Coffee Shop Daily Revenue Prediction

```
# importing required
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Data Exploration

```
# loading the dataframe
df = pd.read_csv("Coffee Sales Project/coffee_shop_revenue.csv")

# quick overview of data
df.head(5)
```

```
   Number_of_Customers_Per_Day  Average_Order_Value  
Operating_Hours_Per_Day  \
0                          152                 6.74                     
14   
1                          485                 4.50                     
12   
2                          398                 9.09                     
6   
3                          320                 8.48                     
17   
4                          156                 7.44                     
17   

   Number_of_Employees  Marketing_Spend_Per_Day  Location_Foot_Traffic 
\
0                    4                   106.62                     97 

1                    8                    57.83                    744 

2                    6                    91.76                    636 

3                    4                   462.63                    770 

4                    2                   412.52                    232 


   Daily_Revenue  
0        1547.81  
1        2084.68  
2        3118.39  
3        2912.20  
4        1663.42  
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Number_of_Customers_Per_Day  2000 non-null   int64  
 1   Average_Order_Value          2000 non-null   float64
 2   Operating_Hours_Per_Day      2000 non-null   int64  
 3   Number_of_Employees          2000 non-null   int64  
 4   Marketing_Spend_Per_Day      2000 non-null   float64
 5   Location_Foot_Traffic        2000 non-null   int64  
 6   Daily_Revenue                2000 non-null   float64
dtypes: float64(3), int64(4)
memory usage: 109.5 KB
```

```
df.describe()
```

```
       Number_of_Customers_Per_Day  Average_Order_Value  \
count                  2000.000000          2000.000000   
mean                    274.296000             6.261215   
std                     129.441933             2.175832   
min                      50.000000             2.500000   
25%                     164.000000             4.410000   
50%                     275.000000             6.300000   
75%                     386.000000             8.120000   
max                     499.000000            10.000000   

       Operating_Hours_Per_Day  Number_of_Employees  
Marketing_Spend_Per_Day  \
count              2000.000000          2000.000000  
2000.000000   
mean                 11.667000             7.947000  
252.614160   
std                   3.438608             3.742218  
141.136004   
min                   6.000000             2.000000  
10.120000   
25%                   9.000000             5.000000  
130.125000   
50%                  12.000000             8.000000  
250.995000   
75%                  15.000000            11.000000  
375.352500   
max                  17.000000            14.000000  
499.740000   

       Location_Foot_Traffic  Daily_Revenue  
count            2000.000000    2000.000000  
```

```
mean                  534.893500    1917.325940
std                   271.662295     976.202746
min                    50.000000     -58.950000
25%                   302.000000    1140.085000
50%                   540.000000    1770.775000
75%                   767.000000    2530.455000
max                   999.000000    5114.600000

df.shape

(2000, 7)
```

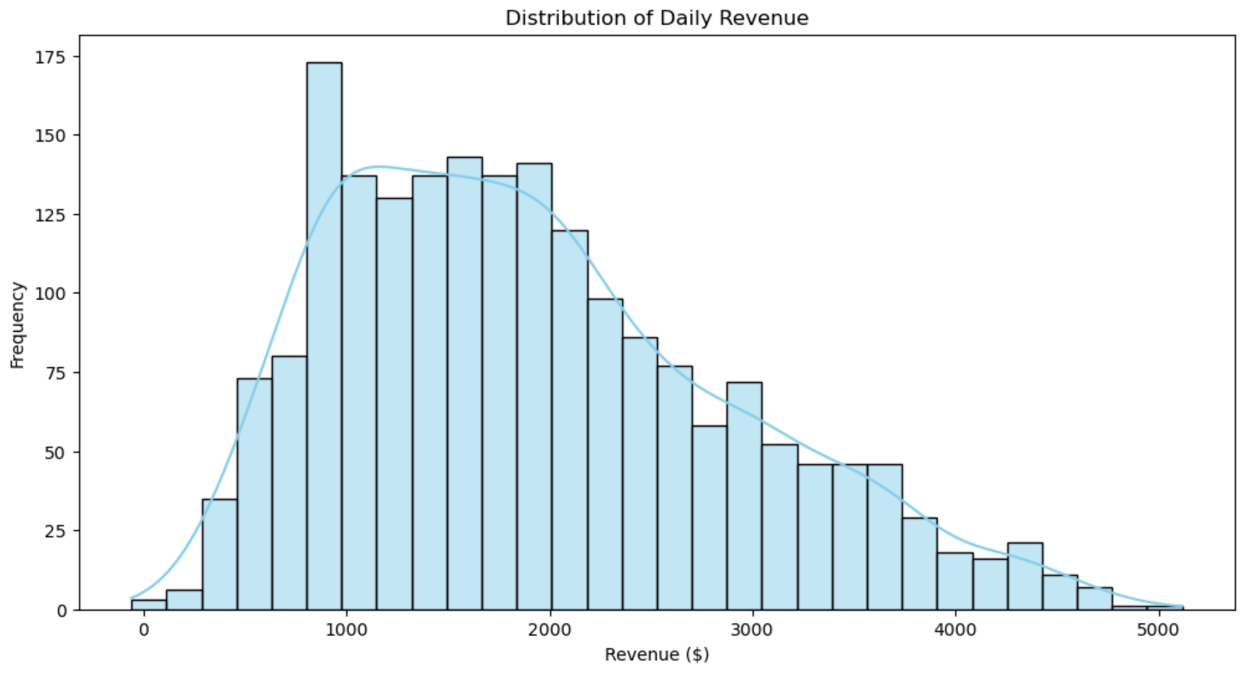
- Number of Customers Per Day: Total daily customer visits to the coffee shop (50 - 500)
- Average Order Value: Average amount spent per customer per visit (2.50 - 10.00),000).
- Operating Hours Per Day: Total hours the coffee shop operates each day (6 - 18 hours)
- Number of Employees: Number of employees working on a given day (2 - 15)
- Marketing Spend Per Day: Daily expenditure on marketing and promotions (10 - 500)
- Location Foot Traffic (people/hour): Number of people passing by the shop per hour (50 - 1000)
- Daily Revenue [Target Variable]: Total revenue generated per day (200 - 10,000).

Data Cleaning and Preprocessing

```
# checking null values
df.isnull().sum()

