Global Energy Consumption Analysis using ANN

1: Import Libraries

📘 Description: This cell imports all Python libraries required for data processing, model training, and evaluation

In [1]:
```
# Import the Pandas library for data manipulation (reading CSV, handling
import pandas as pd

# Import NumPy for mathematical operations on arrays
import numpy as np

# Import tools for splitting data into training and testing sets
from sklearn.model_selection import train_test_split

# Import StandardScaler to scale (normalize) numeric data before training
from sklearn.preprocessing import StandardScaler

# Import mean_absolute_error to measure how far predictions are from true
from sklearn.metrics import mean_absolute_error

# Import TensorFlow Keras modules for building the Artificial Neural Netw
from tensorflow.keras.models import Sequential      # Used to build the m
from tensorflow.keras.layers import Dense, Dropout  # Dense = fully conne

```

```
C:\Users\PMLS\anaconda3\Lib\site-packages\pandas\core\arrays\masked.py:61: U
serWarning: Pandas requires version '1.3.6' or newer of 'bottleneck' (versio
n '1.3.5' currently installed).
  from pandas.core import (
```

2: Load and View Dataset

📘 Description: This cell loads the dataset into Python and displays its shape and first few rows.

In [2]:

```
# Load the dataset from CSV file using Pandas
data = pd.read_csv("global_energy_consumption.csv")

# Print confirmation that dataset loaded successfully
print("Dataset Loaded Successfully!")

# Display how many rows and columns the dataset contains
print("Rows and Columns:", data.shape)

# Display the first 5 rows of data to understand its structure
data.head()

```

```
Dataset Loaded Successfully!
Rows and Columns: (10000, 10)
```

Out[2]:

	Country	Year	Total Energy Consumption (TWh)	Per Capita Energy Use (kWh)	Renewable Energy Share (%)	Fossil Fuel Dependency (%)	Industrial Energy Use (%)	Household Energy Use (%)	C Emi (
0	Canada	2018	9525.38	42301.43	13.70	70.47	45.18	19.96	3
1	Germany	2020	7922.08	36601.38	33.63	41.95	34.32	22.27	2
2	Russia	2002	6630.01	41670.20	10.82	39.32	53.66	26.44	
3	Brazil	2010	8580.19	10969.58	73.24	16.71	30.55	27.60	1
4	Canada	2006	848.88	32190.85	73.60	74.86	42.39	23.43	

3: Check Columns and Data Info

📘 Description: This cell shows column names, data types, and checks for missing values.

In [3]:

```
# Print all column names to understand what features are available
print("Column Names in Dataset:\n", data.columns)

# Show data types of each column and how many non-missing entries each ha
data.info()

```

```
Column Names in Dataset:
 Index(['Country', 'Year', 'Total Energy Consumption (TWh)',
       'Per Capita Energy Use (kWh)', 'Renewable Energy Share (%)',
       'Fossil Fuel Dependency (%)', 'Industrial Energy Use (%)',
       'Household Energy Use (%)', 'Carbon Emissions (Million Tons)',
       'Energy Price Index (USD/kWh)'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   Country                          10000 non-null  object 
 1   Year                             10000 non-null  int64  
 2   Total Energy Consumption (TWh)   10000 non-null  float64
 3   Per Capita Energy Use (kWh)      10000 non-null  float64
 4   Renewable Energy Share (%)       10000 non-null  float64
 5   Fossil Fuel Dependency (%)       10000 non-null  float64
 6   Industrial Energy Use (%)        10000 non-null  float64
 7   Household Energy Use (%)         10000 non-null  float64
 8   Carbon Emissions (Million Tons)  10000 non-null  float64
 9   Energy Price Index (USD/kWh)     10000 non-null  float64
dtypes: float64(8), int64(1), object(1)
memory usage: 781.4+ KB
```

4: Handle Missing Values

📘 Description: This cell removes any rows that contain missing values to ensure clean data for training.

