GPU

```
!nvidia-smi
```

```
Sun Nov 30 02:04:26 2025
+-----------------------------------------------------------------------------------------+
| NVIDIA-SMI 550.54.15              Driver Version: 550.54.15      CUDA Version: 12.4     |
|-----------------------------------------+------------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id          Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage | GPU-Util  Compute M. |
|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  Tesla T4                       Off |   00000000:00:04.0 Off |                    0 |
| N/A   49C    P0             27W /   70W |     376MiB /  15360MiB |      0%      Default |
|                                         |                        |                  N/A |
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+-----------------------------------------------------------------------------------------+
| Processes:                                                                              |
|  GPU   GI   CI        PID   Type   Process name                              GPU Memory |
|        ID   ID                                                               Usage      |
|=========================================================================================|
+-----------------------------------------------------------------------------------------+
```

1. Library Imports

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
import joblib
from sklearn.inspection import PartialDependenceDisplay
from tensorflow import keras
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
```

```
import numpy as np
from tensorflow.keras.callbacks import EarlyStopping
import tensorflow as tf
```

2. Data Loading

```
df = pd.read_csv('/content/Superstore.csv')
```

3. Initial Data Overview

```
df.head()
```

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	...	Postal Code	Region	Product ID	Category	Sub-Category
0	1	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...	42420	South	FUR-BO-10001798	Furniture	Bookcases
1	2	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...	42420	South	FUR-CH-10000454	Furniture	Chairs
2	3	CA-2016-138688	6/12/2016	6/16/2016	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Los Angeles	...	90036	West	OFF-LA-10000240	Office Supplies	Labels
3	4	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...	33311	South	FUR-TA-10000577	Furniture	Tables
4	5	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...	33311	South	OFF-ST-10000760	Office Supplies	Storage

5 rows × 21 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Row ID         9994 non-null   int64  
 1   Order ID       9994 non-null   object 
 2   Order Date     9994 non-null   object 
 3   Ship Date      9994 non-null   object 
 4   Ship Mode      9994 non-null   object 
 5   Customer ID    9994 non-null   object 
 6   Customer Name  9994 non-null   object 
 7   Segment        9994 non-null   object 
 8   Country        9994 non-null   object 
 9   City           9994 non-null   object 
 10  State          9994 non-null   object 
 11  Postal Code    9994 non-null   int64  
 12  Region         9994 non-null   object 
 13  Product ID     9994 non-null   object 
 14  Category       9994 non-null   object 
 15  Sub-Category   9994 non-null   object 
 16  Product Name   9994 non-null   object 
 17  Sales          9994 non-null   float64
 18  Quantity       9994 non-null   int64  
 19  Discount       9994 non-null   float64
 20  Profit         9994 non-null   float64
dtypes: float64(3), int64(3), object(15)
memory usage: 1.6+ MB
```

```
df.describe()
```

	Row ID	Postal Code	Sales	Quantity	Discount	Profit
count	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000
mean	4997.500000	55190.379428	229.858001	3.789574	0.156203	28.656896
std	2885.163629	32063.693350	623.245101	2.225110	0.206452	234.260108
min	1.000000	1040.000000	0.444000	1.000000	0.000000	-6599.978000
25%	2499.250000	23223.000000	17.280000	2.000000	0.000000	1.728750
50%	4997.500000	56430.500000	54.490000	3.000000	0.200000	8.666500
75%	7495.750000	90008.000000	209.940000	5.000000	0.200000	29.364000
max	9994.000000	99301.000000	22638.480000	14.000000	0.800000	8399.976000

```
df.isnull().sum()
```

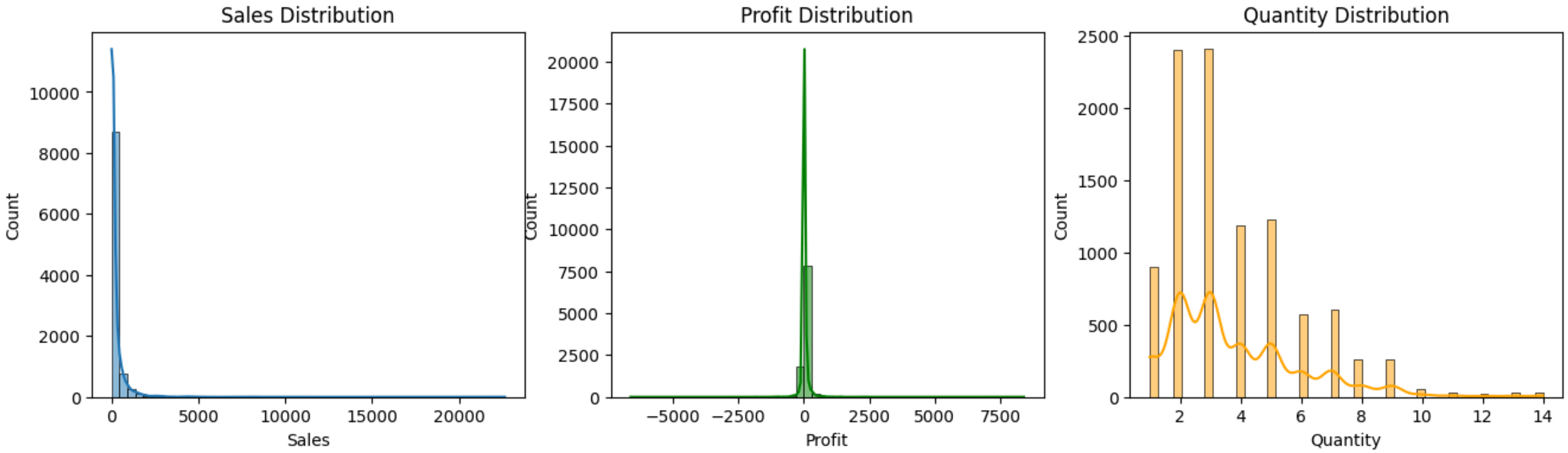
	0
Row ID	0
Order ID	0
Order Date	0
Ship Date	0
Ship Mode	0
Customer ID	0
Customer Name	0
Segment	0
Country	0
City	0
State	0
Postal Code	0
Region	0
Product ID	0
Category	0
Sub-Category	0
Product Name	0
Sales	0
Quantity	0
Discount	0
Profit	0

dtype: int64

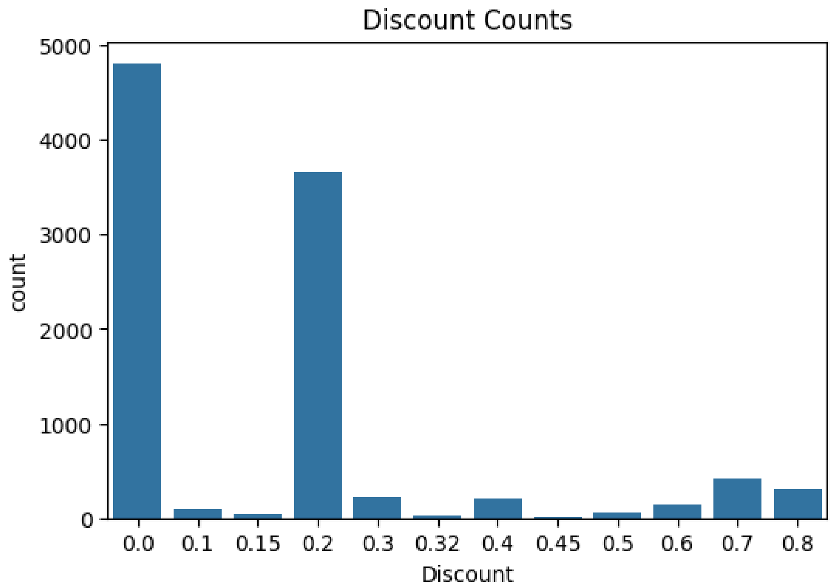
4. Data Visualization and Exploration

```
# Sales, Profit, Quantity distribution
plt.figure(figsize=(16,4))
plt.subplot(1,3,1)
sns.histplot(df['Sales'], bins=50, kde=True)
plt.title("Sales Distribution")
```

