Predicting Delivery time based on different parameters

About the dataset

Link : https://www.kaggle.com/datasets/denkuznetz/food-delivery-time-prediction

Food Delivery Time Prediction Dataset Description

This dataset provides various features related to food delivery times, aiming to help analyze and predict the estimated delivery duration. Below are the details of each column:

- **Delivery_person_ID**: Unique identifier for each delivery person.
- **Order_ID**: Unique identifier for each order.
- **Distance_km**: The delivery distance in kilometers.
- **Weather**: Weather conditions during the delivery, including Clear, Rainy, Snowy, Foggy, and Windy.
- **Traffic_Level**: Traffic conditions categorized as Low, Medium, or High.
- **Time_of_Day**: The time when the delivery took place, categorized as Morning, Afternoon, Evening, or Night.
- **Vehicle_Type**: Type of vehicle used for delivery, including Bike, Scooter, and Car.
- **Preparation_Time_min**: The time required to prepare the order, measured in minutes.
- **Courier_Experience_yrs**: Experience of the courier in years.
- **Delivery_Time_min**: The total delivery time in minutes (target variable).

This dataset can be useful for building predictive models to estimate delivery times based on various factors such as traffic, weather, and order details.

Step 1: Pre-porcessing

In [189…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, m
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

In [190…
```
df = pd.read_csv("Food_Delivery_Dataset.csv")
```

In [191…
```
df.drop(columns=["Order_ID"], inplace=True)
```

In [219…
```
skew_values = df[['Distance_km', 'Preparation_Time_min', 'Courier_Experience_yrs
print(skew_values)
```

```
Distance_km               0.038840
Preparation_Time_min      0.030008
Courier_Experience_yrs   -0.029532
Delivery_Time_min         0.507251
dtype: float64
```

In [192…
```
df.head()
```

Out[192…

	Distance_km	Weather	Traffic_Level	Time_of_Day	Vehicle_Type	Preparation_Time_m
0	7.93	Windy	Low	Afternoon	Scooter	
1	16.42	Clear	Medium	Evening	Bike	
2	9.52	Foggy	Low	Night	Scooter	
3	7.44	Rainy	Medium	Afternoon	Scooter	
4	19.03	Clear	Low	Morning	Bike	

In [193…
```
df.tail()
```

Out[193…

	Distance_km	Weather	Traffic_Level	Time_of_Day	Vehicle_Type	Preparation_Time_
995	8.50	Clear	High	Evening	Car	
996	16.28	Rainy	Low	Morning	Scooter	
997	15.62	Snowy	High	Evening	Scooter	
998	14.17	Clear	Low	Afternoon	Bike	
999	6.63	Foggy	Low	Night	Scooter	

In [194…
```
print("\nMissing values in dataset:")
print(df.isnull().sum())
```

```
Missing values in dataset:
Distance_km               0
Weather                  30
Traffic_Level            30
Time_of_Day              30
Vehicle_Type              0
Preparation_Time_min      0
Courier_Experience_yrs   30
Delivery_Time_min         0
dtype: int64
```

In [195…
```
df.shape
```

Out[195…
```
(1000, 8)
```

In [196…
```
cat_features = ["Weather", "Traffic_Level", "Time_of_Day", "Vehicle_Type"]
num_features = ["Distance_km", "Preparation_Time_min", "Courier_Experience_yrs"]
```

In [197…
```
for col in cat_features:
    comparison_table = df.groupby(col)['Delivery_Time_min'].agg(['count']).reset
    comparison_table.columns = [col, 'count']
    print(f"\nComparative Analysis for '{col}':")
    print(comparison_table)
```

```
Comparative Analysis for 'Weather':
  Weather  count
0   Clear    470
1   Foggy    103
2   Rainy    204
3   Snowy     97
4   Windy     96

Comparative Analysis for 'Traffic_Level':
  Traffic_Level  count
0          High    197
1           Low    383
2        Medium    390

Comparative Analysis for 'Time_of_Day':
  Time_of_Day  count
0   Afternoon    284
1     Evening    293
2     Morning    308
3       Night     85

Comparative Analysis for 'Vehicle_Type':
  Vehicle_Type  count
0         Bike    503
1          Car    195
2      Scooter    302
```

