	3	10.028829	14	0	3	1	
4	17	2	4.672495	17	1	3	0	

5. Check if the columns has any null values:

- Here you now have your final dataset to use in your model training.
- Before moving foward review your data check for any null or empty value that might be needed to be removed

In [9]:

```
missing_values = final_dataset.isnull().sum()

missing_values
```

Out[9]:

	0
Age	0
ParentalEducation	0
StudyTimeWeekly	0
Absences	0
Tutoring	0
ParentalSupport	0
Extracurricular	0
Sports	0
Music	0
GPA	0
GradeClass	0

dtype: int64

6. Prepare your data for training and for testing set:

- First create a dataset named X, with all columns but GPA. These are the features
- Next create another dataset named y, with only GPA column. This is the label
- If you go to your Imports, you will see the following import: **'from sklearn.model_selection import train_test_split'**

- Use that *train_test_split* function to create: X_train, X_test, y_train and y_test respectively. Use X and y datasets as parameters. Other parameters to use are: Test Size = 0.2, Random State = 42.

- Standarize your features (X_train and X_test) by using the StandardScaler (investigate how to use fit_transform and transform functions). This will help the training process by dealing with normilized data.

  Note: Your X_train shape should be around (1913, 10). This means the dataset has 10 columns which should be the input.

In [10]:
```
X = final_dataset.drop(columns=['GPA'])

y = final_dataset['GPA']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

X_train_shape = X_train.shape
X_test_shape = X_test.shape

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train_shape, X_test_shape
```

Out[10]:
```
((1913, 10), (479, 10))
```

7. Define your Deep Neural Network.

- This will be a Sequential Neural Network.
- With a Dense input layer with 64 units, and input dimention of 10 and Relu as the activation function.
- A Dense hidden layer with 32 units, and Relu as the activation function.
- And a Dense output layer with 1 unit, do not define an activation function so it defaults to linear, suitable for regression tasks. e.g. Dense(1)

This last part of the output layer is super important, since we want to predict the GPA, this means that we want a regression and not a classification. Linear activation function is best for regression and Sigmoid is best for Binary Classification

In [11]:
```
model = Sequential()

model.add(Dense(64, input_dim=10, activation='relu'))

model.add(Dense(32, activation='relu'))

model.add(Dense(1))

model.compile(optimizer='adam', loss='mean_squared_error')

model.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarnin
g: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequentia
l models, prefer using an `Input(shape)` object as the first layer in the model inste
ad.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Pa
dense (Dense)	(None, 64)	
dense_1 (Dense)	(None, 32)	
dense_2 (Dense)	(None, 1)	

Total params: 2,817 (11.00 KB)

Trainable params: 2,817 (11.00 KB)

Non-trainable params: 0 (0.00 B)

8. Compile your Neural Network

- Choose Adam as the optimizer
- And MSE as the Loss function
- Also add the following metrics: Mean Absolute Error

In [12]:
```python
model.compile(optimizer='adam',
              loss='mean_squared_error',
              metrics=['mean_absolute_error'])

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Pa
dense (Dense)	(None, 64)	
dense_1 (Dense)	(None, 32)	
dense_2 (Dense)	(None, 1)	

Total params: 2,817 (11.00 KB)

Trainable params: 2,817 (11.00 KB)

Non-trainable params: 0 (0.00 B)

9. Fit (or train) your model

- Use the X_train and y_train datasets for the training

- Do 50 data iterations
- Choose the batch size = 10
- Also select a validation_split of 0.2
- Save the result of the fit function in a variable called 'history'