Number_of_Customers_Per_Day    0
Average_Order_Value            0
Operating_Hours_Per_Day        0
Number_of_Employees            0
Marketing_Spend_Per_Day        0
Location_Foot_Traffic          0
Daily_Revenue                  0
dtype: int64

# checkinig duplicate values
df.duplicated().sum()

0
```

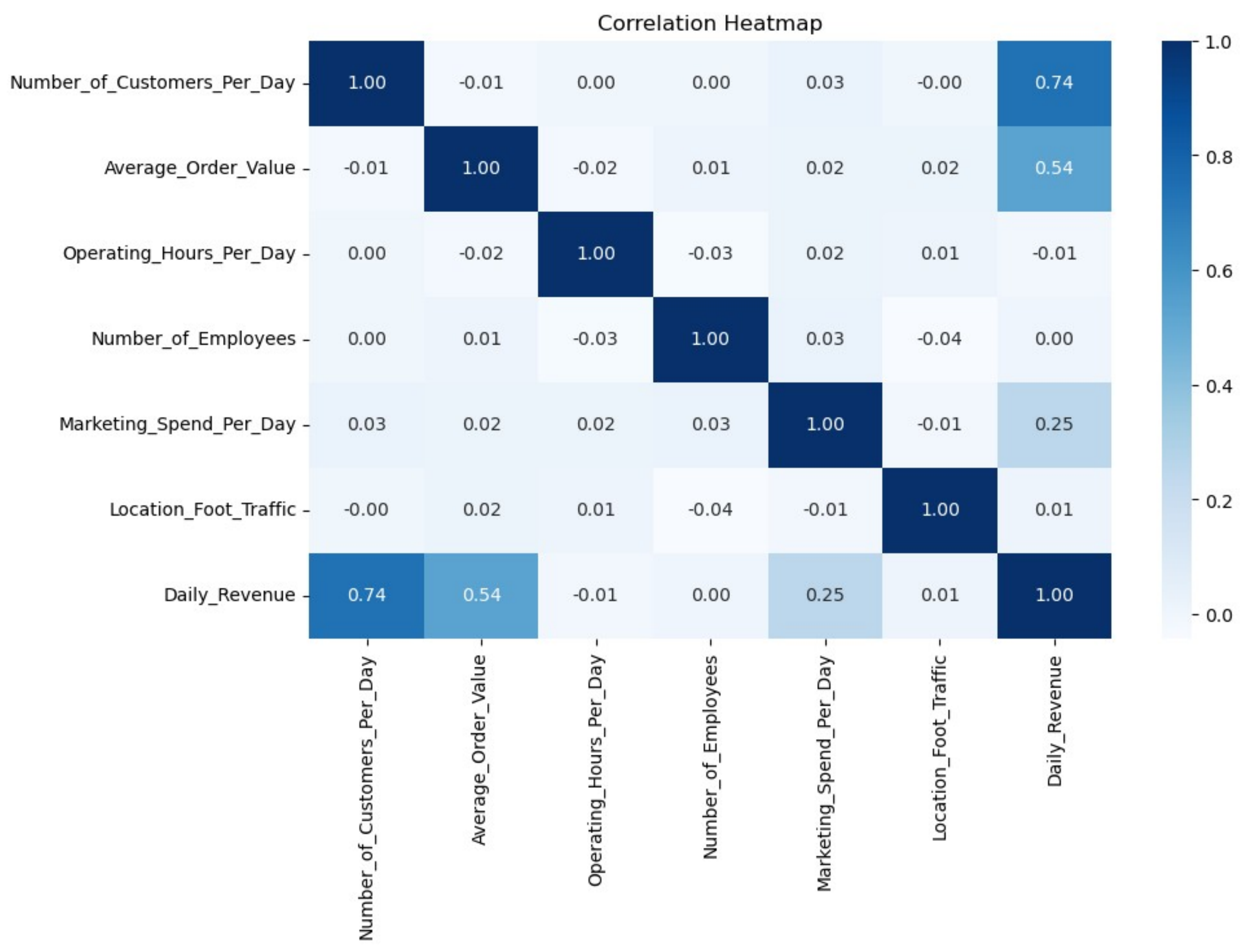
Exploratory Data Analysis (EDA)

```
# Plot daily revenue over time to see patterns
plt.figure(figsize=(12, 6))
sns.histplot(df['Daily_Revenue'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Daily Revenue')
plt.xlabel('Revenue ($)')
plt.ylabel('Frequency')
plt.show()
```



- The distribution is not perfectly normal but skewed to the right.
- Most of the daily revenues are between 500 and 3000, peaking around 1000 to 1500.
- A few days have very high revenue (~5000), which might indicate special events, promotions, or peak seasons. (outliers).
- As revenue increases beyond 3000, the frequency of occurrence decreases.

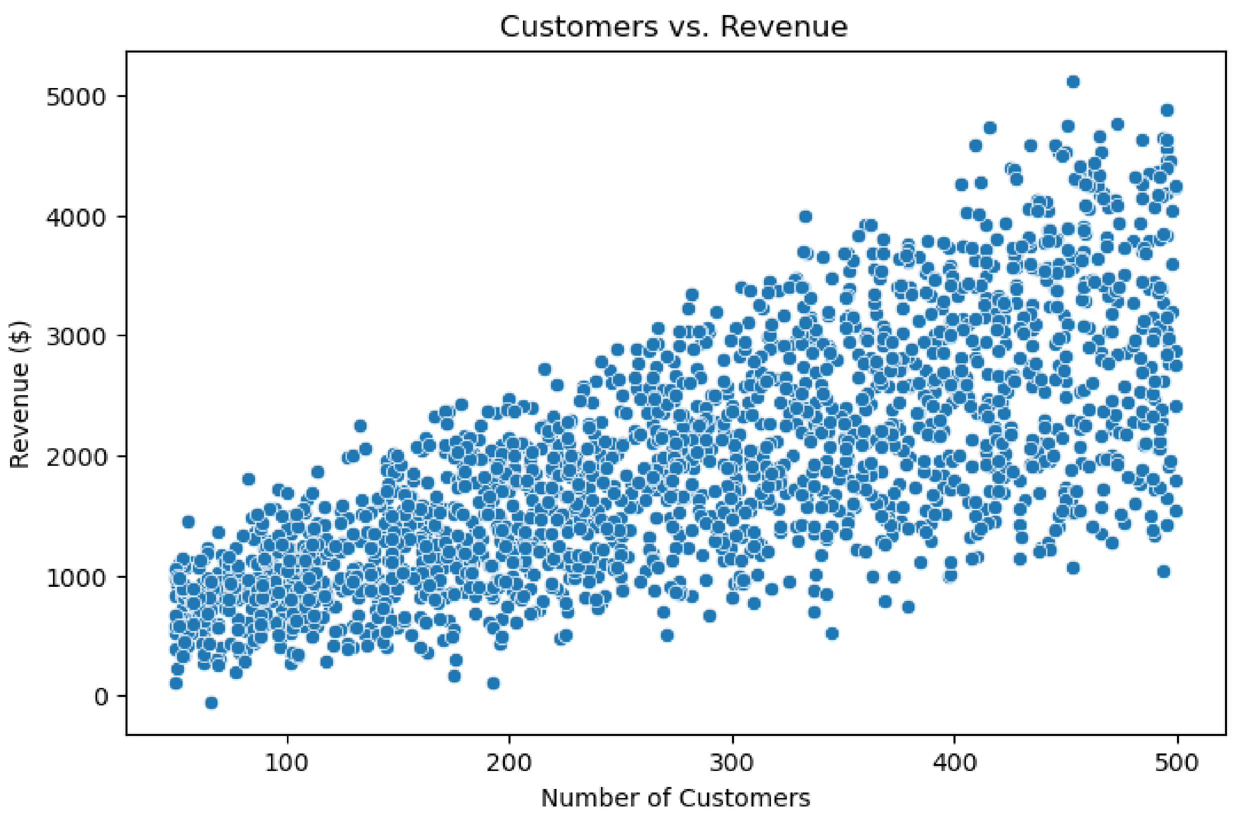
```
# Find relationships between numerical variables.
plt.figure(figsize=(10, 6))
sns.heatmap(df.corr(), annot=True, cmap='Blues', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