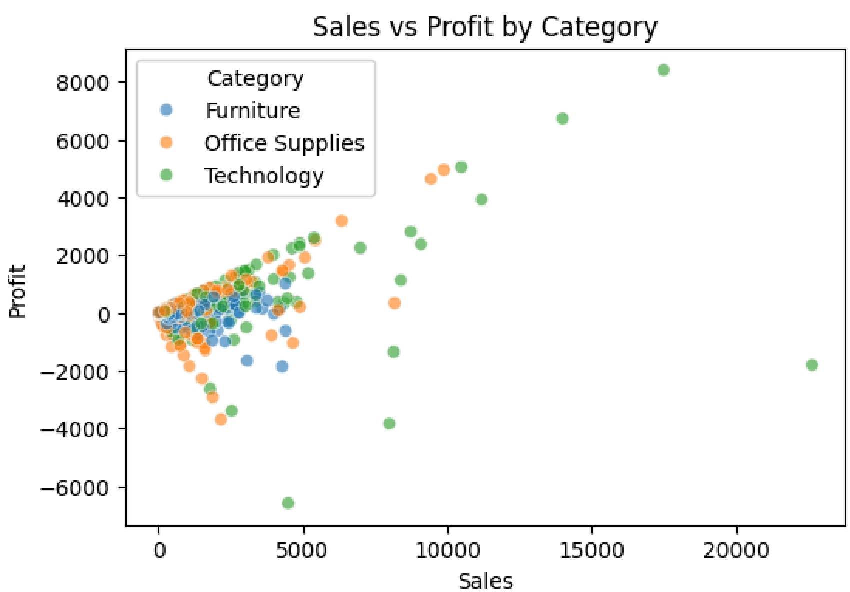
```
plt.subplot(1,3,2)
sns.histplot(df['Profit'], bins=50, kde=True, color='green')
plt.title("Profit Distribution")

plt.subplot(1,3,3)
sns.histplot(df['Quantity'], bins=50, kde=True, color='orange')
plt.title("Quantity Distribution")
plt.show()
```




```
# Discount distribution
plt.figure(figsize=(6,4))
sns.countplot(x='Discount', data=df)
plt.title("Discount Counts")
plt.show()
```

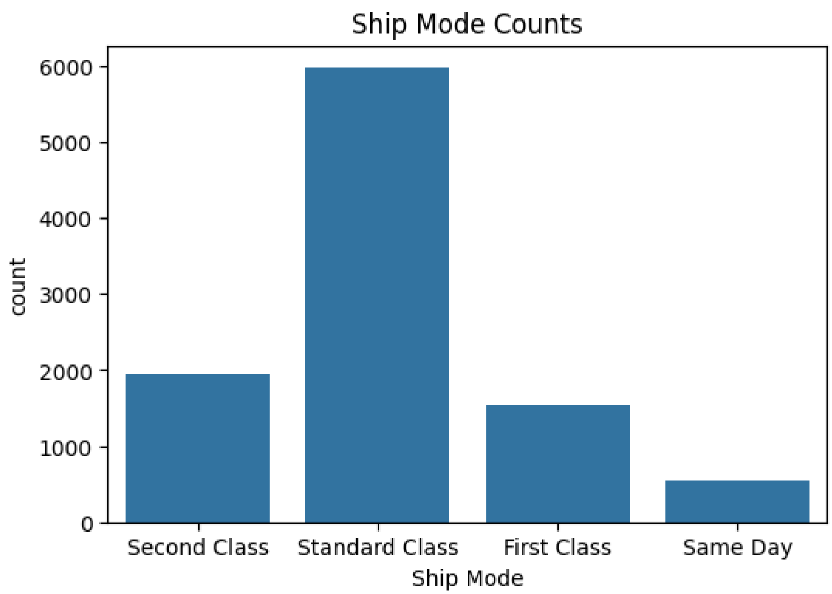



```
#  Sales vs Profit scatter plot
plt.figure(figsize=(6,4))
sns.scatterplot(x='Sales', y='Profit', hue='Category', data=df, alpha=0.6)
plt.title("Sales vs Profit by Category")
plt.show()
```



```
# Profit by Category and Sub-Category
plt.figure(figsize=(12,5))
sns.boxplot(x='Category', y='Profit', data=df)
plt.title("Profit Distribution by Category")
plt.show()

plt.figure(figsize=(15,5))
sns.boxplot(x='Sub-Category', y='Profit', data=df)
plt.xticks(rotation=45)
plt.title("Profit Distribution by Sub-Category")
plt.show()
```

```
#  Ship Mode counts
plt.figure(figsize=(6,4))
sns.countplot(x='Ship Mode', data=df)
plt.title("Ship Mode Counts")
plt.show()
```



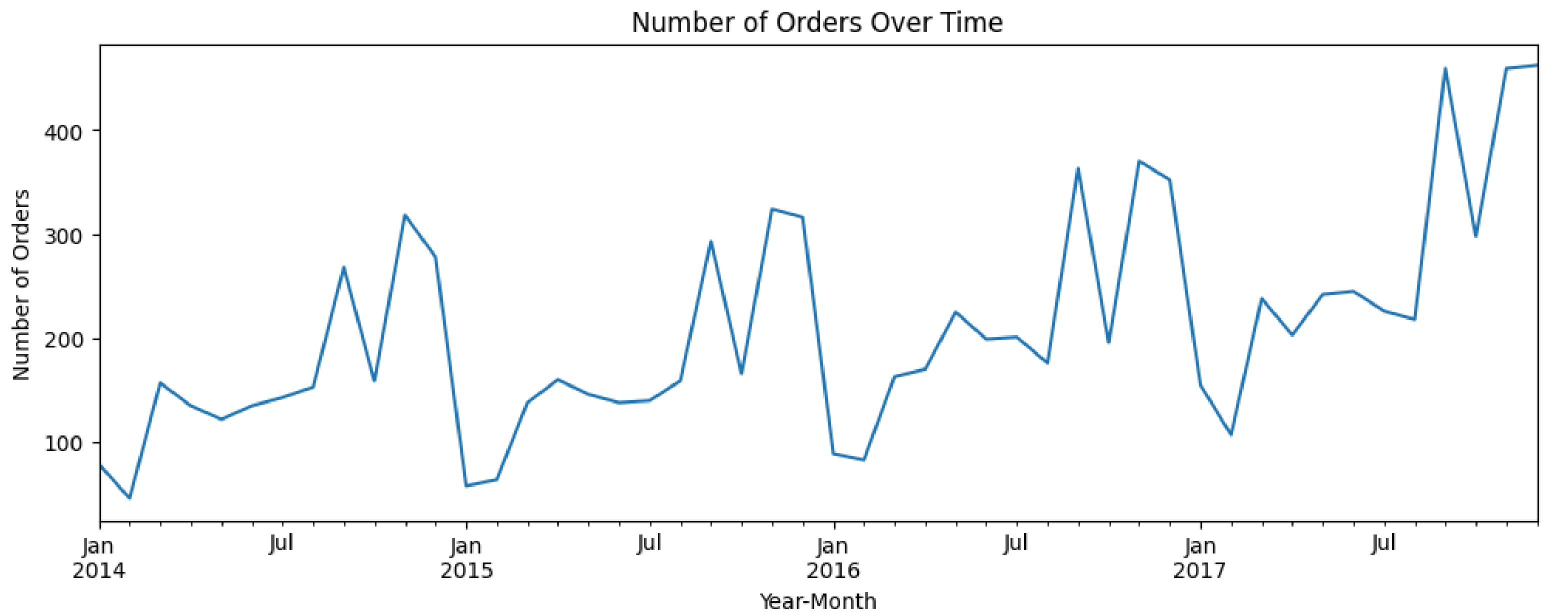
5. Feature Engineering and Preprocessing

```
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Ship Date'] = pd.to_datetime(df['Ship Date'])
```