In [13]:
```
history = model.fit(X_train_scaled, y_train,
                    epochs=50,
                    batch_size=10,
                    validation_split=0.2)
```

```
Epoch 1/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 1.3757 - mean_absolute_error: 0.8708
- val_loss: 0.1178 - val_mean_absolute_error: 0.2791
Epoch 2/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0999 - mean_absolute_error: 0.2548
- val_loss: 0.0727 - val_mean_absolute_error: 0.2172
Epoch 3/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0664 - mean_absolute_error: 0.2061
- val_loss: 0.0570 - val_mean_absolute_error: 0.1931
Epoch 4/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0537 - mean_absolute_error: 0.1889
- val_loss: 0.0546 - val_mean_absolute_error: 0.1875
Epoch 5/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0472 - mean_absolute_error: 0.1738
- val_loss: 0.0509 - val_mean_absolute_error: 0.1782
Epoch 6/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0384 - mean_absolute_error: 0.1593
- val_loss: 0.0479 - val_mean_absolute_error: 0.1745
Epoch 7/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0359 - mean_absolute_error: 0.1537
- val_loss: 0.0424 - val_mean_absolute_error: 0.1655
Epoch 8/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0332 - mean_absolute_error: 0.1457
- val_loss: 0.0461 - val_mean_absolute_error: 0.1739
Epoch 9/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0345 - mean_absolute_error: 0.1487
- val_loss: 0.0436 - val_mean_absolute_error: 0.1634
Epoch 10/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0345 - mean_absolute_error: 0.1492
- val_loss: 0.0434 - val_mean_absolute_error: 0.1672
Epoch 11/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0290 - mean_absolute_error: 0.1349
- val_loss: 0.0428 - val_mean_absolute_error: 0.1641
Epoch 12/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0299 - mean_absolute_error: 0.1380
- val_loss: 0.0539 - val_mean_absolute_error: 0.1839
Epoch 13/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0293 - mean_absolute_error: 0.1357
- val_loss: 0.0431 - val_mean_absolute_error: 0.1636
Epoch 14/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0296 - mean_absolute_error: 0.1366
- val_loss: 0.0455 - val_mean_absolute_error: 0.1674
Epoch 15/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0280 - mean_absolute_error: 0.1318
- val_loss: 0.0441 - val_mean_absolute_error: 0.1647
Epoch 16/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0255 - mean_absolute_error: 0.1266
- val_loss: 0.0472 - val_mean_absolute_error: 0.1714
Epoch 17/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0249 - mean_absolute_error: 0.1244
- val_loss: 0.0431 - val_mean_absolute_error: 0.1635
Epoch 18/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0261 - mean_absolute_error: 0.1288
- val_loss: 0.0465 - val_mean_absolute_error: 0.1670
Epoch 19/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0246 - mean_absolute_error: 0.1259
- val_loss: 0.0439 - val_mean_absolute_error: 0.1640
Epoch 20/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0246 - mean_absolute_error: 0.1236
- val_loss: 0.0488 - val_mean_absolute_error: 0.1701
```

```
Epoch 21/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0252 - mean_absolute_error: 0.1261
- val_loss: 0.0472 - val_mean_absolute_error: 0.1705
Epoch 22/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0238 - mean_absolute_error: 0.1220
- val_loss: 0.0443 - val_mean_absolute_error: 0.1623
Epoch 23/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0241 - mean_absolute_error: 0.1245
- val_loss: 0.0473 - val_mean_absolute_error: 0.1703
Epoch 24/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0243 - mean_absolute_error: 0.1238
- val_loss: 0.0422 - val_mean_absolute_error: 0.1606
Epoch 25/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0225 - mean_absolute_error: 0.1179
- val_loss: 0.0458 - val_mean_absolute_error: 0.1708
Epoch 26/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0230 - mean_absolute_error: 0.1188
- val_loss: 0.0467 - val_mean_absolute_error: 0.1671
Epoch 27/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0216 - mean_absolute_error: 0.1168
- val_loss: 0.0473 - val_mean_absolute_error: 0.1709
Epoch 28/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0205 - mean_absolute_error: 0.1137
- val_loss: 0.0460 - val_mean_absolute_error: 0.1679
Epoch 29/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0222 - mean_absolute_error: 0.1177
- val_loss: 0.0504 - val_mean_absolute_error: 0.1745
Epoch 30/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0221 - mean_absolute_error: 0.1171
- val_loss: 0.0440 - val_mean_absolute_error: 0.1621
Epoch 31/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0211 - mean_absolute_error: 0.1144
- val_loss: 0.0440 - val_mean_absolute_error: 0.1625
Epoch 32/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0219 - mean_absolute_error: 0.1173
- val_loss: 0.0451 - val_mean_absolute_error: 0.1673
Epoch 33/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0222 - mean_absolute_error: 0.1177
- val_loss: 0.0463 - val_mean_absolute_error: 0.1685
Epoch 34/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0188 - mean_absolute_error: 0.1094
- val_loss: 0.0432 - val_mean_absolute_error: 0.1603
Epoch 35/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0207 - mean_absolute_error: 0.1135
- val_loss: 0.0563 - val_mean_absolute_error: 0.1883
Epoch 36/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0189 - mean_absolute_error: 0.1096
- val_loss: 0.0488 - val_mean_absolute_error: 0.1744
Epoch 37/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0201 - mean_absolute_error: 0.1114
- val_loss: 0.0474 - val_mean_absolute_error: 0.1687
Epoch 38/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0200 - mean_absolute_error: 0.1108
- val_loss: 0.0461 - val_mean_absolute_error: 0.1667
Epoch 39/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0210 - mean_absolute_error: 0.1177
- val_loss: 0.0452 - val_mean_absolute_error: 0.1635
Epoch 40/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0184 - mean_absolute_error: 0.1056
- val_loss: 0.0459 - val_mean_absolute_error: 0.1639
```

```
Epoch 41/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0198 - mean_absolute_error: 0.1096
- val_loss: 0.0480 - val_mean_absolute_error: 0.1678
Epoch 42/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0195 - mean_absolute_error: 0.1120
- val_loss: 0.0463 - val_mean_absolute_error: 0.1685
Epoch 43/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0180 - mean_absolute_error: 0.1062
- val_loss: 0.0440 - val_mean_absolute_error: 0.1632
Epoch 44/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0184 - mean_absolute_error: 0.1071
- val_loss: 0.0464 - val_mean_absolute_error: 0.1673
Epoch 45/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0172 - mean_absolute_error: 0.1045
- val_loss: 0.0445 - val_mean_absolute_error: 0.1643
Epoch 46/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0173 - mean_absolute_error: 0.1044
- val_loss: 0.0448 - val_mean_absolute_error: 0.1627
Epoch 47/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0174 - mean_absolute_error: 0.1032
- val_loss: 0.0482 - val_mean_absolute_error: 0.1705
Epoch 48/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0172 - mean_absolute_error: 0.1033
- val_loss: 0.0451 - val_mean_absolute_error: 0.1647
Epoch 49/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0167 - mean_absolute_error: 0.1027
- val_loss: 0.0531 - val_mean_absolute_error: 0.1806
Epoch 50/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0176 - mean_absolute_error: 0.1040
- val_loss: 0.0490 - val_mean_absolute_error: 0.1746
```