	Number_of_Customers_Per_Day	Average_Order_Value	Operating_Hours_Per_Day	Number_of_Employees	Marketing_Spend_Per_Day	Location_Foot_Traffic	Daily_Revenue
Number_of_Customers_Per_Day	1.00	-0.01	0.00	0.00	0.03	-0.00	0.74
Average_Order_Value	-0.01	1.00	-0.02	0.01	0.02	0.02	0.54
Operating_Hours_Per_Day	0.00	-0.02	1.00	-0.03	0.02	0.01	-0.01
Number_of_Employees	0.00	0.01	-0.03	1.00	0.03	-0.04	0.00
Marketing_Spend_Per_Day	0.03	0.02	0.02	0.03	1.00	-0.01	0.25
Location_Foot_Traffic	-0.00	0.02	0.01	-0.04	-0.01	1.00	0.01
Daily_Revenue	0.74	0.54	-0.01	0.00	0.25	0.01	1.00

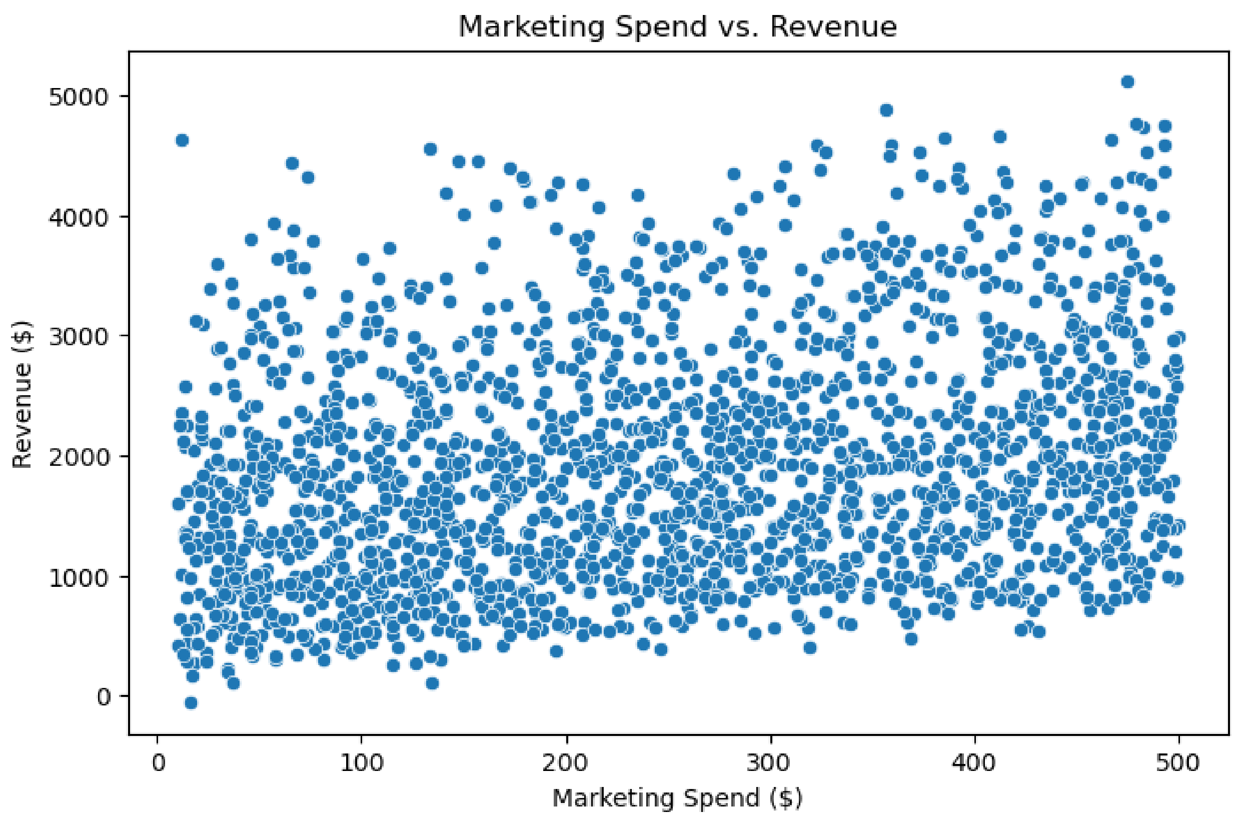
- Key Revenue Drivers – The number of customers per day (0.74) and average order value (0.54) have the highest positive correlations with daily revenue.
- Low Impact Factors – Operating hours, number of employees, and location foot traffic show minimal correlation with revenue, suggesting they don't directly influence sales.
- Marketing Influence – Marketing spend has a weak correlation (0.25) with revenue, indicating its effectiveness may depend on other factors like timing and campaign quality.

```
# Customers vs. Revenue
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df["Number_of_Customers_Per_Day"],
y=df["Daily_Revenue"])
plt.title("Customers vs. Revenue")
plt.xlabel("Number of Customers")
plt.ylabel("Revenue ($)")
plt.show()
```