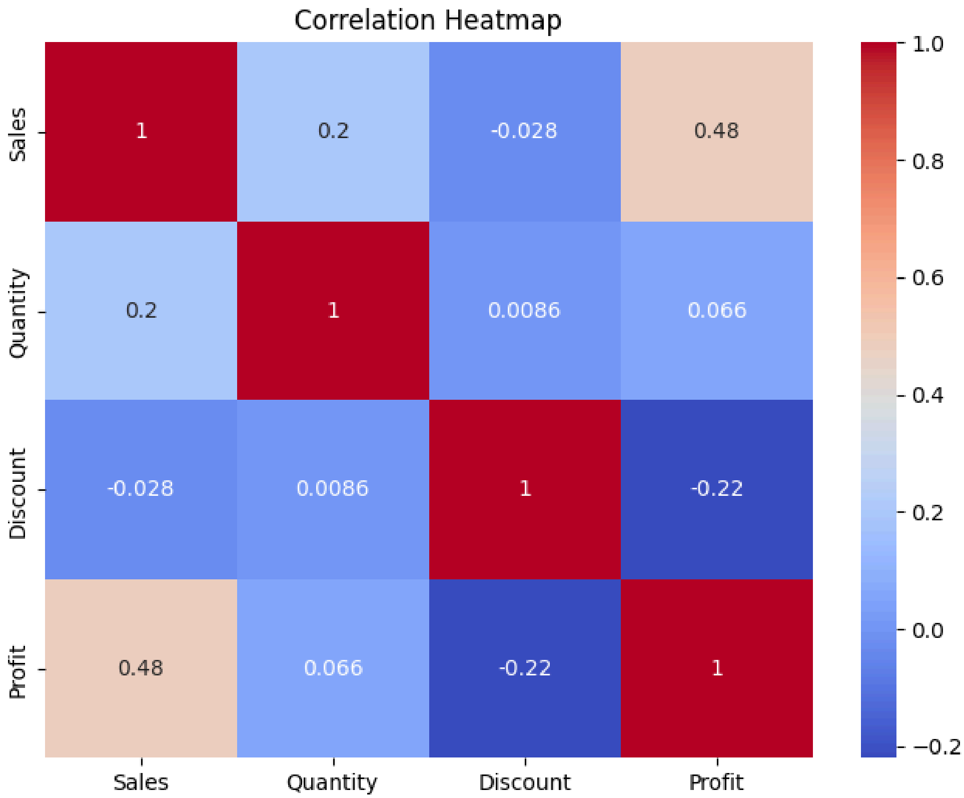
```
df['OrderYear'] = df['Order Date'].dt.year.astype(int)
df['OrderMonth'] = df['Order Date'].dt.month.astype(int)
```

```
# Orders over Time
df['OrderYearMonth'] = df['Order Date'].dt.to_period('M')
orders_per_month = df.groupby('OrderYearMonth').size()

plt.figure(figsize=(12,4))
orders_per_month.plot()
plt.title("Number of Orders Over Time")
plt.xlabel("Year-Month")
```

```
plt.ylabel("Number of Orders")
plt.show()
```




```
# Correlation heatmap for numeric features
plt.figure(figsize=(8,6))
sns.heatmap(df[['Sales','Quantity','Discount','Profit']].corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```




```
df.columns
```

```
Index(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'State',
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Sales', 'Quantity', 'Discount', 'Profit', 'OrderYear',
       'OrderMonth', 'OrderYearMonth'],
      dtype='object')
```

```
df.shape
```

```
(9994, 24)
```

```
print(df.City.nunique())
df.City.value_counts()
```

```
531
```

City	count
New York City	915
Los Angeles	747
Philadelphia	537
San Francisco	510
Seattle	428
...	...
Abilene	1
Montebello	1
Kissimmee	1
Danbury	1
Springdale	1

531 rows × 1 columns

dtype: int64

```
print(df.Country.nunique())
df.Country.value_counts()
```

```
1
```

Country	count
United States	9994

dtype: int64

```
print(df.State.nunique())
df.State.value_counts()
```

49

State	count
California	2001
New York	1128
Texas	985
Pennsylvania	587
Washington	506
Illinois	492
Ohio	469
Florida	383
Michigan	255
North Carolina	249
Arizona	224
Virginia	224
Georgia	184
Tennessee	183
Colorado	182
Indiana	149
Kentucky	139
Massachusetts	135
New Jersey	130
Oregon	124
Wisconsin	110
Maryland	105
Alabama	61

5.1. Dropping Unnecessary Columns

```
# Drop UnNeeded Coulmns
cols_to_drop = [
    'Row ID', 'Order ID', 'Customer ID', 'Customer Name','Product ID', 'Country'
]
df = df.drop(columns=cols_to_drop)
```

```
df.OrderYearMonth[0]
```

```
Period('2016-11', 'M')
```

Arkansas 60

Rhode Island 56

5.2. Date Feature Extraction and Dropping Date Columns

Utah 53

```
# Exreact New Features From Dates
df['OrderYear'] = df['Order Date'].dt.year
df['OrderMonth'] = df['Order Date'].dt.month
df['ShippingDelay'] = (df['Ship Date'] - df['Order Date']).dt.days

df = df.drop(columns=['Order Date', 'Ship Date','OrderYearMonth'])
```

Nebraska 38

New Mexico 37

5.3. Categorical Feature Encoding

Iowa 30

```
# Lable Encoding
cat_cols = ['Ship Mode', 'Segment', 'Region', 'Category', 'Sub-Category','Product Name', "City", "State"]
encoders = {}
for col in cat_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    encoders[col] = le
```

Vermont 11

5.4. Outlier Handling (Clipping)

District of Columbia 10

```
# Handling Outliers
lower = df['Profit'].quantile(0.01)
upper = df['Profit'].quantile(0.99)
df['Profit_clipped'] = df['Profit'].clip(lower, upper)

# Sales
lower_sales = df['Sales'].quantile(0.01)
upper_sales = df['Sales'].quantile(0.99)
df['Sales_clipped'] = df['Sales'].clip(lower_sales, upper_sales)

# Quantity
lower_qty = df['Quantity'].quantile(0.01)
upper_qty = df['Quantity'].quantile(0.99)
df['Quantity_clipped'] = df['Quantity'].clip(lower_qty, upper_qty)
```

6. Data Splitting and Scaling

```
# Split Data
y = df['Sales_clipped']
```

```
y = df['Sales_clipped']
X = df.drop(columns=['Sales', 'Sales_clipped','Profit'])

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

```
# Save the Feature Order
joblib.dump(X.columns.tolist(), "feature_order.joblib")
```

```
['feature_order.joblib']
```

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

7. ML Model Training and Evaluation

7.1. Support Vector Regressor (SVR)

```
svr = SVR(kernel='rbf', C=100, epsilon=0.1)
svr.fit(X_train_scaled, y_train)
y_pred_svr = svr.predict(X_test_scaled)

# Evalluate Decision Tree
mae_dt = mean_absolute_error(y_test, y_pred_svr)
mse_dt = mean_squared_error(y_test, y_pred_svr)
rmse_dt = mse_dt ** 0.5
r2_dt = r2_score(y_test, y_pred_svr)
```

```
print("SVR Evaluation:")
print("------------------------------------")
print("MAE :", mae_dt)
print("MSE :", mse_dt)
print("RMSE:", rmse_dt)
print("R²  :", r2_dt)
```

```
SVR Evaluation:
------------------------------------
MAE : 96.98692412337483
MSE : 62853.12599573185
RMSE: 250.7052572159823
R²  : 0.6508089961379162
```

7.2. Decision Tree Regressor

```
# Train Decision Tree
dt = DecisionTreeRegressor(
    max_depth=10,
    min_samples_leaf=5,
    random_state=42
)

dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
```

```
# Evalluate Decision Tree
mae_dt = mean_absolute_error(y_test, y_pred_dt)
mse_dt = mean_squared_error(y_test, y_pred_dt)
rmse_dt = mse_dt ** 0.5
r2_dt = r2_score(y_test, y_pred_dt)

print("Decision Tree Evaluation:")
print("------------------------------------")
print("MAE :", mae_dt)
print("MSE :", mse_dt)
print("RMSE:", rmse_dt)
print("R²  :", r2_dt)
```

```
Decision Tree Evaluation:
------------------------------------
MAE : 72.54262425810613
MSE : 38164.71877835814
RMSE: 195.3579247902632
R²  : 0.7879695520118764
```

7.3. Random Forest Regressor

```
# Train Random Forest model
rf = RandomForestRegressor(n_estimators=500, max_depth=15, min_samples_leaf=5,
                           random_state=42, n_jobs=-1)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
```

```
# Evaluate Random Forest Model
mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
rmse_rf = mse_rf ** 0.5
r2_rf = r2_score(y_test, y_pred_rf)
```

```
print("Random Forest Evaluation:")
print("----------------------------------------------")
print("MAE :", mae_rf)
print("MSE :", mse_rf)
print("RMSE:", rmse_rf)
print("R²  :", r2_rf)
```

```
Random Forest Evaluation:
----------------------------------------------
MAE : 64.06244436073729
MSE : 31078.00637819716
RMSE: 176.289552663217
R²  : 0.8273409623894944
```