10. View your history variable:

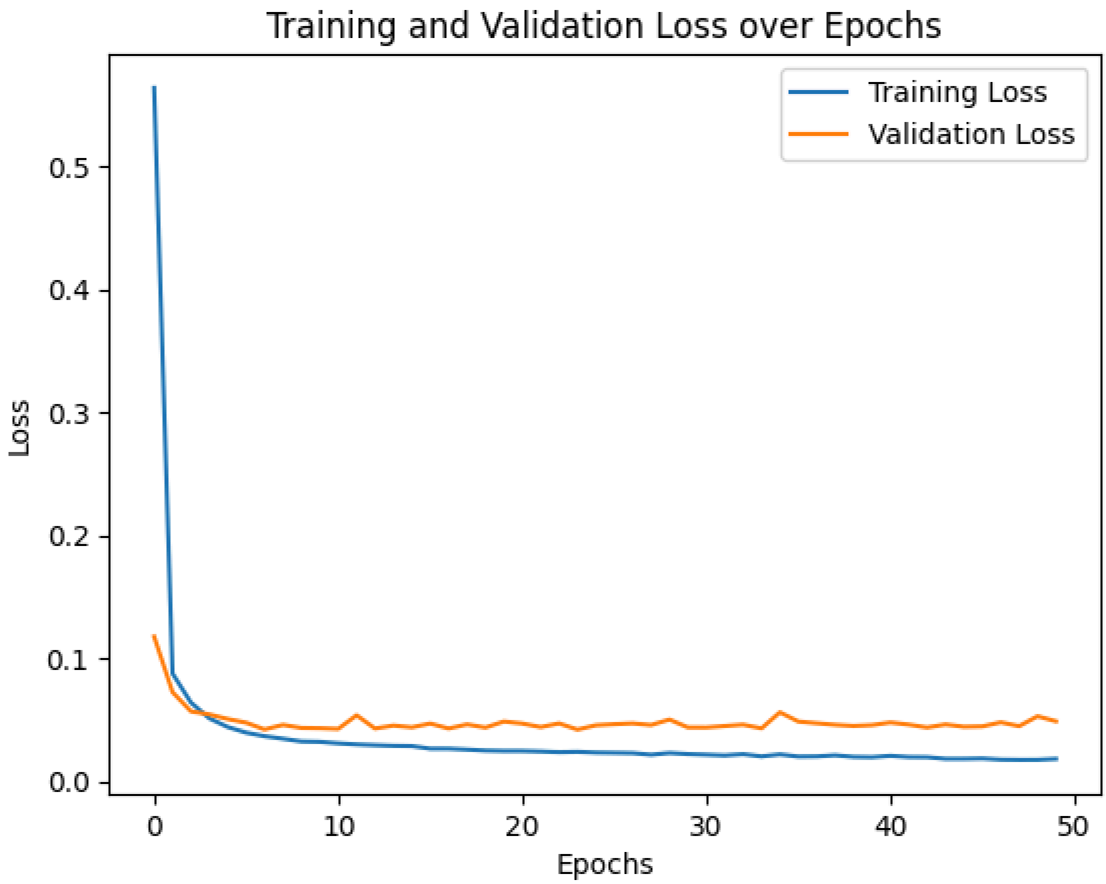
- Use Matplotlib.pyplot to show graphs of your model traning history
- In one graph:
  - Plot the Training Loss and the Validation Loss
  - X Label = Epochs
  - Y Label = Loss
  - Title = Training and Validation Loss over Epochs
- In a second graph:
  - Plot the Training MAE and the Validation MAE
  - X Label = Epochs
  - Y Label = Mean Absolute Error (MAE)
  - Title = Training and Validation MAE over Epochs