In [198…
```
df[num_features] = df[num_features].fillna(df[num_features].mean())
df[cat_features] = df[cat_features].fillna(df[cat_features].mode().iloc[0])
```

In [199…
```
print("\nMissing values in dataset:")
print(df.isnull().sum())
```

```
Missing values in dataset:
Distance_km               0
Weather                   0
Traffic_Level             0
Time_of_Day               0
Vehicle_Type              0
Preparation_Time_min      0
Courier_Experience_yrs    0
Delivery_Time_min         0
dtype: int64
```

In [200…
```
df.shape
```

Out[200…
```
(1000, 8)
```

In [201…
```
weather_mapping = {"Clear": 0, "Foggy": 1, "Rainy": 2, "Snowy": 3, "Windy": 4}
traffic_mapping = {"Low": 0, "Medium": 1, "High": 2}
time_mapping = {"Morning": 0, "Afternoon": 1, "Evening": 2, "Night": 3}
vehicle_mapping = {"Bike": 0, "Scooter": 1, "Car": 2}

df["Weather"] = df["Weather"].map(weather_mapping)
```

```
df["Traffic_Level"] = df["Traffic_Level"].map(traffic_mapping)
df["Time_of_Day"] = df["Time_of_Day"].map(time_mapping)
df["Vehicle_Type"] = df["Vehicle_Type"].map(vehicle_mapping)
```

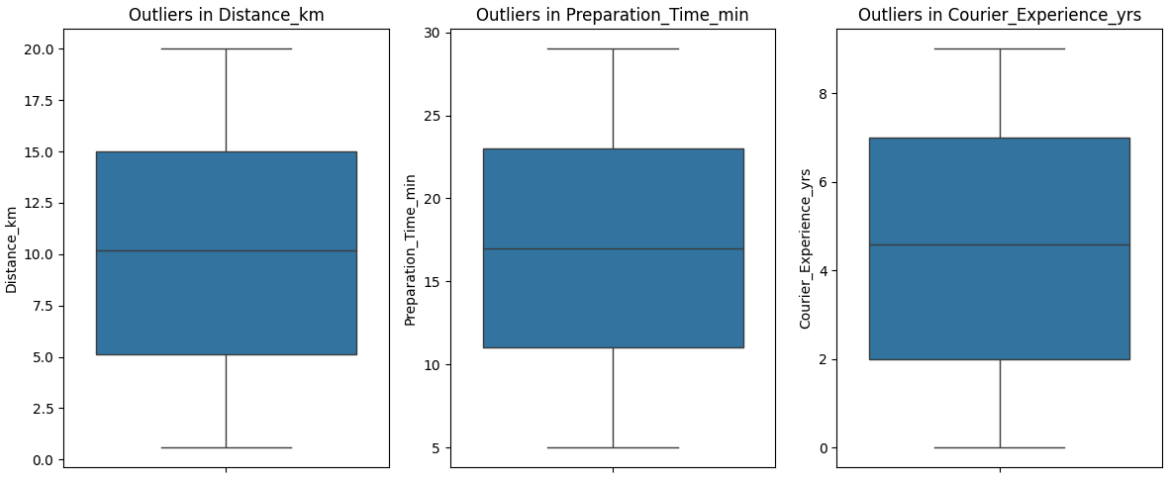
In [202…
```
df.head()
```

Out[202…

	Distance_km	Weather	Traffic_Level	Time_of_Day	Vehicle_Type	Preparation_Time_m
0	7.93	4	0	1	1	
1	16.42	0	1	2	0	
2	9.52	1	0	3	1	
3	7.44	2	1	1	1	
4	19.03	0	0	0	0	