8. Model Persistence (Saving Models)

```
# Save SVR model
joblib.dump(svr, 'SVR_model.joblib')
print("SVR model saved as SVR_model.joblib")

# Save Decision Tree model
joblib.dump(dt, 'DecisionTree_model.joblib')
print("Decision Tree model saved as DecisionTree_model.joblib")

# Save Random Forest model
joblib.dump(rf, 'RandomForest_model.joblib')
print("Random Forest model saved as RandomForest_model.joblib")
```

```
SVR model saved as SVR_model.joblib
Decision Tree model saved as DecisionTree_model.joblib
Random Forest model saved as RandomForest_model.joblib
```

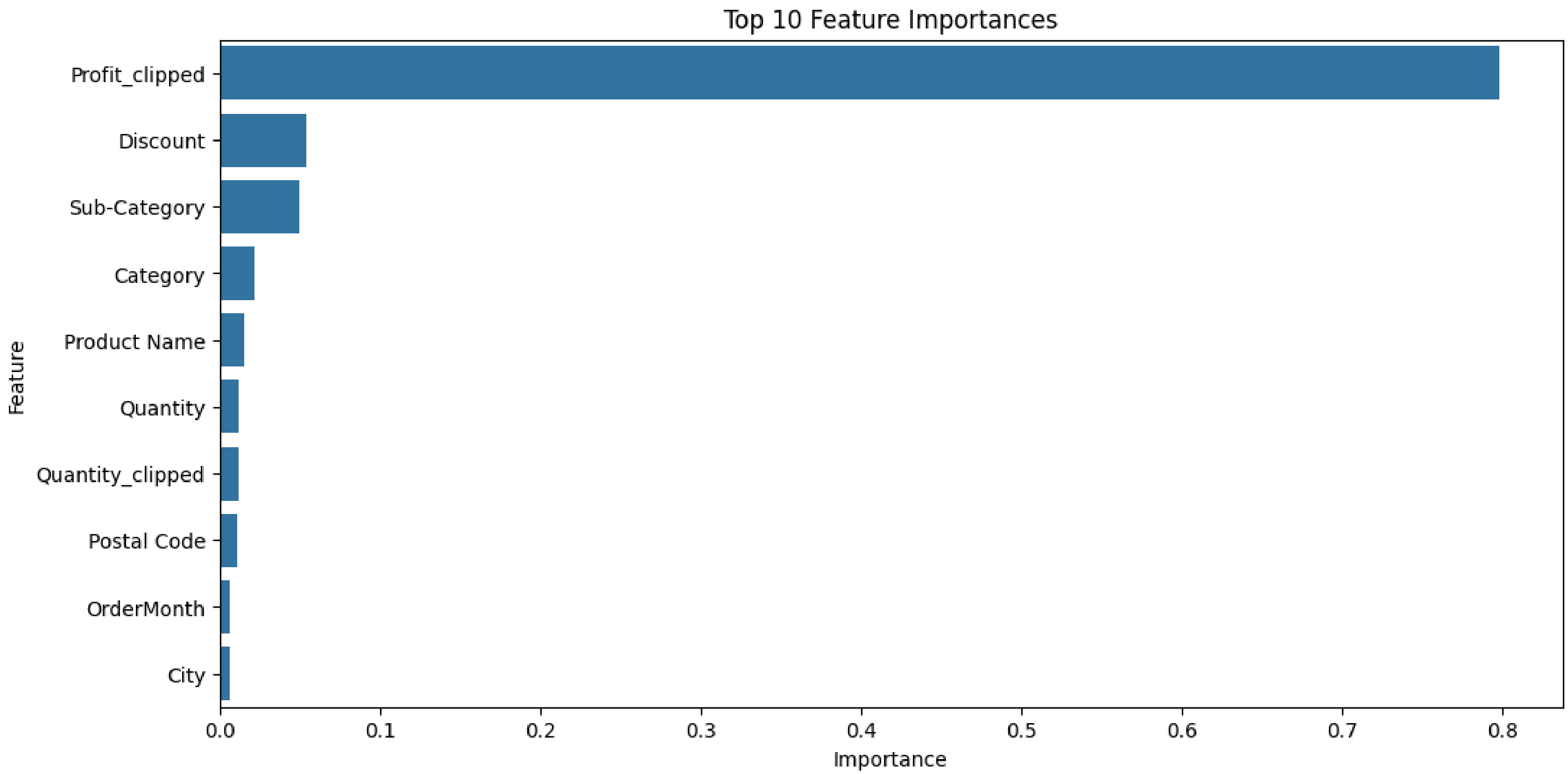
```
# Save LabelEncoder
joblib.dump(encoders, "label_encoders.joblib")
print("LabelEncoder saved as label_encoder.joblib")

# Save the StandardScaler used for scikit-learn models
joblib.dump(scaler, 'standard_scaler_sklearn.joblib')
print("StandardScaler (for scikit-learn models) saved as standard_scaler_sklearn.joblib")
```

```
LabelEncoder saved as label_encoder.joblib
StandardScaler (for scikit-learn models) saved as standard_scaler_sklearn.joblib
```

9. Random Forest Model Analysis

```
#  Feature Importance
```

```
importances = rf.feature_importances_
feature_names = X_train.columns
feat_imp = pd.Series(importances, index=feature_names).sort_values(ascending=False)

plt.figure(figsize=(12,6))
sns.barplot(x=feat_imp[:10], y=feat_imp.index[:10])
plt.title("Top 10 Feature Importances")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```



9.1. Partial Dependence Plots

```
# Top 5 Features
top_features = feat_imp.index[:5]