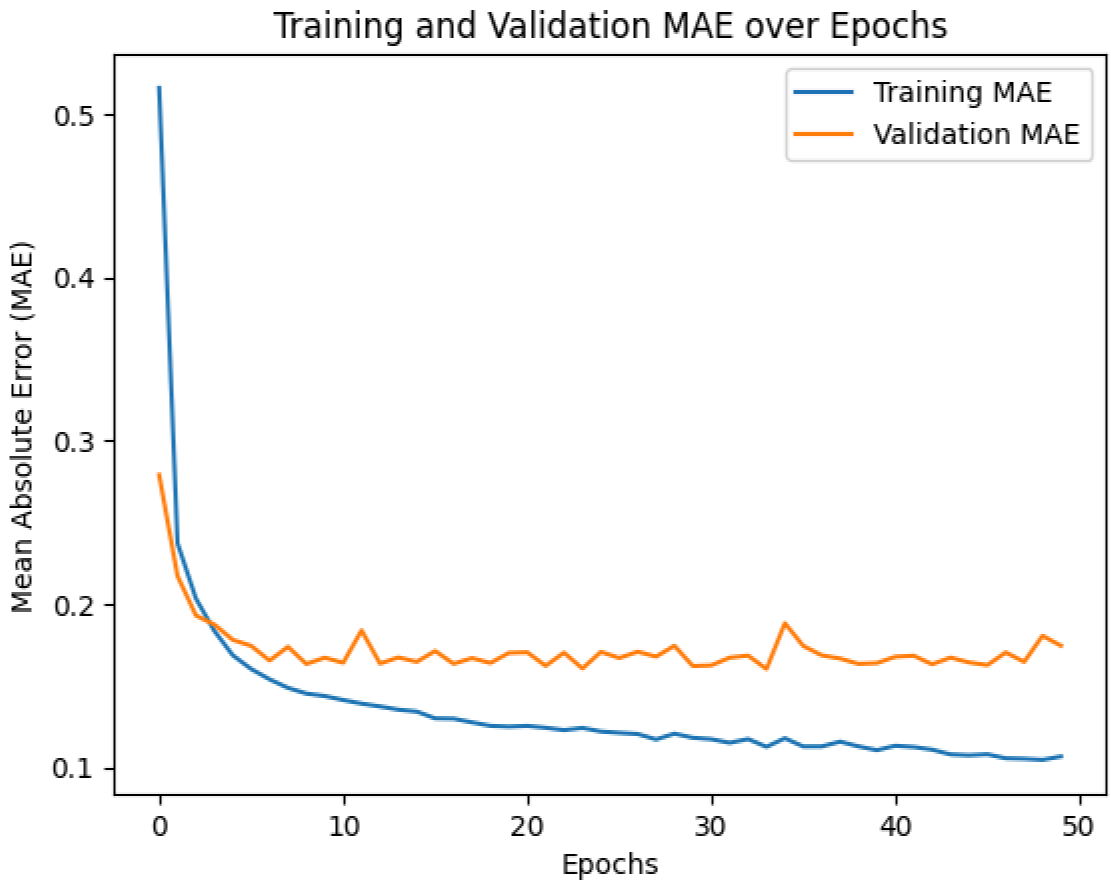
In [14]:

```python
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss over Epochs')
plt.legend()
plt.show()

plt.plot(history.history['mean_absolute_error'], label='Training MAE')
plt.plot(history.history['val_mean_absolute_error'], label='Validation MAE')
```

```
plt.xlabel('Epochs')
plt.ylabel('Mean Absolute Error (MAE)')
plt.title('Training and Validation MAE over Epochs')
plt.legend()
plt.show()
```





11. Evaluate your model:

- See the result of your loss function.
- What can you deduct from there?

In [15]:
```
loss, mae = model.evaluate(X_test_scaled, y_test)
print(f'Loss: {loss}, Mean Absolute Error: {mae}')
```

```
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0475 - mean_absolute_error: 0.1703
Loss: 0.045884568244218826, Mean Absolute Error: 0.16879822313785553
```

12. Use your model to make some predictions:

- Make predictions of your X_test dataset
- Print the each of the predictions and the actual value (which is in y_test)
- How good was your model?