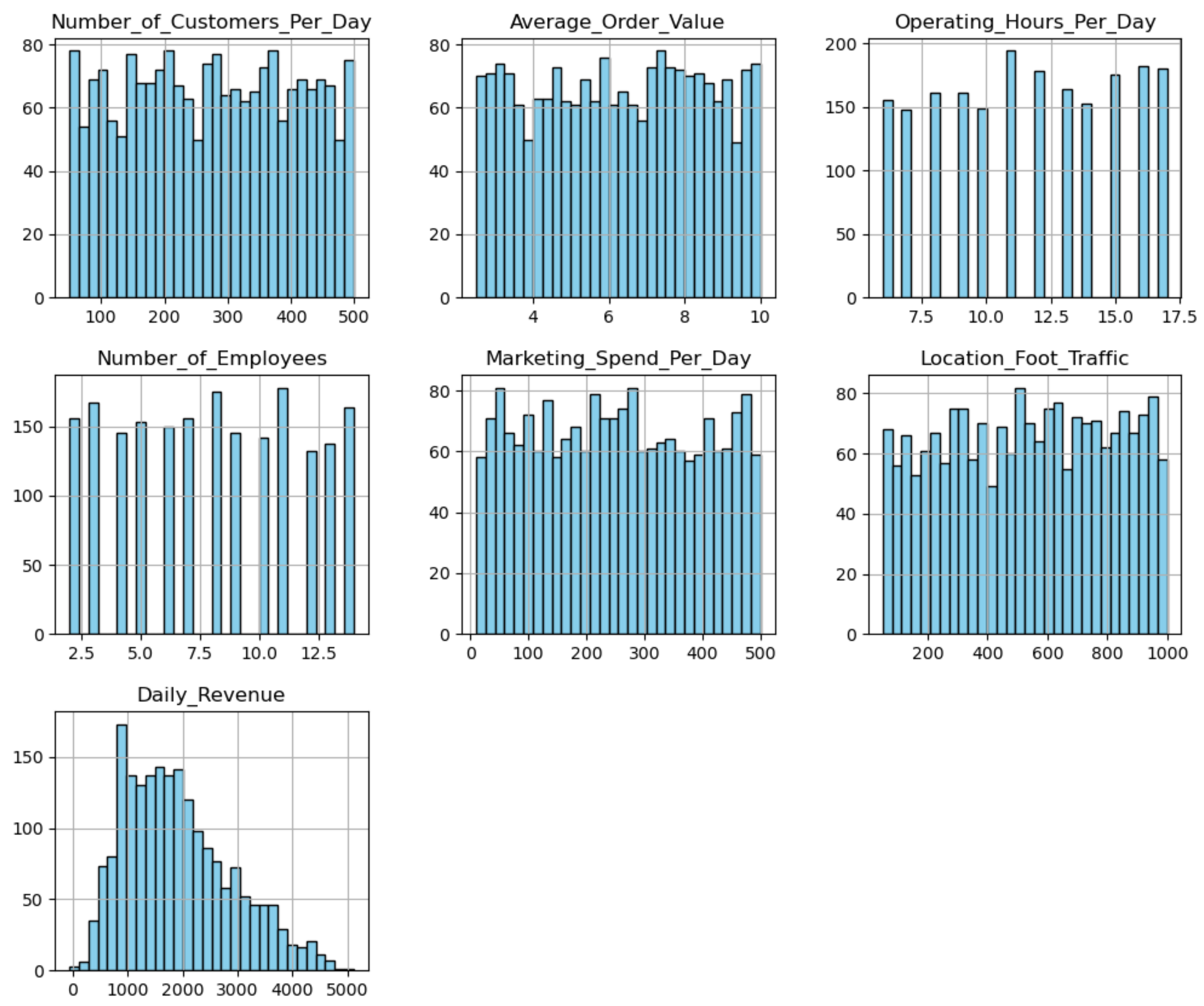
- Positive Correlation – More customers lead to higher revenue, showing a strong relationship.
- Revenue Variability – Revenue fluctuates at higher customer counts, likely due to spending differences.
- Outliers & Insights – Some days deviate from the trend, requiring analysis of promotions, pricing, or operations.

```
# Marketing Spend vs. Revenue
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df["Marketing_Spend_Per_Day"],
y=df["Daily_Revenue"])
plt.title("Marketing Spend vs. Revenue")
plt.xlabel("Marketing Spend ($)")
plt.ylabel("Revenue ($)")
plt.show()
```



- Positive trend but high variance: Revenue generally increases with marketing spend, but data points are widely scattered, meaning higher spend doesn't always guarantee higher revenue.
- Diminishing returns: Beyond 300 in marketing spend, revenue growth appears inconsistent, suggesting that additional spending may not always yield proportional revenue gains.
- High-revenue outliers: Some points show revenue exceeding 4000 even with lower marketing spend (~100-200), indicating that factors beyond marketing influence revenue.

```
# Check how features are distributed to identify patterns.
df.hist(figsize=(12, 10), bins=30,color='skyblue', edgecolor="black")
plt.show()
```



- Number of Customers Per Day: The distribution is relatively uniform, with most days seeing between 100 to 500 customers, indicating steady foot traffic.
- Average Order Value: Most orders fall between 4 to 10, suggesting a consistent spending pattern among customers.
- Operating Hours Per Day: The business operates mostly between 7 to 17 hours, with little variation, meaning extended hours may not significantly impact revenue.
- Number of Employees: Employee count ranges from 3 to 13, with frequent peaks, suggesting optimized staffing based on demand.
- Marketing Spend Per Day: Spending is spread across 0 to 500, but there's a slight concentration towards higher spending, indicating aggressive marketing.
- Location Foot Traffic: The foot traffic varies between 200 to 1000, showing a wide range of customer influx depending on external factors.
- Daily Revenue: Revenue is right-skewed, with most values between 500 to 3000, meaning occasional high-earning days significantly impact overall revenue.