# Plot Partial Dependence
fig, ax = plt.subplots(figsize=(16,12))
display = PartialDependenceDisplay.from_estimator(
```

```
        rf,
        X_train,
        features=top_features,
        kind="average",
        grid_resolution=50,
        ax=ax
    )
    plt.suptitle("Partial Dependence Plots (Top 5 Features)", fontsize=16)
    plt.subplots_adjust(top=0.92)
    plt.show()
```

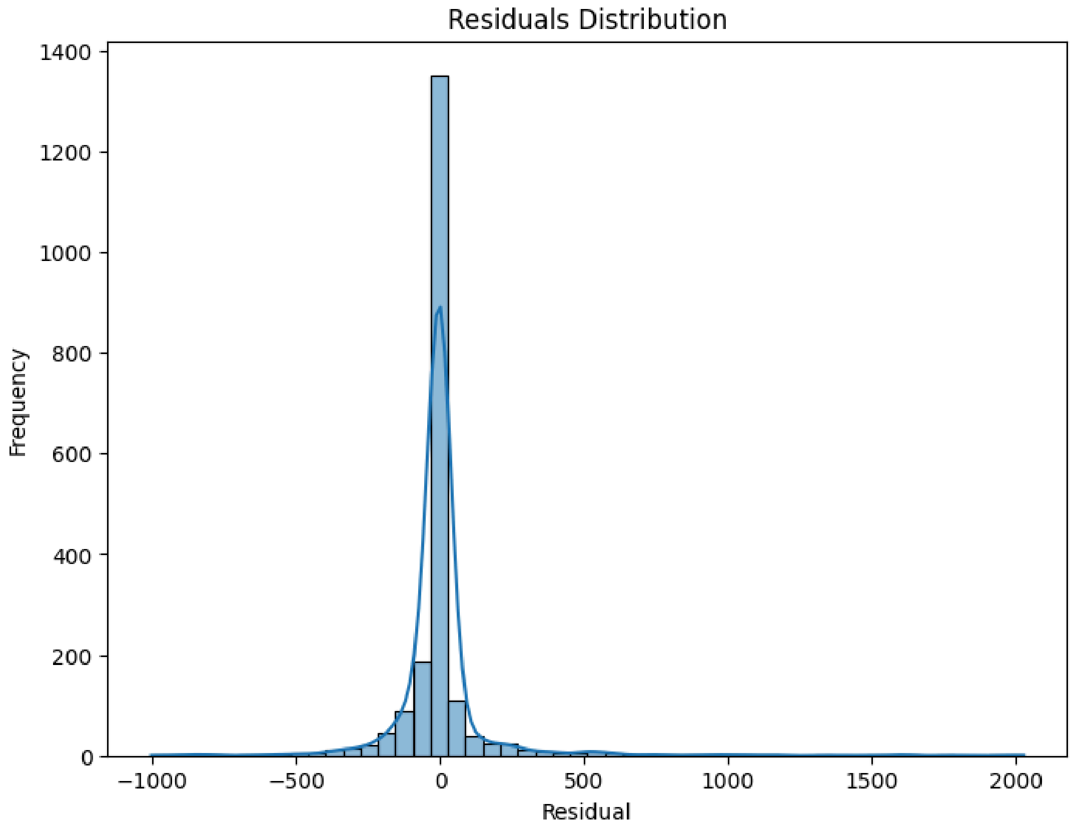
Partial Dependence Plots (Top 5 Features)

9.2. Random Forest Residual Analysis

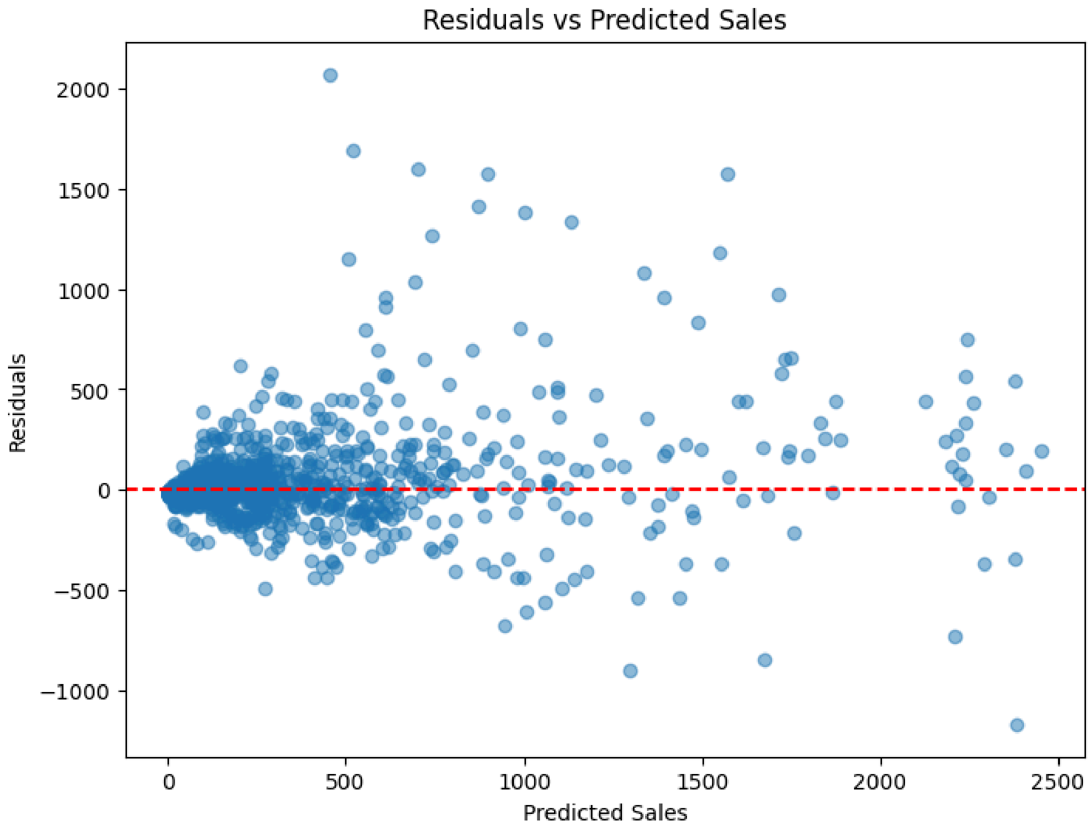
```
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred_rf, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.xlabel("Actual Sales")
plt.ylabel("Predicted Sales")
plt.title("Actual vs Predicted Sales")
plt.show()
```


```
residuals = y_test - y_pred_rf
plt.figure(figsize=(8,6))
sns.histplot(residuals, bins=50, kde=True)
plt.title("Residuals Distribution")
plt.xlabel("Residual")
plt.ylabel("Frequency")
```

```
plt.ylabel('Frequency')
plt.show()
```




```
plt.figure(figsize=(8,6))
plt.scatter(y_pred_rf, residuals, alpha=0.5)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel("Predicted Sales")
plt.ylabel("Residuals")
plt.title("Residuals vs Predicted Sales")
plt.show()
```



10. Neural Network Model (Keras)

```
kerasmodel = keras.models.Sequential([
    keras.layers.Input(shape=(16,)),
    keras.layers.Dense(64, activation='tanh'),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dropout(0.3),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dropout(0.1),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(1, activation='linear')
])
```

```
MyOptimizer = tf.keras.optimizers.AdamW(
    learning_rate=0.001,
    weight_decay=0.004,
    beta_1=0.9,
```

```
    beta_2=0.999,
    epsilon=1e-07,
    amsgrad=False,
    clipnorm=None,
    clipvalue=None,
    global_clipnorm=None,
    use_ema=False,
    ema_momentum=0.99,
    ema_overwrite_frequency=None,
    name="AdamW"
)
```

```
scaler_x = StandardScaler()
scaler_y = StandardScaler()

X_train_scaled = scaler_x.fit_transform(X_train)
X_test_scaled = scaler_x.transform(X_test)

y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1,1))
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1,1))
```

```
kerasmodel.compile(
    optimizer='adam',
    loss='mse',
    metrics=['mae', 'mse']
)

early_stop = EarlyStopping(
    monitor='val_loss',
    patience=10,
    mode='min',
    restore_best_weights=True
)


history = kerasmodel.fit(
    X_train_scaled, y_train_scaled,
    validation_data=(X_test_scaled, y_test_scaled),
    epochs=100,
    batch_size=64,
    verbose=1
)
```

```
Epoch 75/100
```

```
Epoch 75/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0912 - mae: 0.1645 - mse: 0.0912 - val_loss: 0.2420 - val_mae: 0.2017 - val_mse: 0.2420
Epoch 76/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0974 - mae: 0.1706 - mse: 0.0974 - val_loss: 0.2474 - val_mae: 0.2066 - val_mse: 0.2474
Epoch 77/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0986 - mae: 0.1710 - mse: 0.0986 - val_loss: 0.2307 - val_mae: 0.1932 - val_mse: 0.2307
Epoch 78/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0962 - mae: 0.1650 - mse: 0.0962 - val_loss: 0.2387 - val_mae: 0.2124 - val_mse: 0.2387
Epoch 79/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0891 - mae: 0.1691 - mse: 0.0891 - val_loss: 0.2536 - val_mae: 0.2040 - val_mse: 0.2536
Epoch 80/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0884 - mae: 0.1635 - mse: 0.0884 - val_loss: 0.2607 - val_mae: 0.2107 - val_mse: 0.2607
Epoch 81/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0936 - mae: 0.1679 - mse: 0.0936 - val_loss: 0.2364 - val_mae: 0.2035 - val_mse: 0.2364
Epoch 82/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.0840 - mae: 0.1617 - mse: 0.0840 - val_loss: 0.2523 - val_mae: 0.2136 - val_mse: 0.2523
Epoch 83/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - loss: 0.1007 - mae: 0.1740 - mse: 0.1007 - val_loss: 0.2493 - val_mae: 0.2064 - val_mse: 0.2493
Epoch 84/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0968 - mae: 0.1658 - mse: 0.0968 - val_loss: 0.2698 - val_mae: 0.2146 - val_mse: 0.2698
Epoch 85/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0833 - mae: 0.1623 - mse: 0.0833 - val_loss: 0.2629 - val_mae: 0.2060 - val_mse: 0.2629
Epoch 86/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0888 - mae: 0.1631 - mse: 0.0888 - val_loss: 0.2532 - val_mae: 0.2091 - val_mse: 0.2532
Epoch 87/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0996 - mae: 0.1690 - mse: 0.0996 - val_loss: 0.2404 - val_mae: 0.1985 - val_mse: 0.2404
Epoch 88/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0927 - mae: 0.1636 - mse: 0.0927 - val_loss: 0.2459 - val_mae: 0.2052 - val_mse: 0.2459
Epoch 89/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0862 - mae: 0.1626 - mse: 0.0862 - val_loss: 0.2412 - val_mae: 0.2016 - val_mse: 0.2412
Epoch 90/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0840 - mae: 0.1618 - mse: 0.0840 - val_loss: 0.2555 - val_mae: 0.2070 - val_mse: 0.2555
Epoch 91/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0840 - mae: 0.1576 - mse: 0.0840 - val_loss: 0.2798 - val_mae: 0.2177 - val_mse: 0.2798
Epoch 92/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0865 - mae: 0.1650 - mse: 0.0865 - val_loss: 0.2362 - val_mae: 0.1982 - val_mse: 0.2362
Epoch 93/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0819 - mae: 0.1573 - mse: 0.0819 - val_loss: 0.2379 - val_mae: 0.1963 - val_mse: 0.2379
Epoch 94/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0910 - mae: 0.1634 - mse: 0.0910 - val_loss: 0.2526 - val_mae: 0.2126 - val_mse: 0.2526
Epoch 95/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0981 - mae: 0.1664 - mse: 0.0981 - val_loss: 0.2320 - val_mae: 0.1985 - val_mse: 0.2320
Epoch 96/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 0.0772 - mae: 0.1556 - mse: 0.0772 - val_loss: 0.2622 - val_mae: 0.2042 - val_mse: 0.2622
Epoch 97/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0805 - mae: 0.1565 - mse: 0.0805 - val_loss: 0.2346 - val_mae: 0.2015 - val_mse: 0.2346
Epoch 98/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0820 - mae: 0.1581 - mse: 0.0820 - val_loss: 0.2601 - val_mae: 0.2087 - val_mse: 0.2601
Epoch 99/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.0767 - mae: 0.1556 - mse: 0.0767 - val_loss: 0.2336 - val_mae: 0.2015 - val_mse: 0.2336
Epoch 100/100
125/125 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0791 - mae: 0.1575 - mse: 0.0791 - val_loss: 0.2179 - val_mae: 0.1977 - val_mse: 0.2179
```