In [19]:
```
y_pred = model.predict(X_test_scaled)

for i in range(len(y_test)):
    print(f"Predicted: {y_pred[i][0]}, Actual: {y_test.iloc[i]}")
```

```
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
Predicted: 1.434401035308838, Actual: 1.4277243762746905
Predicted: 2.8287594318389893, Actual: 3.117354434785501
Predicted: 1.7671840190887451, Actual: 2.037768574636005
Predicted: 3.5548267364501953, Actual: 3.5485205508668662
Predicted: 0.6627643704414368, Actual: 0.2489771312307257
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Predicted: 2.2186262607574463, Actual: 2.248337588471201
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Predicted: 1.6188112497329712, Actual: 1.8154017176022967
Predicted: 0.2207823544740677, Actual: 0.1005921480894177
```

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Predicted: 2.5379319190979004, Actual: 2.777966932491008
Predicted: 0.9285194873809814, Actual: 0.863545351686935
```

13. Compete against this model:

- Create two more different models to compete with this model
- Here are a few ideas of things you can change:
  - During Dataset data engineering:
    - You can remove features that you think do not help in the training and prediction
    - Feature Scaling: Ensure all features are on a similar scale (as you already did with StandardScaler)
  - During Model Definition:
    - You can change the Model Architecture (change the type or number of layers or the number of units)
    - You can add dropout layers to prevent overfitting
  - During Model Compile:
    - You can try other optimizer when compiling your model, here some optimizer samples: Adam, RMSprop, or Adagrad.
    - Try another Loss Function
  - During Model Training:
    - Encrease the number of Epochs
    - Adjust the size of your batch
- Explain in a Markdown cell which changes are you implementing
- Show the comparison of your model versus the original model

Model 2:

- Changes:
  - Dataset Data Engineering
  - Model Definition
  - Model Compile
  - Model Training

In [21]:
```
model2 = Sequential()
model2.add(Dense(128, input_dim=10, activation='relu'))
model2.add(Dense(64, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(32, activation='relu'))
model2.add(Dense(1))

model2.compile(optimizer='RMSprop', loss='mean_squared_error', metrics=['mean_absolute

history2 = model2.fit(X_train_scaled, y_train, epochs=50, batch_size=10, validation_sp

final_dataset2 = dataset.drop(columns=['Gender', 'Ethnicity', 'Volunteering', 'Music']

X2 = final_dataset2.drop(columns=['GPA'])
y2 = final_dataset2['GPA']

X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2, random_

scaler2 = StandardScaler()
```

```
X_train_scaled2 = scaler2.fit_transform(X_train2)
X_test_scaled2 = scaler2.transform(X_test2)
```