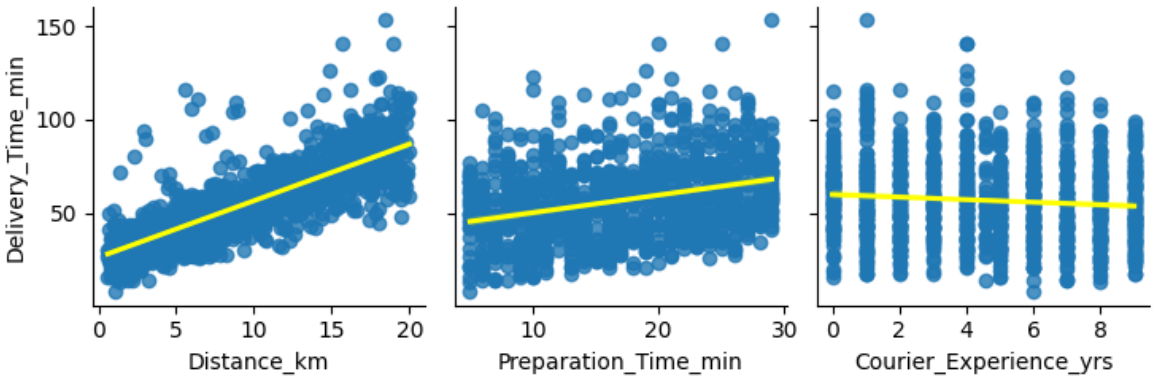
In [203…
```
plt.figure(figsize=(12, 5))
for i, col in enumerate(num_features, 1):
    plt.subplot(1, 3, i)
    sns.boxplot(y=df[col])
    plt.title(f"Outliers in {col}")

plt.tight_layout()
plt.show()
```