□ Next step: Moving towards predictive modeling for revenue forecasting! □

Data Preprocessing

```
# Since revenue is right-skewed, use the IQR method to remove extreme
outliers:
Q1 = df['Daily_Revenue'].quantile(0.25)
Q3 = df['Daily_Revenue'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

df = df[(df['Daily_Revenue'] >= lower_bound) & (df['Daily_Revenue'] <=
upper_bound)]
```

Feature Selection (Choosing the Right Inputs for the Model)

- **Based on EDA:**
- *Number of Customers Per Day (Strongest Correlation: 0.74)*
- *Average Order Value (0.54 correlation)*
- *Marketing Spend (0.25 correlation,Weak, but might contribute)*

```
X = df[['Number_of_Customers_Per_Day', 'Average_Order_Value',
'Marketing_Spend_Per_Day']]
y = df['Daily_Revenue']

X.head(5)

   Number_of_Customers_Per_Day  Average_Order_Value
Marketing_Spend_Per_Day
0                          152                 6.74
106.62
1                          485                 4.50
57.83
2                          398                 9.09
91.76
3                          320                 8.48
462.63
4                          156                 7.44
412.52

y.head(5)

0    1547.81
1    2084.68
2    3118.39
3    2912.20
4    1663.42
Name: Daily_Revenue, dtype: float64
```

Train-Test Split & Model Training

```
#Train-Test Split
# importing the train_test_split from sklearn
from sklearn.model_selection import train_test_split

# Split data: 80% train, 20% test
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Check shapes of new datasets
print("Training Data:", X_train.shape, y_train.shape)
print("Testing Data:", X_test.shape, y_test.shape)
```

```
Training Data: (1592, 3) (1592,)
Testing Data: (399, 3) (399,)
```

```
# linear regression: revenue continuous numeric valueabsfrom
sklearn.linear_model import LinearRegression
from sklearn.linear_model import LinearRegression
# Initialize Model
model = LinearRegression()

# Train Model
model.fit(X_train, y_train)

# Make Predictions on Test Data
y_pred = model.predict(X_test)

# Check Model Accuracy (R² Score & RMSE)
from sklearn.metrics import r2_score, mean_squared_error

# Calculate R² Score
r2 = r2_score(y_test, y_pred)

# Calculate RMSE
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f"R² Score: {r2:.2f}")
print(f"RMSE: {rmse:.2f}")
```

```
R² Score: 0.90
RMSE: 309.28
```

```
mean = df['Daily_Revenue'].mean() #checking the mean
mean
```

```
1904.4886539427423
```

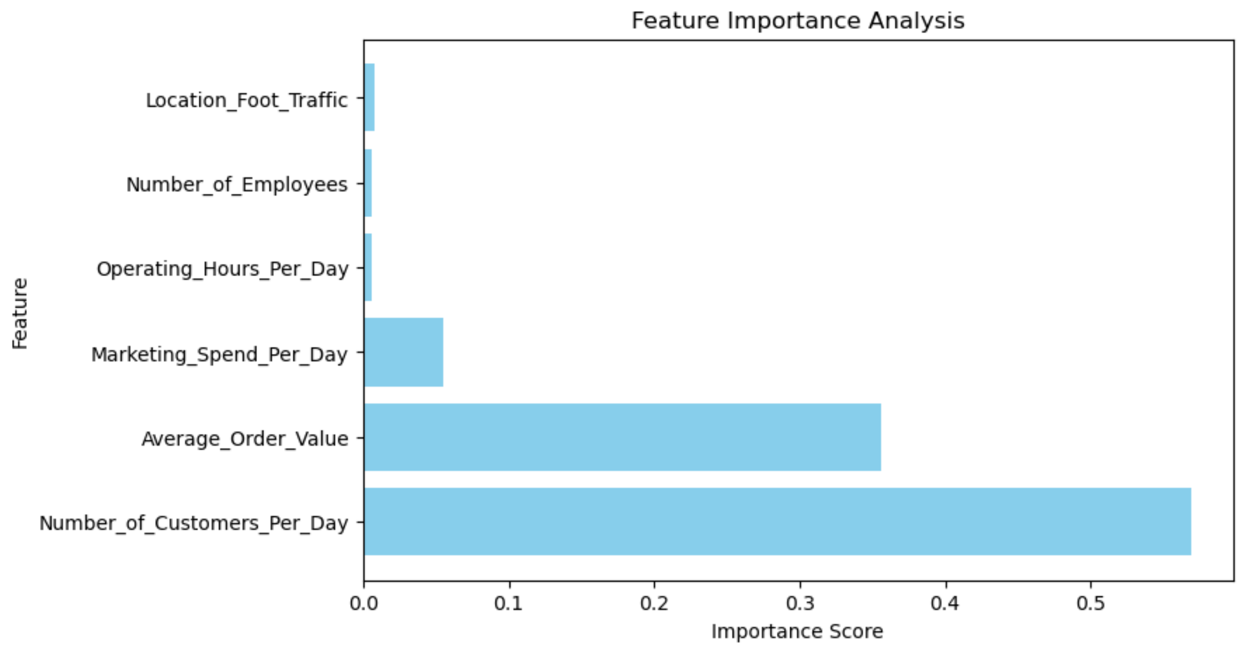
Checking RMSE Accuracy with Mean Revenue

```
Percentage_Error = (rmse/mean) *100
print(f'Percentage Error:{Percentage_Error:.2f}%')
```

```
Percentage Error:16.24%
```