```
Epoch 1/50
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarnin
g: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequentia
l models, prefer using an `Input(shape)` object as the first layer in the model inste
ad.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - loss: 0.6306 - mean_absolute_error: 0.5730
- val_loss: 0.0725 - val_mean_absolute_error: 0.2199
Epoch 2/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - loss: 0.1204 - mean_absolute_error: 0.2749
- val_loss: 0.0774 - val_mean_absolute_error: 0.2304
Epoch 3/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0919 - mean_absolute_error: 0.2429
- val_loss: 0.0586 - val_mean_absolute_error: 0.1959
Epoch 4/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0738 - mean_absolute_error: 0.2130
- val_loss: 0.0524 - val_mean_absolute_error: 0.1826
Epoch 5/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0663 - mean_absolute_error: 0.2033
- val_loss: 0.0473 - val_mean_absolute_error: 0.1740
Epoch 6/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0617 - mean_absolute_error: 0.1980
- val_loss: 0.0447 - val_mean_absolute_error: 0.1679
Epoch 7/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - loss: 0.0550 - mean_absolute_error: 0.1852
- val_loss: 0.0684 - val_mean_absolute_error: 0.2134
Epoch 8/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0536 - mean_absolute_error: 0.1838
- val_loss: 0.0417 - val_mean_absolute_error: 0.1616
Epoch 9/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0540 - mean_absolute_error: 0.1834
- val_loss: 0.0566 - val_mean_absolute_error: 0.1900
Epoch 10/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0482 - mean_absolute_error: 0.1724
- val_loss: 0.0466 - val_mean_absolute_error: 0.1697
Epoch 11/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0491 - mean_absolute_error: 0.1785
- val_loss: 0.0426 - val_mean_absolute_error: 0.1628
Epoch 12/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0419 - mean_absolute_error: 0.1616
- val_loss: 0.0453 - val_mean_absolute_error: 0.1676
Epoch 13/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0436 - mean_absolute_error: 0.1665
- val_loss: 0.0446 - val_mean_absolute_error: 0.1674
Epoch 14/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0433 - mean_absolute_error: 0.1644
- val_loss: 0.0544 - val_mean_absolute_error: 0.1845
Epoch 15/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0425 - mean_absolute_error: 0.1655
- val_loss: 0.0568 - val_mean_absolute_error: 0.1883
Epoch 16/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0379 - mean_absolute_error: 0.1523
- val_loss: 0.1131 - val_mean_absolute_error: 0.2777
Epoch 17/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0410 - mean_absolute_error: 0.1602
- val_loss: 0.0462 - val_mean_absolute_error: 0.1647
Epoch 18/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0411 - mean_absolute_error: 0.1580
- val_loss: 0.0461 - val_mean_absolute_error: 0.1692
Epoch 19/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0432 - mean_absolute_error: 0.1644
- val_loss: 0.0515 - val_mean_absolute_error: 0.1803
Epoch 20/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0399 - mean_absolute_error: 0.1554
- val_loss: 0.0419 - val_mean_absolute_error: 0.1607
Epoch 21/50
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0382 - mean_absolute_error: 0.1554
- val_loss: 0.0857 - val_mean_absolute_error: 0.2446
Epoch 22/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0339 - mean_absolute_error: 0.1452
- val_loss: 0.0581 - val_mean_absolute_error: 0.1948
Epoch 23/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0365 - mean_absolute_error: 0.1517
- val_loss: 0.0601 - val_mean_absolute_error: 0.2002
Epoch 24/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0341 - mean_absolute_error: 0.1459
- val_loss: 0.0540 - val_mean_absolute_error: 0.1855
Epoch 25/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0369 - mean_absolute_error: 0.1514
- val_loss: 0.0497 - val_mean_absolute_error: 0.1773
Epoch 26/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0317 - mean_absolute_error: 0.1410
- val_loss: 0.0658 - val_mean_absolute_error: 0.2101
Epoch 27/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0362 - mean_absolute_error: 0.1487
- val_loss: 0.0723 - val_mean_absolute_error: 0.2198
Epoch 28/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0330 - mean_absolute_error: 0.1424
- val_loss: 0.0514 - val_mean_absolute_error: 0.1818
Epoch 29/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0306 - mean_absolute_error: 0.1366
- val_loss: 0.0612 - val_mean_absolute_error: 0.2033
Epoch 30/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0336 - mean_absolute_error: 0.1451
- val_loss: 0.0592 - val_mean_absolute_error: 0.1948
Epoch 31/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0301 - mean_absolute_error: 0.1354
- val_loss: 0.0677 - val_mean_absolute_error: 0.2098
Epoch 32/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0327 - mean_absolute_error: 0.1405
- val_loss: 0.0532 - val_mean_absolute_error: 0.1848
Epoch 33/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0314 - mean_absolute_error: 0.1389
- val_loss: 0.0652 - val_mean_absolute_error: 0.2092
Epoch 34/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0315 - mean_absolute_error: 0.1415
- val_loss: 0.0832 - val_mean_absolute_error: 0.2408
Epoch 35/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0293 - mean_absolute_error: 0.1315
- val_loss: 0.0992 - val_mean_absolute_error: 0.2599
Epoch 36/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0285 - mean_absolute_error: 0.1300
- val_loss: 0.0787 - val_mean_absolute_error: 0.2295
Epoch 37/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0274 - mean_absolute_error: 0.1282
- val_loss: 0.0527 - val_mean_absolute_error: 0.1858
Epoch 38/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0297 - mean_absolute_error: 0.1342
- val_loss: 0.0431 - val_mean_absolute_error: 0.1600
Epoch 39/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0279 - mean_absolute_error: 0.1341
- val_loss: 0.1151 - val_mean_absolute_error: 0.2786
Epoch 40/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0298 - mean_absolute_error: 0.1335
- val_loss: 0.0761 - val_mean_absolute_error: 0.2266
Epoch 41/50
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0284 - mean_absolute_error: 0.1326
- val_loss: 0.1087 - val_mean_absolute_error: 0.2733
Epoch 42/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0268 - mean_absolute_error: 0.1301
- val_loss: 0.0560 - val_mean_absolute_error: 0.1873
Epoch 43/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0264 - mean_absolute_error: 0.1272
- val_loss: 0.0875 - val_mean_absolute_error: 0.2468
Epoch 44/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0268 - mean_absolute_error: 0.1293
- val_loss: 0.0632 - val_mean_absolute_error: 0.2010
Epoch 45/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0242 - mean_absolute_error: 0.1229
- val_loss: 0.0612 - val_mean_absolute_error: 0.2000
Epoch 46/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0236 - mean_absolute_error: 0.1197
- val_loss: 0.0521 - val_mean_absolute_error: 0.1858
Epoch 47/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0240 - mean_absolute_error: 0.1222
- val_loss: 0.0812 - val_mean_absolute_error: 0.2361
Epoch 48/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0258 - mean_absolute_error: 0.1268
- val_loss: 0.0721 - val_mean_absolute_error: 0.2172
Epoch 49/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0238 - mean_absolute_error: 0.1186
- val_loss: 0.0663 - val_mean_absolute_error: 0.2088
Epoch 50/50
153/153 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0244 - mean_absolute_error: 0.1222
- val_loss: 0.0915 - val_mean_absolute_error: 0.2513
```

Model 3:

- Changes:
  - Dataset Data Engineering
  - Model Definition
  - Model Compile
  - Model Training

In [22]:
```
model3 = Sequential()
model3.add(Dense(64, input_dim=X_train_scaled2.shape[1], activation='relu'))
model3.add(Dense(32, activation='relu'))
model3.add(Dense(1))