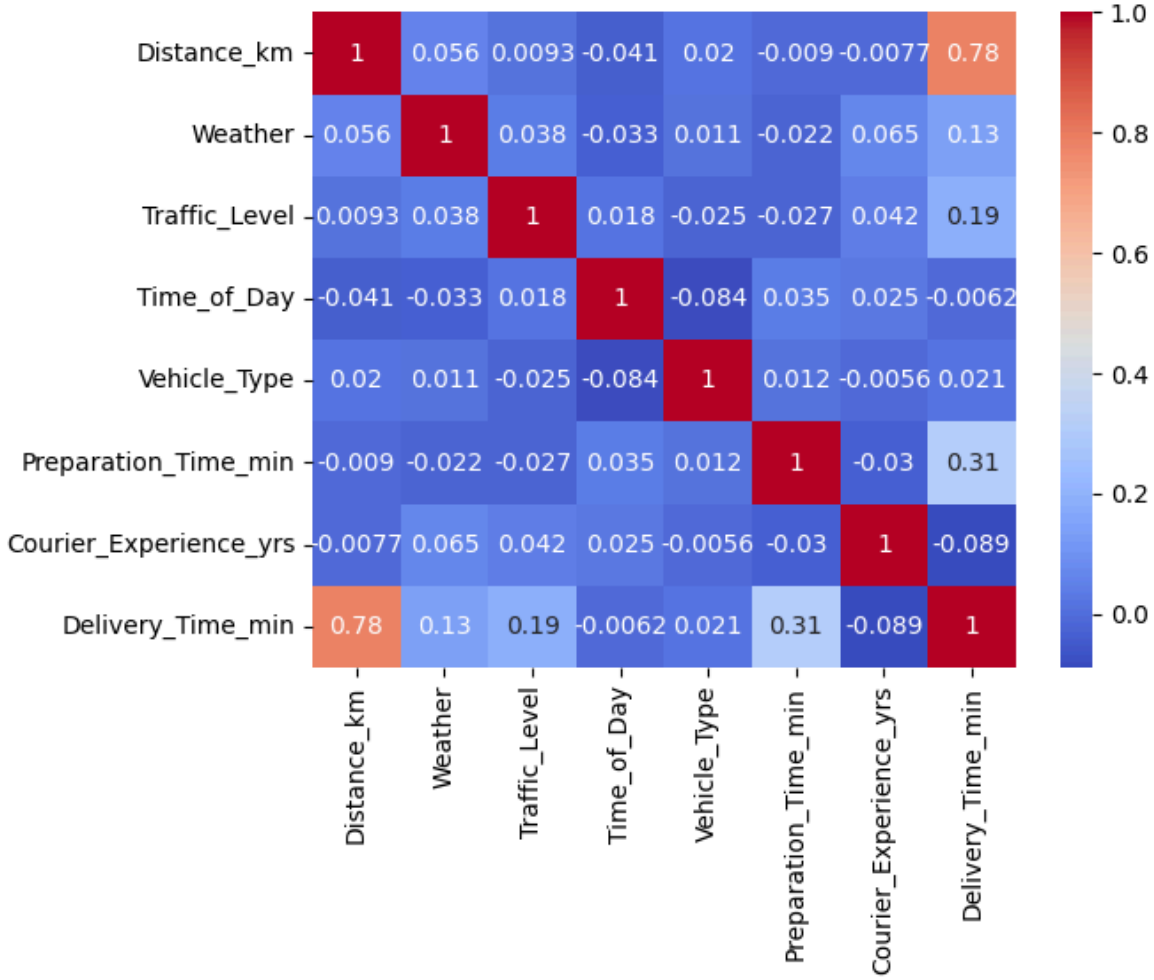
Assumption 1 : Linearity check

In [204…
```
sns.pairplot(df, x_vars=['Distance_km', 'Preparation_Time_min', 'Courier_Experie
plt.show()
```



In [205…

```
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.show()
```



Assumption 2 : Multicollinearity Check (VIF Test)

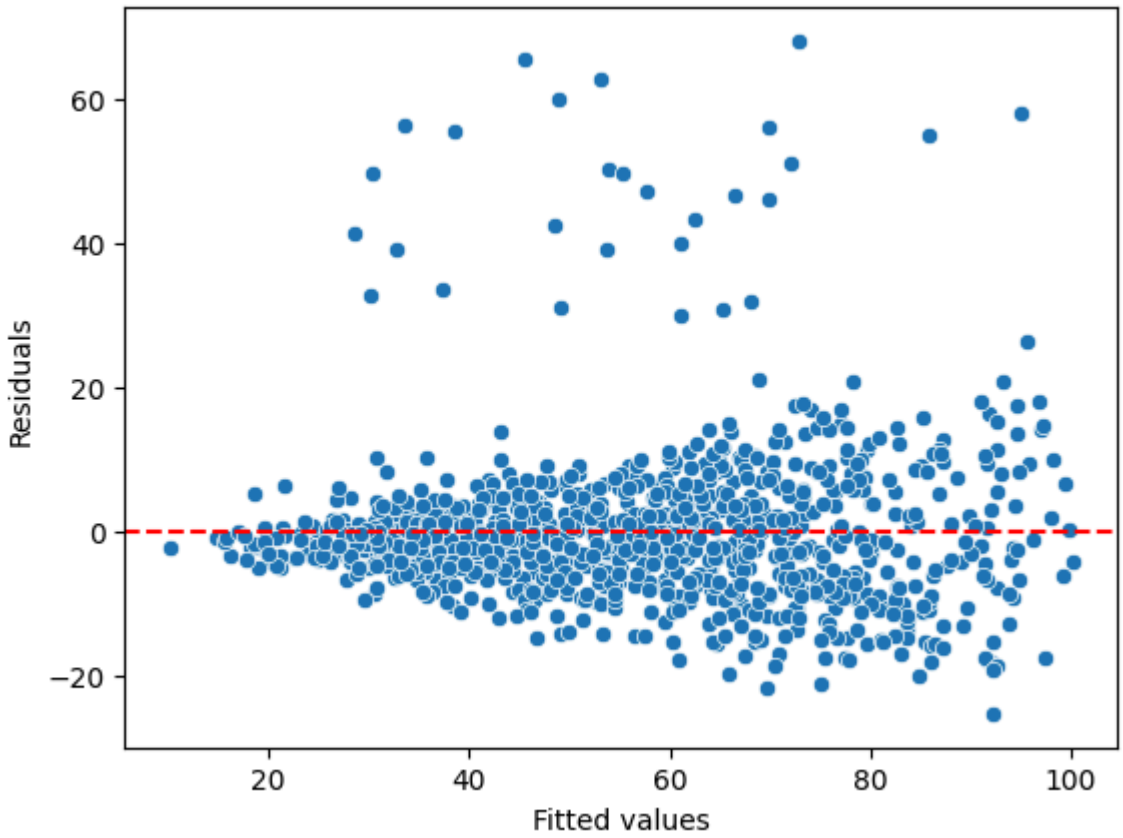
In [206…

```
X = df[['Distance_km', 'Preparation_Time_min', 'Courier_Experience_yrs',"Weather
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.c
print(vif_data)
```

	Feature	VIF
0	Distance_km	3.341987
1	Preparation_Time_min	4.242295
2	Courier_Experience_yrs	3.039329
3	Weather	1.698736
4	Traffic_Level	2.072561
5	Time_of_Day	2.152661
6	Vehicle_Type	1.708954