Check Feature Importance

```
from sklearn.ensemble import RandomForestRegressor

# Load data
X = df[['Number_of_Customers_Per_Day', 'Average_Order_Value',
'Marketing_Spend_Per_Day', 'Operating_Hours_Per_Day',
'Number_of_Employees', 'Location_Foot_Traffic']]
y = df['Daily_Revenue']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train Random Forest Regressor (better for feature importance
analysis)
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Get feature importance
importance = model.feature_importances_

# Plot feature importance
plt.figure(figsize=(8,5))
plt.barh(X.columns, importance, color='skyblue')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.title('Feature Importance Analysis')
plt.show()
```



```
pd.DataFrame({'Feature': X.columns, 'Importance':
model.feature_importances_})

                       Feature  Importance
0  Number_of_Customers_Per_Day    0.569522
1          Average_Order_Value    0.356280
2      Marketing_Spend_Per_Day    0.054862
3      Operating_Hours_Per_Day    0.005623
4          Number_of_Employees    0.005613
5        Location_Foot_Traffic    0.008100

# Implement Ridge Regression
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV

# Keep only the most important features
X_selected = df[['Number_of_Customers_Per_Day', 'Average_Order_Value',
'Marketing_Spend_Per_Day']]
y = df['Daily_Revenue']
# Define hyperparameters to tune
ridge_params = {'alpha': [0.01, 0.1, 1, 10, 100]}

# Train Ridge Regression with cross-validation
ridge = Ridge()
ridge_cv = GridSearchCV(ridge, ridge_params, scoring='r2', cv=5)
ridge_cv.fit(X_train, y_train)

# Best model
best_ridge = ridge_cv.best_estimator_
y_pred_ridge = best_ridge.predict(X_test)
```

```
# Evaluate Performance
r2_ridge = r2_score(y_test, y_pred_ridge)
rmse_ridge = np.sqrt(mean_squared_error(y_test, y_pred_ridge))

print(f"Best Alpha: {ridge_cv.best_params_['alpha']}")
print(f"R² Score (Ridge): {r2_ridge:.2f}")
print(f"RMSE (Ridge): {rmse_ridge:.2f}")
```

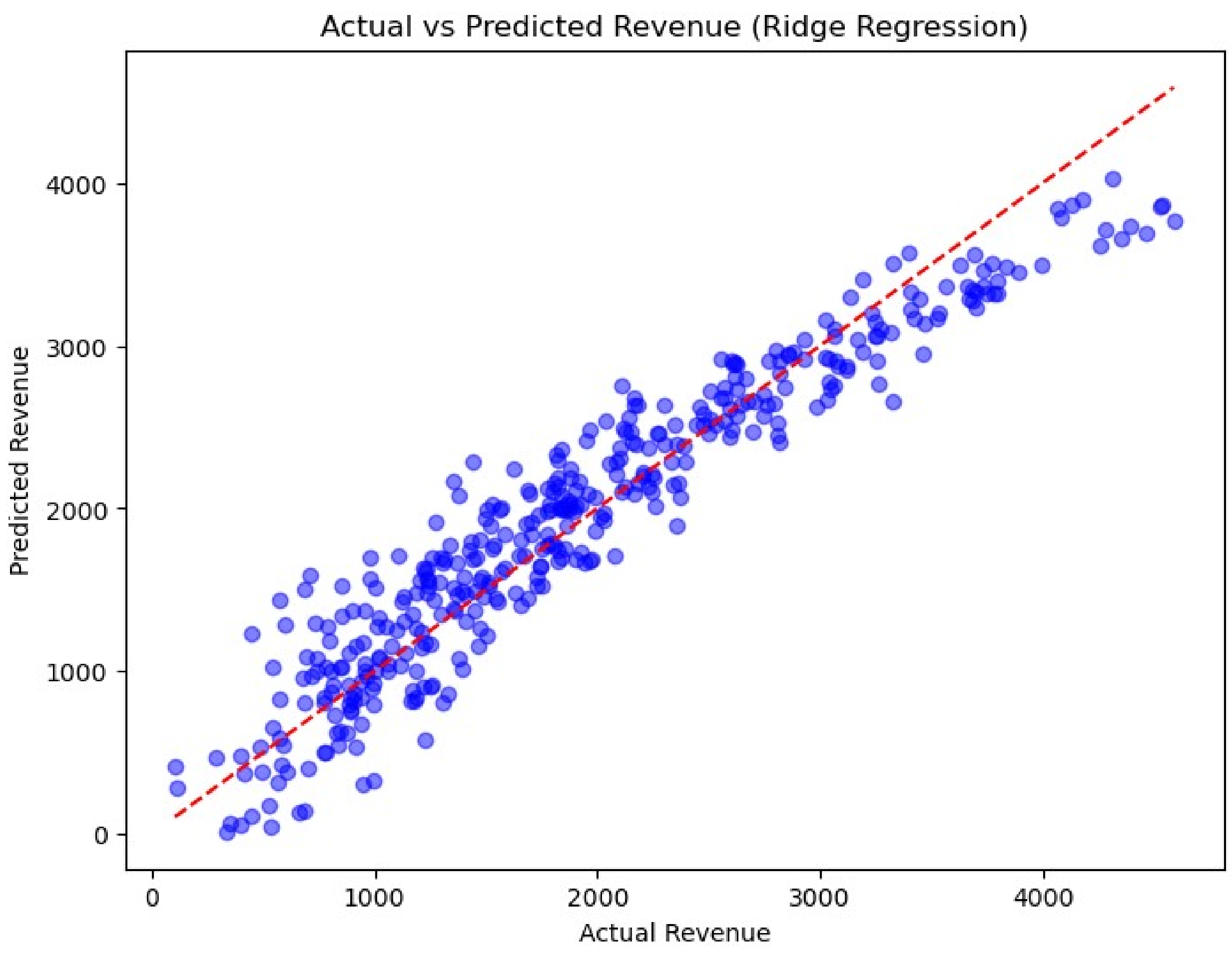
```
Best Alpha: 0.01
R² Score (Ridge): 0.90
RMSE (Ridge): 309.15
```

Checking RMSE Accuracy with Mean Revenue

```
Percentage_Error = (rmse_ridge/mean) *100
print(f'Percentage Error:{Percentage_Error:.2f}%')
```

```
Percentage Error:16.23%
```

```
# Scatter plot for actual vs predicted values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_ridge, color='blue', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)],
color='red', linestyle='--')  # Perfect prediction line
plt.xlabel("Actual Revenue")
plt.ylabel("Predicted Revenue")
plt.title("Actual vs Predicted Revenue (Ridge Regression)")
plt.show()
```