```
print(kerasmodel.summary())
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	1,088
dense_1 (Dense)	(None, 128)	8,320
dropout (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8,256
dropout_1 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 32)	2,080
dense_4 (Dense)	(None, 1)	33

Total params: 59,333 (231.77 KB)
Trainable params: 19,777 (77.25 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 39,556 (154.52 KB)

```
kerasmodel.save("KerasModel.keras")

# Save the StandardScaler for X (Keras model)
joblib.dump(scaler_x, 'standard_scaler_X_keras.joblib')
print("StandardScaler (for Keras X) saved as standard_scaler_X_keras.joblib")

# Save the StandardScaler for y (Keras model)
joblib.dump(scaler_y, 'standard_scaler_y_keras.joblib')
print("StandardScaler (for Keras y) saved as standard_scaler_y_keras.joblib")
```

```
StandardScaler (for Keras X) saved as standard_scaler_X_keras.joblib
StandardScaler (for Keras y) saved as standard_scaler_y_keras.joblib
```

```
y_pred_scaled = kerasmodel.predict(X_test_scaled)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
```

```
NewKerasModel = keras.models.load_model('KerasModel.keras')
```

```
y_pred_scaled = NewKerasModel.predict(X_test_scaled)
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
```

```
print('Prediction Shape is {}'.format(y_pred_scaled.shape))
```

```
Prediction Shape is (1999, 1)
```

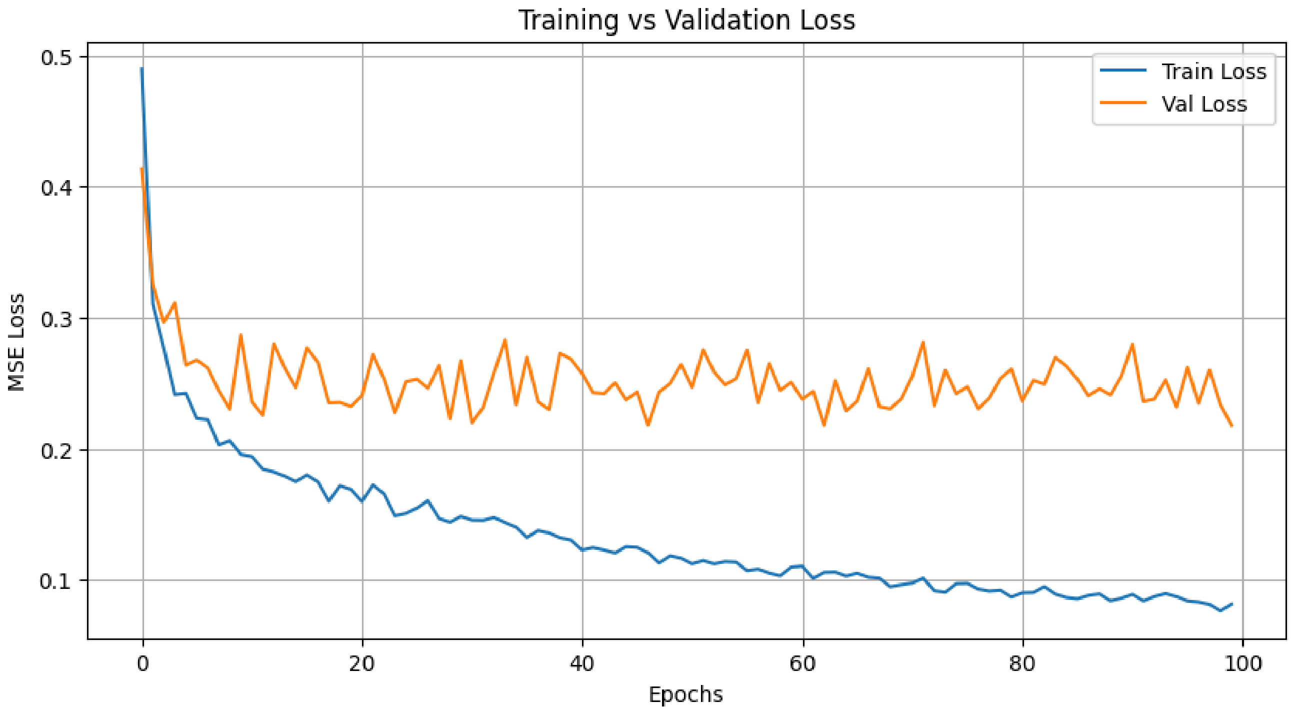
```
print('Prediction items are {}'.format(y_pred[:5]))
```

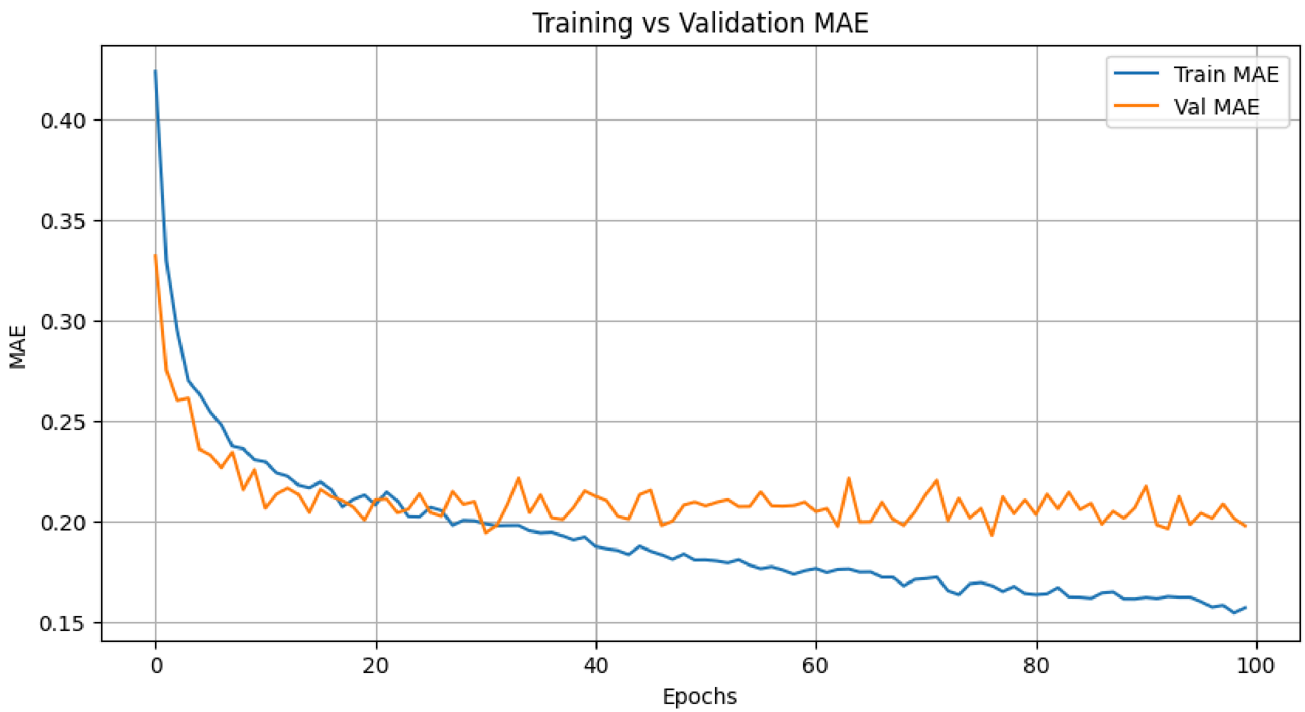
```
Prediction items are [[ 98.35385 ]
 [ 25.387032]
 [ 26.733635]
 [470.91507 ]
 [296.91318 ]]
```

```
ModelLoss = NewKerasModel.evaluate(X_test_scaled, y_test_scaled)
print('Model Loss is {}'.format(ModelLoss))
```