model3.compile(optimizer='Adam', loss='mean_squared_error', metrics=['mean_absolute_er

history3 = model3.fit(X_train_scaled2, y_train2, epochs=50, batch_size=15, validation_
```

```
Epoch 1/50
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarnin
g: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequentia
l models, prefer using an `Input(shape)` object as the first layer in the model inste
ad.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 2.3189 - mean_absolute_error: 1.2584
- val_loss: 0.2466 - val_mean_absolute_error: 0.4064
Epoch 2/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.1723 - mean_absolute_error: 0.3305
- val_loss: 0.1149 - val_mean_absolute_error: 0.2792
Epoch 3/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0933 - mean_absolute_error: 0.2487
- val_loss: 0.0811 - val_mean_absolute_error: 0.2325
Epoch 4/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0700 - mean_absolute_error: 0.2141
- val_loss: 0.0657 - val_mean_absolute_error: 0.2051
Epoch 5/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0578 - mean_absolute_error: 0.1970
- val_loss: 0.0590 - val_mean_absolute_error: 0.1956
Epoch 6/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0482 - mean_absolute_error: 0.1776
- val_loss: 0.0534 - val_mean_absolute_error: 0.1839
Epoch 7/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0429 - mean_absolute_error: 0.1674
- val_loss: 0.0519 - val_mean_absolute_error: 0.1803
Epoch 8/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0418 - mean_absolute_error: 0.1653
- val_loss: 0.0499 - val_mean_absolute_error: 0.1747
Epoch 9/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0431 - mean_absolute_error: 0.1682
- val_loss: 0.0452 - val_mean_absolute_error: 0.1685
Epoch 10/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0420 - mean_absolute_error: 0.1633
- val_loss: 0.0453 - val_mean_absolute_error: 0.1700
Epoch 11/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0363 - mean_absolute_error: 0.1530
- val_loss: 0.0434 - val_mean_absolute_error: 0.1662
Epoch 12/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0354 - mean_absolute_error: 0.1494
- val_loss: 0.0431 - val_mean_absolute_error: 0.1654
Epoch 13/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0359 - mean_absolute_error: 0.1504
- val_loss: 0.0424 - val_mean_absolute_error: 0.1648
Epoch 14/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0349 - mean_absolute_error: 0.1464
- val_loss: 0.0418 - val_mean_absolute_error: 0.1620
Epoch 15/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0323 - mean_absolute_error: 0.1407
- val_loss: 0.0412 - val_mean_absolute_error: 0.1623
Epoch 16/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0309 - mean_absolute_error: 0.1396
- val_loss: 0.0410 - val_mean_absolute_error: 0.1600
Epoch 17/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0300 - mean_absolute_error: 0.1369
- val_loss: 0.0418 - val_mean_absolute_error: 0.1596
Epoch 18/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0306 - mean_absolute_error: 0.1383
- val_loss: 0.0439 - val_mean_absolute_error: 0.1649
Epoch 19/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0303 - mean_absolute_error: 0.1365
- val_loss: 0.0404 - val_mean_absolute_error: 0.1562
Epoch 20/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0312 - mean_absolute_error: 0.1398
- val_loss: 0.0401 - val_mean_absolute_error: 0.1578
Epoch 21/50
```