In [4]:
```
# Drop all rows that contain missing (NaN) values
data = data.dropna()

# Check again to confirm that no missing values remain
data.isnull().sum()

```

Out[4]:
```
Country                          0
Year                             0
Total Energy Consumption (TWh)   0
Per Capita Energy Use (kWh)      0
Renewable Energy Share (%)       0
Fossil Fuel Dependency (%)       0
Industrial Energy Use (%)        0
Household Energy Use (%)         0
Carbon Emissions (Million Tons)  0
Energy Price Index (USD/kWh)     0
dtype: int64
```

5: Select Features (X) and Target (y)

📘 Description: Here we select which column we want to predict (target) and which columns will be used as inputs (features).

In [5]:
```
# 1. Convert the 'Country' column into dummy variables using One-Hot Enco
# This ensures the model understands geographical differences in energy p
data_final = pd.get_dummies(data, columns=['Country'], drop_first=True)

# 2. Define the target variable (y)
# We are predicting 'Total Energy Consumption (TWh)'
y = data_final['Total Energy Consumption (TWh)']

# 3. Define the input features (X)
# We drop the target column but keep the newly created country dummy colu
X = data_final.drop(['Total Energy Consumption (TWh)'], axis=1)

# Verify the new shape of features
print("Features shape after encoding:", X.shape)
```

```
Features shape after encoding: (10000, 17)
```

6: Feature Scaling

📘 Description: This cell scales all numeric features so that they have similar ranges — this helps the ANN learn efficiently.

In [6]:
```
# 1. Initialize StandardScalers for both features (X) and target (y)
scaler_X = StandardScaler()
scaler_y = StandardScaler()

# 2. Fit and transform the input features (X)
X_scaled = scaler_X.fit_transform(X)

# 3. Fit and transform the target variable (y)
# Note: We reshape y because the scaler expects a 2D array
y_scaled = scaler_y.fit_transform(y.values.reshape(-1, 1))

print("Feature and Target scaling completed.")

```

```
Feature and Target scaling completed.
```

7: Split Data into Train and Test Sets

📘 Description: We divide the dataset into two parts — training (for model learning) and testing (for evaluation).

In [7]:
```
# Split the scaled data into 80% training and 20% testing
# We now use y_scaled instead of the original y
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_scaled, test_size=0.2, random_state=42
)

print("Data split into training and testing sets successfully.")

```

```
Data split into training and testing sets successfully.
```

8: Build the ANN Model

📘 Description: This cell defines the structure of the Artificial Neural Network — how many layers and neurons it has.

In [19]:
```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, I

model = Sequential()
model.add(Input(shape=(X_train.shape[1],)))

# Layer 1: Stronger dropout to prevent memorization
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.4))

# Layer 2
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))

# Layer 3
model.add(Dense(64, activation='relu'))

# Output
model.add(Dense(1, activation='linear'))

# Lower Learning Rate for better convergence
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
              loss='mse',
              metrics=['mae'])

print("Final Robust ANN Model Built.")
```

```
Final Robust ANN Model Built.
```

9: Train the Model

📘 Description: This cell trains the model using the training data. The network adjusts its internal weights to reduce error.

In [21]:
```
from tensorflow.keras.callbacks import EarlyStopping

# Monitor validation loss and stop if it doesn't improve for 10 epochs
# restore_best_weights ensures we keep the weights from the lowest val_lo
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_

history = model.fit(
    X_train, y_train,
    epochs=200,
    batch_size=32,
    validation_split=0.2,
    callbacks=[early_stop],
    verbose=1
)
```

```
Epoch 1/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 1.0573 - mae: 0.8833 - val_
loss: 0.9875 - val_mae: 0.8505
Epoch 2/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0518 - mae: 0.8836 - val_
loss: 0.9869 - val_mae: 0.8510
Epoch 3/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0314 - mae: 0.8683 - val_
loss: 0.9853 - val_mae: 0.8493
Epoch 4/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0114 - mae: 0.8607 - val_
loss: 0.9874 - val_mae: 0.8506
Epoch 5/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 1.0437 - mae: 0.8761 - val_
loss: 0.9867 - val_mae: 0.8498
Epoch 6/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0242 - mae: 0.8700 - val_
loss: 0.9870 - val_mae: 0.8505
Epoch 7/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0226 - mae: 0.8729 - val_
loss: 0.9870 - val_mae: 0.8502
Epoch 8/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0310 - mae: 0.8753 - val_
loss: 0.9860 - val_mae: 0.8494
Epoch 9/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0325 - mae: 0.8726 - val_
loss: 0.9855 - val_mae: 0.8499
Epoch 10/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0104 - mae: 0.8653 - val_
loss: 0.9868 - val_mae: 0.8501
Epoch 11/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 1.0291 - mae: 0.8730 - val_
loss: 0.9880 - val_mae: 0.8500
Epoch 12/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 1.0173 - mae: 0.8665 - val_
loss: 0.9920 - val_mae: 0.8523
Epoch 13/200
200/200 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.0316 - mae: 0.8707 - val_
loss: 0.9914 - val_mae: 0.8516
```