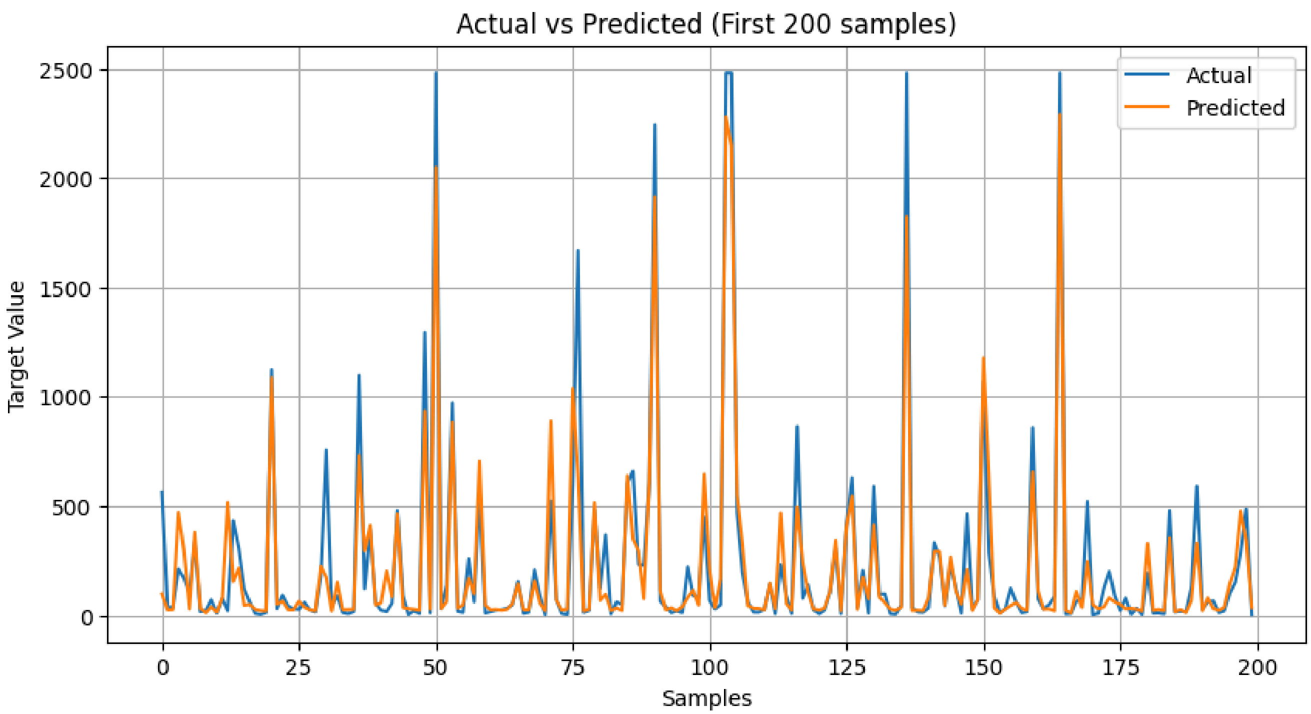
```
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - loss: 0.2384 - mae: 0.2072 - mse: 0.2384
Model Loss is [0.2179267257452011, 0.19773264229297638, 0.2179267257452011]
```

```
# --- Plot Training vs Validation Loss ---
plt.figure(figsize=(10,5))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.legend()
plt.grid(True)
plt.show()

# --- Plot Training vs Validation MAE ---
plt.figure(figsize=(10,5))
plt.plot(history.history['mae'], label='Train MAE')
plt.plot(history.history['val_mae'], label='Val MAE')
plt.title('Training vs Validation MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.grid(True)
plt.show()
```


Training vs Validation Loss
Train Loss
Val Loss
MSE Loss
0.5
0.4
0.3
0.2
0.1
0
20
40
60
80
100
Epochs

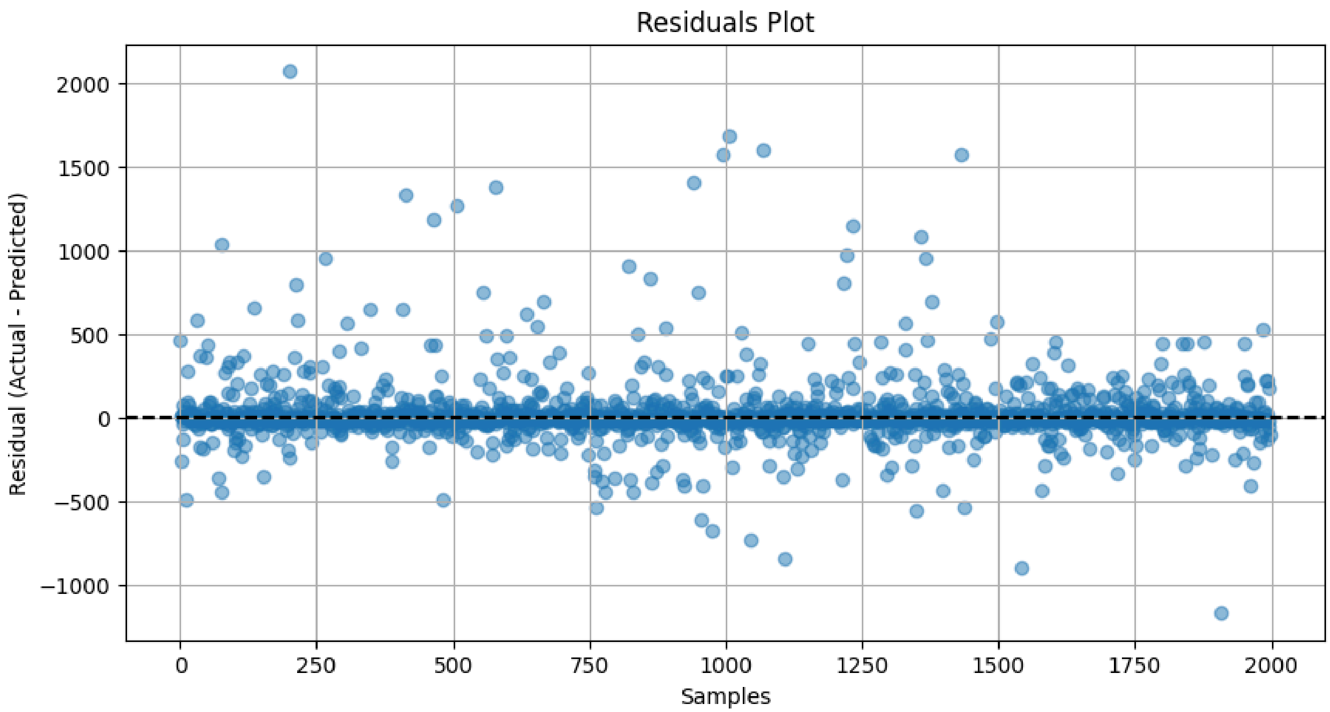

Training vs Validation MAE
Train MAE
Val MAE
MAE
0.40
0.35
0.30
0.25
0.20
0.15
0
20
40
60
80
100
Epochs

```
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_test_original = scaler_y.inverse_transform(y_test_scaled)

plt.figure(figsize=(10,5))
plt.plot(y_test_original[:200], label='Actual')
plt.plot(y_pred[:200], label='Predicted')
plt.title("Actual vs Predicted (First 200 samples)")
plt.xlabel("Samples")
plt.ylabel("Target Value")
plt.legend()
plt.grid(True)
plt.show()
```