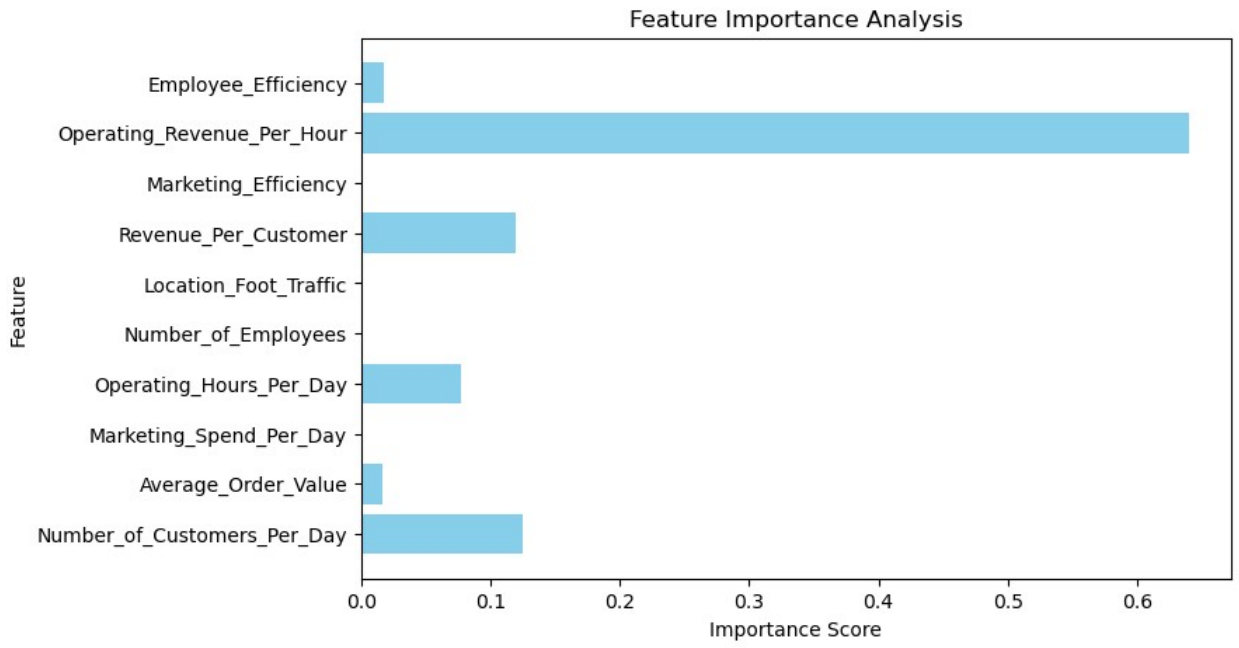
Feature Engineering for Better Predictions

```
# Create new features
df['Revenue_Per_Customer'] = df['Daily_Revenue'] /
df['Number_of_Customers_Per_Day']
df['Marketing_Efficiency'] = df['Daily_Revenue'] /
df['Marketing_Spend_Per_Day']
df['Operating_Revenue_Per_Hour'] = df['Daily_Revenue'] /
df['Operating_Hours_Per_Day']
df['Employee_Efficiency'] = df['Daily_Revenue'] /
df['Number_of_Employees']

df.head(5)

   Number_of_Customers_Per_Day  Average_Order_Value
Operating_Hours_Per_Day  \
0                          152                 6.74
14
1                          485                 4.50
12
2                          398                 9.09
```

```
6
3                        320                 8.48
17
4                        156                 7.44
17

   Number_of_Employees  Marketing_Spend_Per_Day  Location_Foot_Traffic
\
0                    4                   106.62                     97

1                    8                    57.83                    744

2                    6                    91.76                    636

3                    4                   462.63                    770

4                    2                   412.52                    232


   Daily_Revenue  Revenue_Per_Customer  Marketing_Efficiency  \
0        1547.81             10.182961             14.517070
1        2084.68              4.298309             36.048418
2        3118.39              7.835151             33.984198
3        2912.20              9.100625              6.294879
4        1663.42             10.662949              4.032338

   Operating_Revenue_Per_Hour  Employee_Efficiency
0                  110.557857           386.952500
1                  173.723333           260.585000
2                  519.731667           519.731667
3                  171.305882           728.050000
4                   97.848235           831.710000
```

Check Feature Importance

```
from sklearn.ensemble import RandomForestRegressor

# Load data
X = df[['Number_of_Customers_Per_Day', 'Average_Order_Value',
'Marketing_Spend_Per_Day', 'Operating_Hours_Per_Day',
'Number_of_Employees', 'Location_Foot_Traffic',
       'Revenue_Per_Customer', 'Marketing_Efficiency',
'Operating_Revenue_Per_Hour', 'Employee_Efficiency']]
y = df['Daily_Revenue']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Train Random Forest Regressor (better for feature importance
analysis)
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Get feature importance
importance = model.feature_importances_

# Plot feature importance
plt.figure(figsize=(8,5))
plt.barh(X.columns, importance, color='skyblue')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.title('Feature Importance Analysis')
plt.show()
```



```
pd.DataFrame({'Feature': X.columns, 'Importance':
model.feature_importances_})

                      Feature  Importance
0  Number_of_Customers_Per_Day    0.124890
1          Average_Order_Value    0.016328
2      Marketing_Spend_Per_Day    0.001051
3      Operating_Hours_Per_Day    0.077004
4          Number_of_Employees    0.001249
5        Location_Foot_Traffic    0.000791
6         Revenue_Per_Customer    0.119677
7         Marketing_Efficiency    0.000976
8   Operating_Revenue_Per_Hour    0.640533
9          Employee_Efficiency    0.017501
```

```python
# Select updated features
selected_features = ['Number_of_Customers_Per_Day',
'Average_Order_Value', 'Marketing_Spend_Per_Day',
                     'Revenue_Per_Customer', 'Marketing_Efficiency',
'Operating_Revenue_Per_Hour', 'Employee_Efficiency']

# Updated training data
X_new = df[selected_features]
y_new = df['Daily_Revenue']

# Split data
X_train_new, X_test_new, y_train_new, y_test_new =
train_test_split(X_new, y_new, test_size=0.2, random_state=42)

# Train Ridge Regression again
ridge_new = Ridge(alpha=0.01)
ridge_new.fit(X_train_new, y_train_new)

# Predict on test set
y_pred_new = ridge_new.predict(X_test_new)

# Evaluate new model
r2_ridge_new = r2_score(y_test_new, y_pred_new)
rmse_ridge_new = np.sqrt(mean_squared_error(y_test_new, y_pred_new))

print(f"Updated R² Score (Ridge): {r2_ridge_new:.4f}")
print(f"Updated RMSE (Ridge): {rmse_ridge_new:.2f}")
```