10: Evaluate the Model

📘 Description: We use test data to check how well the model learned and calculate the Mean Absolute Error (MAE).

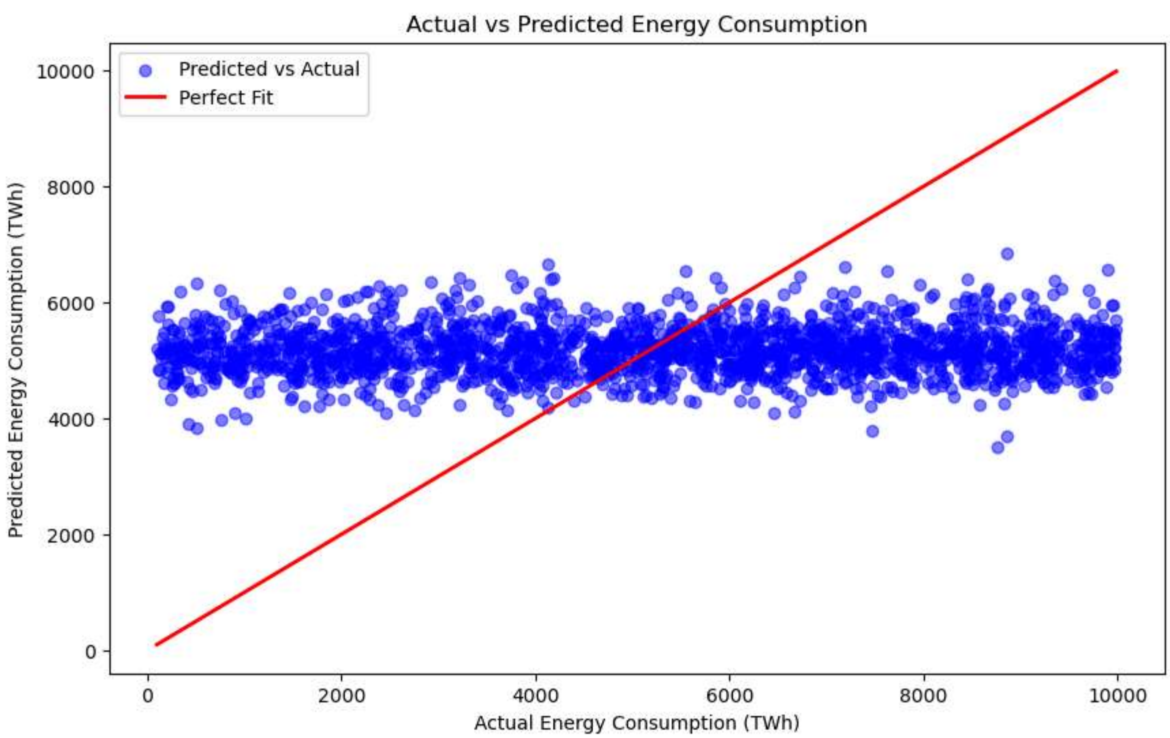
In [22]:
```
# 1. Predict on the test data
y_pred_scaled = model.predict(X_test)

# 2. Reverse the scaling for both predictions and actual test values
# This is crucial because we scaled 'y' in Step 6
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_test_actual = scaler_y.inverse_transform(y_test)

# 3. Calculate and print the final Mean Absolute Error (MAE)
from sklearn.metrics import mean_absolute_error
final_mae = mean_absolute_error(y_test_actual, y_pred)

print(f"✅ Final Optimized MAE: {final_mae:.2f} TWh")
```