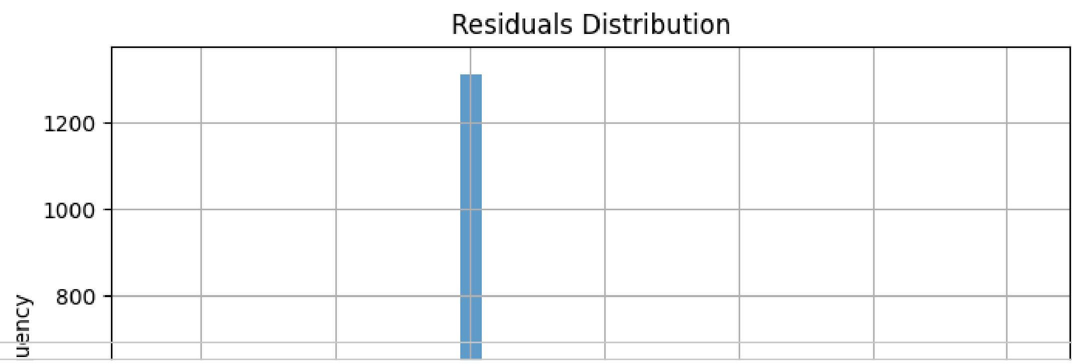



```
residuals = y_test_original - y_pred

plt.figure(figsize=(10,5))
plt.scatter(range(len(residuals)), residuals, alpha=0.5)
plt.axhline(0, color='black', linestyle='--')
plt.title("Residuals Plot")
plt.xlabel("Samples")
plt.ylabel("Residual (Actual - Predicted)")
```

```
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(8,5))
plt.hist(residuals, bins=40, alpha=0.7)
plt.title("Residuals Distribution")
plt.xlabel("Residual Value")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```




```
y_pred_scaled = kerasmodel.predict(X_test_scaled)
y_pred = scaler_y.inverse_transform(y_pred_scaled)
y_test_original = scaler_y.inverse_transform(y_test_scaled)
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

```
mae_nn = mean_absolute_error(y_test_original, y_pred)
mse_nn = mean_squared_error(y_test_original, y_pred)
rmse_nn = mse_rf ** 0.5
r2_nn = r2_score(y_test_original, y_pred)

print("Neural Network Evaluation:")
print("------------------------------------------------")
print("MAE :", mae_nn)
print("MSE :", mse_nn)
print("RMSE:", rmse_nn)
print("R²  :", r2_nn)
```

```
Neural Network Evaluation:
------------------------------------------------
MAE : 76.53025399058163
MSE : 32645.24775081094
RMSE: 176.289552663217
R²  : 0.8186338920643946
```

Hyperparameter Tuning:

Experiment with Learning Rate and Batch Size

```
def create_and_compile_model(learning_rate):
    model = keras.models.Sequential([
        keras.layers.Input(shape=(16,)),
```

```
        keras.layers.Dense(64, activation='tanh'),
        keras.layers.Dense(128, activation='relu'),
        keras.layers.Dropout(0.3),
        keras.layers.Dense(64, activation='relu'),
        keras.layers.Dropout(0.1),
        keras.layers.Dense(32, activation='relu'),
        keras.layers.Dense(1, activation='linear')
    ])

    optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)
    model.compile(
        optimizer=optimizer,
        loss='mse',
        metrics=['mae', 'mse']
    )
    return model

print("Defined create_and_compile_model function.")
```

```
Defined create_and_compile_model function.
```

```
learning_rates = [0.01, 0.001, 0.0001]
batch_sizes = [32, 64, 128]
epochs = 50

results = []

for lr in learning_rates:
    for bs in batch_sizes:
        print(f"\nTraining with Learning Rate: {lr}, Batch Size: {bs}")
        model = create_and_compile_model(learning_rate=lr)

        history = model.fit(
            X_train_scaled, y_train_scaled,
            validation_data=(X_test_scaled, y_test_scaled),
            epochs=epochs,
            batch_size=bs,
            verbose=0
        )

        # Evaluate the model
        y_pred_scaled_exp = model.predict(X_test_scaled)
        y_pred_exp = scaler_y.inverse_transform(y_pred_scaled_exp)
        y_test_original_exp = scaler_y.inverse_transform(y_test_scaled)

        mae_exp = mean_absolute_error(y_test_original_exp, y_pred_exp)
        mse_exp = mean_squared_error(y_test_original_exp, y_pred_exp)
        rmse_exp = mse_exp ** 0.5
        r2_exp = r2_score(y_test_original_exp, y_pred_exp)
```

```
        results.append({
            'optimizer': 'Adam',
            'learning_rate': lr,
            'batch_size': bs,
            'mae': mae_exp,
            'mse': mse_exp,
            'rmse': rmse_exp,
            'r2': r2_exp,
            'history': history.history
        })

        print(f"  MAE: {mae_exp:.4f}, MSE: {mse_exp:.4f}, R2: {r2_exp:.4f}")

print("\nExperimentation complete. Results stored.")
```

```
Training with Learning Rate: 0.01, Batch Size: 32
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
  MAE: 135.9199, MSE: 57128.4323, R2: 0.6826

Training with Learning Rate: 0.01, Batch Size: 64
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 111.3315, MSE: 51123.6975, R2: 0.7160

Training with Learning Rate: 0.01, Batch Size: 128
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 88.1997, MSE: 42750.5519, R2: 0.7625

Training with Learning Rate: 0.001, Batch Size: 32
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step
  MAE: 84.9429, MSE: 36150.7856, R2: 0.7992

Training with Learning Rate: 0.001, Batch Size: 64
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 75.0818, MSE: 33309.9928, R2: 0.8149

Training with Learning Rate: 0.001, Batch Size: 128
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 72.9170, MSE: 32925.7470, R2: 0.8171

Training with Learning Rate: 0.0001, Batch Size: 32
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 85.3650, MSE: 36826.2580, R2: 0.7954

Training with Learning Rate: 0.0001, Batch Size: 64
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
  MAE: 83.0086, MSE: 36822.5719, R2: 0.7954

Training with Learning Rate: 0.0001, Batch Size: 128
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
  MAE: 92.4923, MSE: 39212.0516, R2: 0.7822

Experimentation complete. Results stored.
```

```
print("\n--- Experiment Results ---")
for res in results:
    print(f"Learning Rate: {res['learning_rate']}, Batch Size: {res['batch_size']}")
    print(f"  MAE: {res['mae']:.4f}")
    print(f"  MSE: {res['mse']:.4f}")
    print(f"  RMSE: {res['rmse']:.4f}")
    print(f"  R2: {res['r2']:.4f}")
    print("------------------------------------")
```

```
--- Experiment Results ---
Learning Rate: 0.01, Batch Size: 32
  MAE: 102.6197
  MSE: 48909.6911
  RMSE: 221.1554
  R2: 0.7283
-------------------------------------
Learning Rate: 0.01, Batch Size: 64
  MAE: 89.3748
  MSE: 39402.5446
  RMSE: 198.5007
  R2: 0.7811
-------------------------------------
Learning Rate: 0.01, Batch Size: 128
  MAE: 100.0023
  MSE: 44490.8832
  RMSE: 210.9286
  R2: 0.7528
-------------------------------------
Learning Rate: 0.001, Batch Size: 32
  MAE: 76.9474
  MSE: 34480.3880
  RMSE: 185.6890
  R2: 0.8084
-------------------------------------
Learning Rate: 0.001, Batch Size: 64
  MAE: 79.7325
  MSE: 38531.9798
  RMSE: 196.2956
  R2: 0.7859
-------------------------------------
Learning Rate: 0.001, Batch Size: 128
  MAE: 75.6608
  MSE: 32865.7719
  RMSE: 181.2892
  R2: 0.8174
-------------------------------------
Learning Rate: 0.0001, Batch Size: 32
  MAE: 80.1344
  MSE: 35087.2408
  RMSE: 187.3159
  R2: 0.8051
-------------------------------------
```