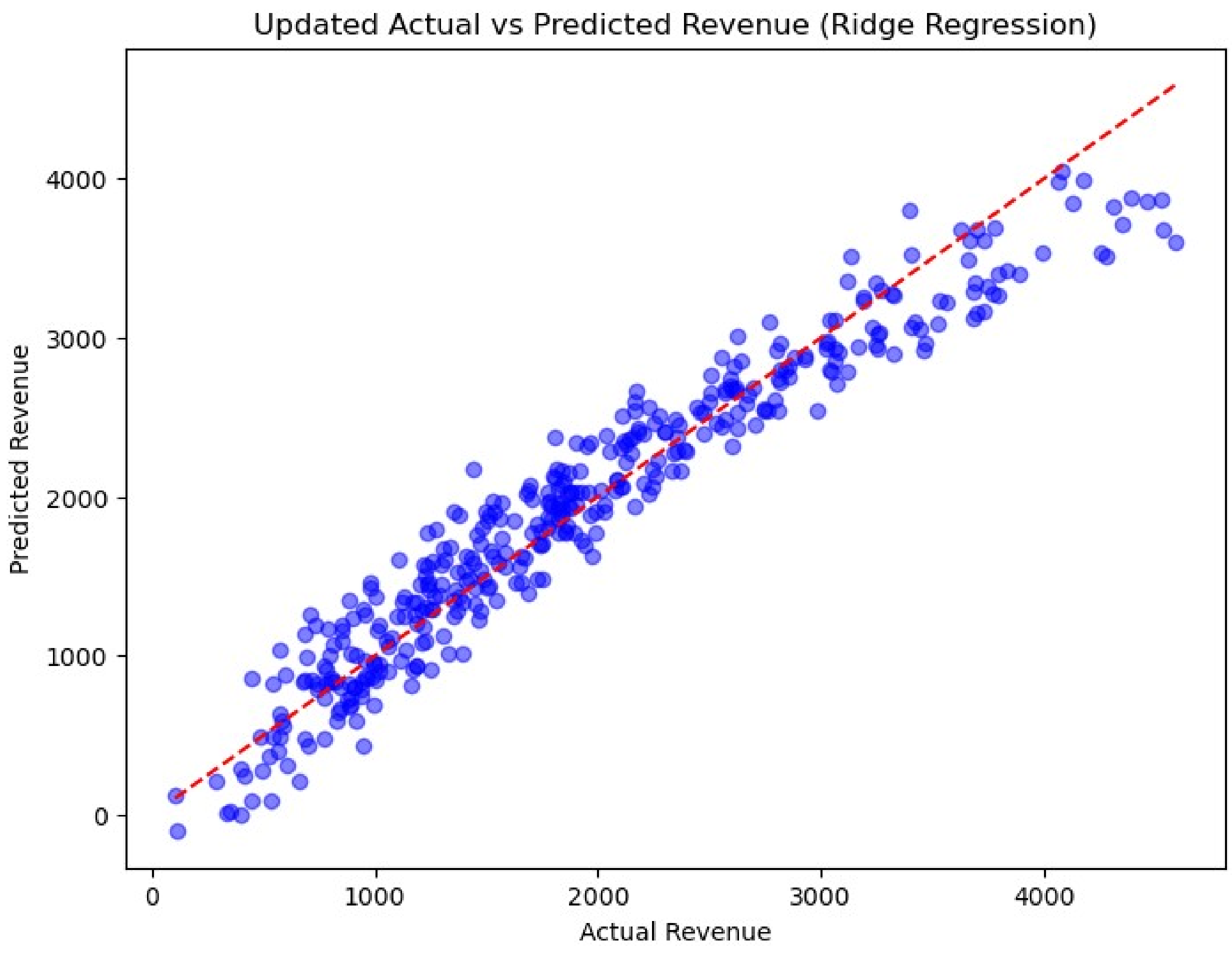
```
Updated R² Score (Ridge): 0.9294
Updated RMSE (Ridge): 262.20
```

```python
# Predict on training data using the trained Ridge model
y_train_pred_ridge = ridge_new.predict(X_train_new)

# Calculate R² and RMSE for training data
r2_ridge_train = r2_score(y_train_new, y_train_pred_ridge)
rmse_ridge_train = np.sqrt(mean_squared_error(y_train_new,
y_train_pred_ridge))

print(f"Ridge R² Score (Train Data): {r2_ridge_train:.4f}")
print(f"Ridge RMSE (Train Data): {rmse_ridge_train:.2f}")
```

```
Ridge R² Score (Train Data): 0.9234
Ridge RMSE (Train Data): 263.59
```

```python
# Scatter plot for actual vs predicted values
plt.figure(figsize=(8, 6))
plt.scatter(y_test_new, y_pred_new, color='blue', alpha=0.5)
plt.plot([min(y_test_new), max(y_test_new)], [min(y_test_new),
max(y_test_new)], color='red', linestyle='--')  # Perfect prediction
line
```

```
plt.xlabel("Actual Revenue")
plt.ylabel("Predicted Revenue")
plt.title("Updated Actual vs Predicted Revenue (Ridge Regression)")
plt.show()
```



Checking RMSE Accuracy with Mean Revenue

```
Percentage_Error = (rmse_ridge_new/mean) *100
print(f"Percentage Error:{Percentage_Error:.2f}%")

Percentage Error:13.77%
```

Saving the model

```
import joblib

# Save the trained Ridge model
joblib.dump(ridge_new, "ridge_regression_model.pkl")

['ridge_regression_model.pkl']
```

Checking with an example

```
# Load the updated model
loaded_model = joblib.load("ridge_regression_model.pkl")

# Example new data
new_data = pd.DataFrame({
    "Number_of_Customers_Per_Day": [550],
    "Average_Order_Value": [22],
    "Marketing_Spend_Per_Day": [150],
    "Operating_Hours_Per_Day": [12],
    "Number_of_Employees": [5],
    "Location_Foot_Traffic": [300],
    "Revenue_Per_Customer": [12.5],
    "Marketing_Efficiency": [0.8],
    "Operating_Revenue_Per_Hour": [200],
    "Employee_Efficiency": [40]
})

# Ensure the new data has the same feature order
new_data = new_data[selected_features]

# Predict revenue
predicted_revenue = loaded_model.predict(new_data)
print("Predicted Revenue:", predicted_revenue[0])
```

```
Predicted Revenue: 5651.173124206319
```