```
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0287 - mean_absolute_error: 0.1329
- val_loss: 0.0448 - val_mean_absolute_error: 0.1654
Epoch 22/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0288 - mean_absolute_error: 0.1354
- val_loss: 0.0424 - val_mean_absolute_error: 0.1624
Epoch 23/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0307 - mean_absolute_error: 0.1376
- val_loss: 0.0410 - val_mean_absolute_error: 0.1598
Epoch 24/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0306 - mean_absolute_error: 0.1384
- val_loss: 0.0422 - val_mean_absolute_error: 0.1611
Epoch 25/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0268 - mean_absolute_error: 0.1293
- val_loss: 0.0398 - val_mean_absolute_error: 0.1566
Epoch 26/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0262 - mean_absolute_error: 0.1284
- val_loss: 0.0488 - val_mean_absolute_error: 0.1733
Epoch 27/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0275 - mean_absolute_error: 0.1309
- val_loss: 0.0405 - val_mean_absolute_error: 0.1575
Epoch 28/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0251 - mean_absolute_error: 0.1247
- val_loss: 0.0410 - val_mean_absolute_error: 0.1589
Epoch 29/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0267 - mean_absolute_error: 0.1294
- val_loss: 0.0404 - val_mean_absolute_error: 0.1578
Epoch 30/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0250 - mean_absolute_error: 0.1247
- val_loss: 0.0399 - val_mean_absolute_error: 0.1551
Epoch 31/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0259 - mean_absolute_error: 0.1291
- val_loss: 0.0421 - val_mean_absolute_error: 0.1604
Epoch 32/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0256 - mean_absolute_error: 0.1239
- val_loss: 0.0460 - val_mean_absolute_error: 0.1661
Epoch 33/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0262 - mean_absolute_error: 0.1280
- val_loss: 0.0424 - val_mean_absolute_error: 0.1626
Epoch 34/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0246 - mean_absolute_error: 0.1244
- val_loss: 0.0442 - val_mean_absolute_error: 0.1619
Epoch 35/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0266 - mean_absolute_error: 0.1274
- val_loss: 0.0408 - val_mean_absolute_error: 0.1564
Epoch 36/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0247 - mean_absolute_error: 0.1252
- val_loss: 0.0422 - val_mean_absolute_error: 0.1594
Epoch 37/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0244 - mean_absolute_error: 0.1237
- val_loss: 0.0448 - val_mean_absolute_error: 0.1661
Epoch 38/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0253 - mean_absolute_error: 0.1245
- val_loss: 0.0426 - val_mean_absolute_error: 0.1592
Epoch 39/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0234 - mean_absolute_error: 0.1196
- val_loss: 0.0445 - val_mean_absolute_error: 0.1618
Epoch 40/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0254 - mean_absolute_error: 0.1257
- val_loss: 0.0427 - val_mean_absolute_error: 0.1593
Epoch 41/50
```

```
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0235 - mean_absolute_error: 0.1217
- val_loss: 0.0430 - val_mean_absolute_error: 0.1601
Epoch 42/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0230 - mean_absolute_error: 0.1184
- val_loss: 0.0438 - val_mean_absolute_error: 0.1642
Epoch 43/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0242 - mean_absolute_error: 0.1198
- val_loss: 0.0453 - val_mean_absolute_error: 0.1658
Epoch 44/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0243 - mean_absolute_error: 0.1238
- val_loss: 0.0476 - val_mean_absolute_error: 0.1692
Epoch 45/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0241 - mean_absolute_error: 0.1211
- val_loss: 0.0435 - val_mean_absolute_error: 0.1620
Epoch 46/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0229 - mean_absolute_error: 0.1189
- val_loss: 0.0442 - val_mean_absolute_error: 0.1636
Epoch 47/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0218 - mean_absolute_error: 0.1157
- val_loss: 0.0476 - val_mean_absolute_error: 0.1731
Epoch 48/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0235 - mean_absolute_error: 0.1201
- val_loss: 0.0470 - val_mean_absolute_error: 0.1681
Epoch 49/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0236 - mean_absolute_error: 0.1220
- val_loss: 0.0483 - val_mean_absolute_error: 0.1730
Epoch 50/50
102/102 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0234 - mean_absolute_error: 0.1217
- val_loss: 0.0473 - val_mean_absolute_error: 0.1688
```

In [23]:

```python
loss1, mae1 = model.evaluate(X_test_scaled, y_test)
loss2, mae2 = model2.evaluate(X_test_scaled, y_test)
loss3, mae3 = model3.evaluate(X_test_scaled2, y_test2)

print(f"Model 1 - Loss: {loss1}, MAE: {mae1}")
print(f"Model 2 - Loss: {loss2}, MAE: {mae2}")
print(f"Model 3 - Loss: {loss3}, MAE: {mae3}")
```

```
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0475 - mean_absolute_error: 0.1703
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0860 - mean_absolute_error: 0.2364
15/15 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0473 - mean_absolute_error: 0.1715
Model 1 - Loss: 0.045884568244218826, MAE: 0.16879822313785553
Model 2 - Loss: 0.0872996523976326, MAE: 0.24258054792881012
Model 3 - Loss: 0.043446801602840424, MAE: 0.16504491865634918
```