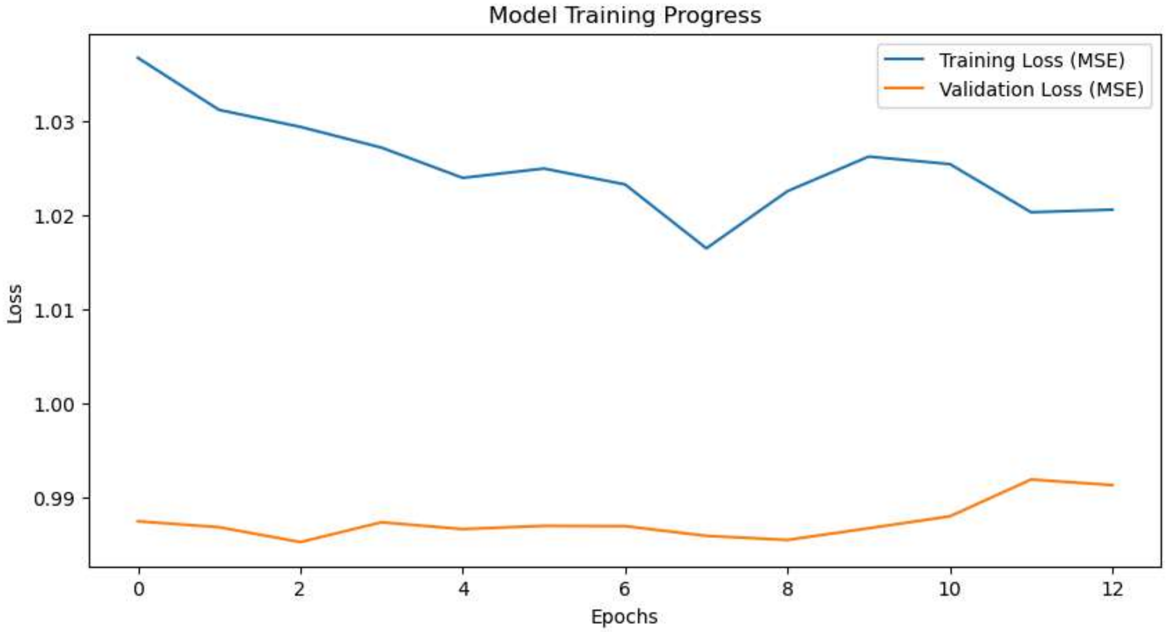
```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
✅ Final Optimized MAE: 2410.10 TWh
```

11 : Visualize Training Progress

📘 Description: This cell plots how the model’s error changed over time during training and validation.

In [23]:
```
import matplotlib.pyplot as plt

# 1. Scatter Plot: Actual vs Predicted
plt.figure(figsize=(10, 6))
plt.scatter(y_test_actual, y_pred, alpha=0.5, color='blue', label='Predic

# 2. Diagonal Line (Perfect Prediction Line)
# If dots are on this line, the model is 100% accurate
plt.plot([y_test_actual.min(), y_test_actual.max()],
         [y_test_actual.min(), y_test_actual.max()],
         color='red', lw=2, label='Perfect Fit')

plt.xlabel('Actual Energy Consumption (TWh)')
plt.ylabel('Predicted Energy Consumption (TWh)')
plt.title('Actual vs Predicted Energy Consumption')
plt.legend()
plt.show()

# 3. Training Loss Curve
plt.figure(figsize=(10, 5))
plt.plot(history.history['loss'], label='Training Loss (MSE)')
plt.plot(history.history['val_loss'], label='Validation Loss (MSE)')
plt.title('Model Training Progress')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```





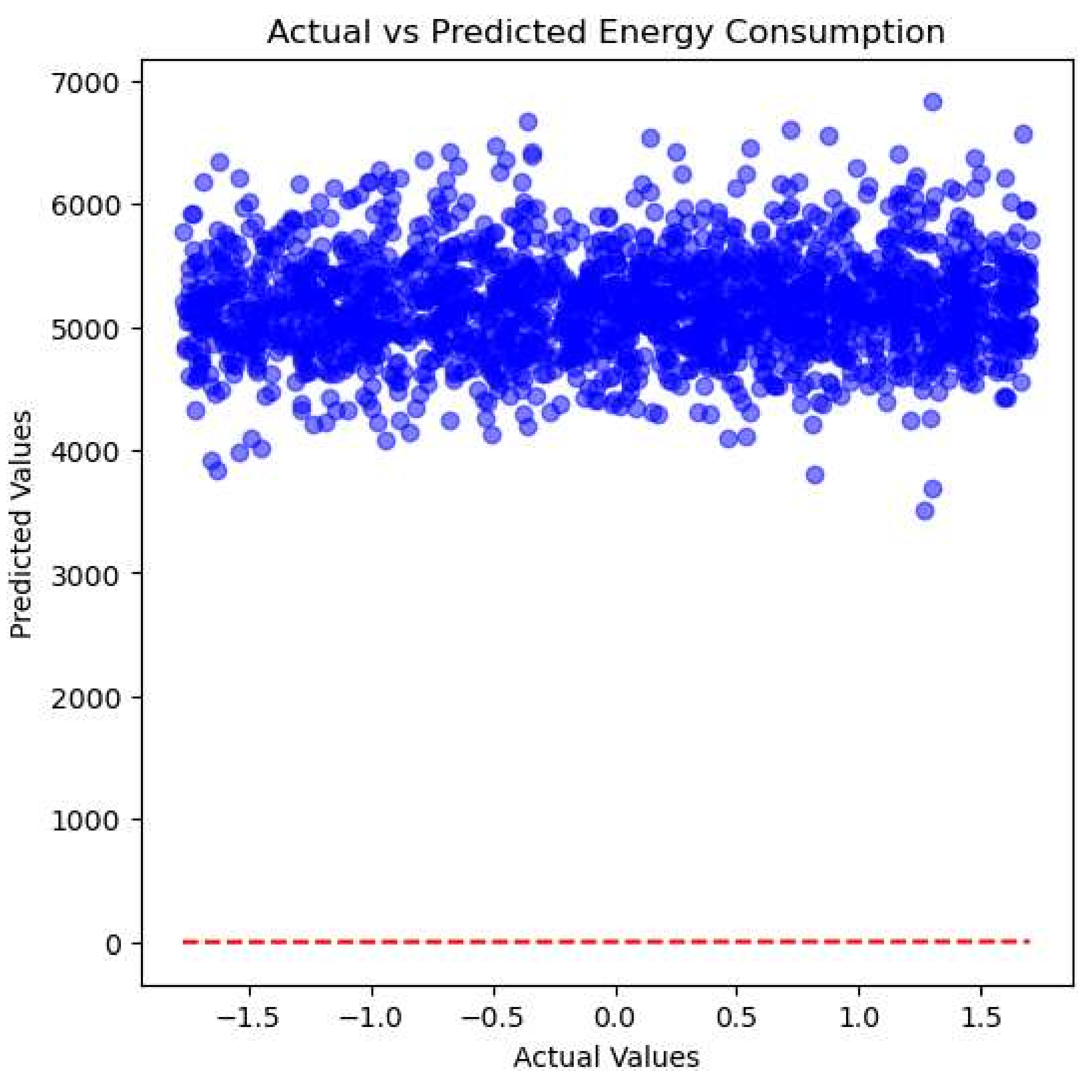
Actual vs Predicted Values Plot

📝 Description:

This scatter plot shows how close the predicted energy values are to the actual values. If most points are near the red diagonal line, your model is performing well.

In [24]:

```
# 🔮 Actual vs Predicted Plot - To check model prediction accuracy visual

plt.figure(figsize=(6, 6))

# Plot actual values on x-axis and predicted values on y-axis
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)

# Draw a red diagonal line showing perfect predictions
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--

# Label the axes
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')

# Add a title to the chart
plt.title('Actual vs Predicted Energy Consumption')

# Show the scatter plot
plt.show()

```



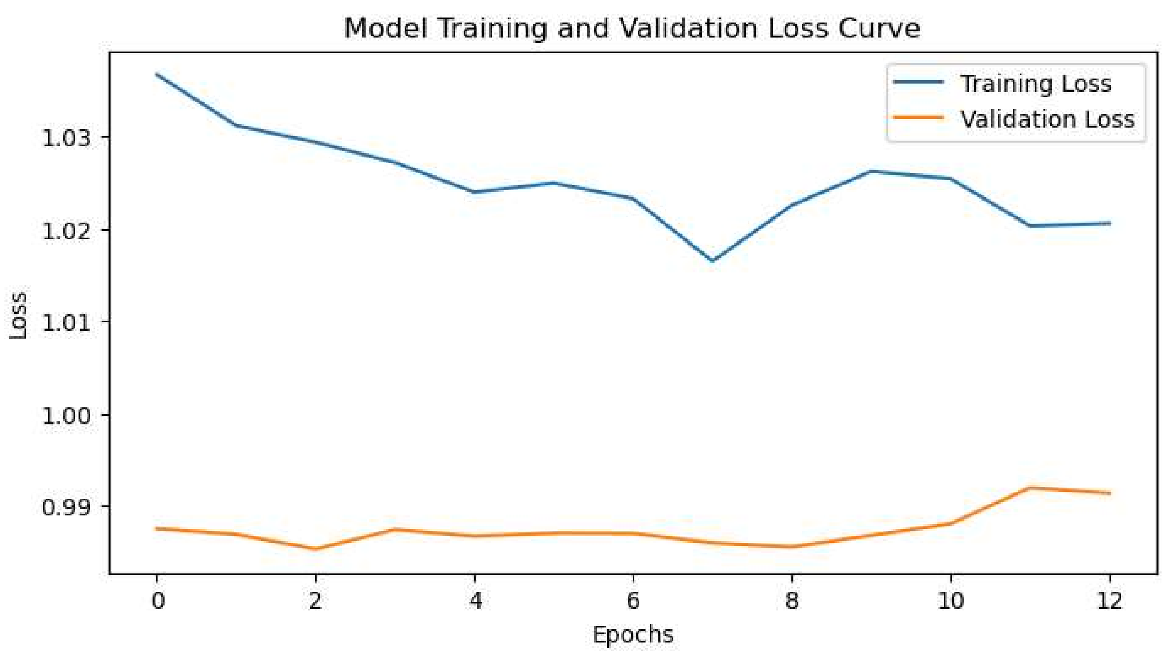
Model Training Loss Curve

📝 Description:

This plot shows how your model's error (loss) changed during training and validation. It helps you understand whether your model is learning properly or overfitting.

In [25]:

```
# 📈 Model Training and Validation Loss Curve - To check model learning p

plt.figure(figsize=(8, 4))

# Plot training loss values
plt.plot(history.history['loss'], label='Training Loss')

# Plot validation loss values
plt.plot(history.history['val_loss'], label='Validation Loss')

# Add a title and labels
plt.title('Model Training and Validation Loss Curve')
plt.xlabel('Epochs')
plt.ylabel('Loss')

# Add a legend to differentiate both curves
plt.legend()

# Display the plot
plt.show()

```



Step 8: Summary

✅ In this experiment, we used a global energy dataset

✅ We performed preprocessing, scaling, and built an ANN model

✅ The model learned to predict Carbon Emissions based on energy data

✅ Graphs helped visualize training performance and prediction accuracy

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In [ ]:

```

```