Assumption 3: Homoscedasticity Check

In [207…
```
import statsmodels.api as sm
X = sm.add_constant(X)  # Add constant for regression
model = sm.OLS(df['Delivery_Time_min'], X).fit()
residuals = model.resid
sns.scatterplot(x=model.fittedvalues, y=residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Fitted values')
plt.ylabel('Residuals')
plt.show()
```

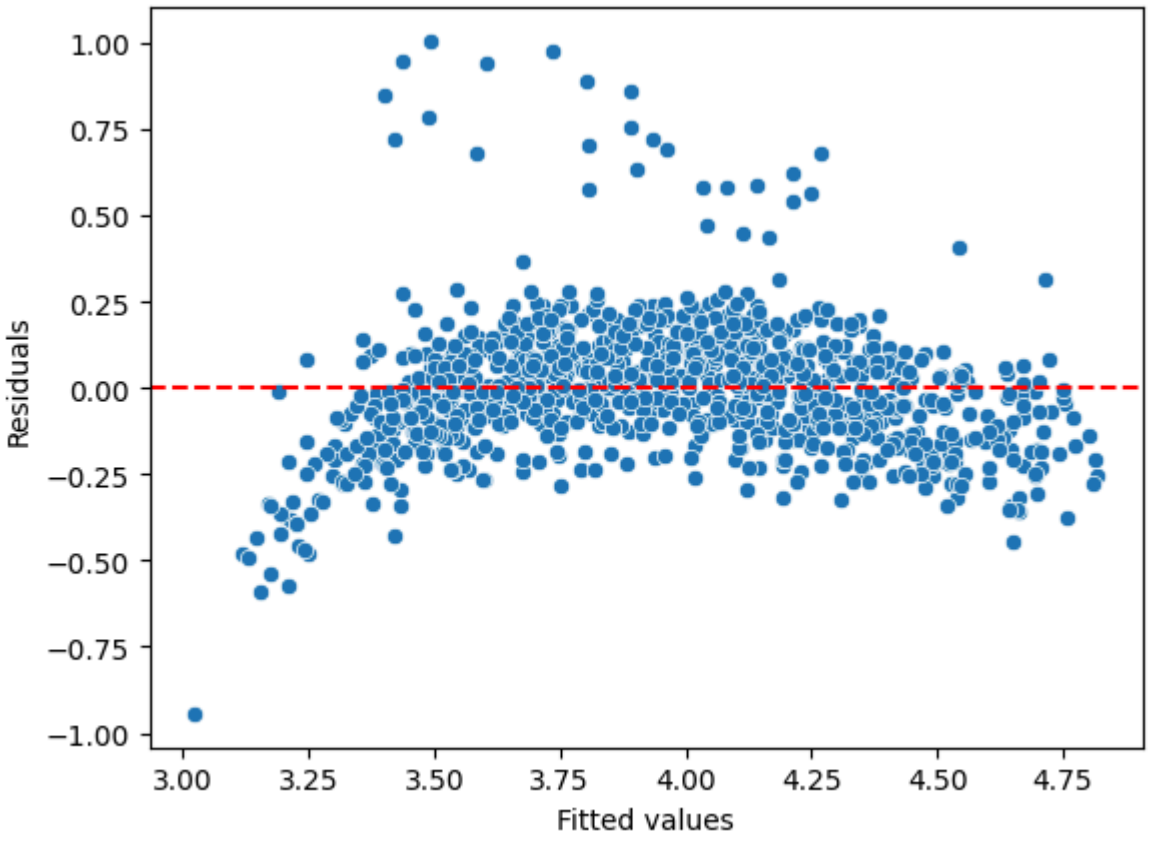


In [208…
```
df2=df.copy()
df2['Delivery_Time_min'] = np.log(df2['Delivery_Time_min'])
```

In [209…
```
X = sm.add_constant(X)  # Add constant for regression
model = sm.OLS(df2['Delivery_Time_min'], X).fit()
residuals = model.resid

sns.scatterplot(x=model.fittedvalues, y=residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel('Fitted values')
```

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



Assumption 4 : Durbin-Watson test

In [210…
```
from statsmodels.stats.stattools import durbin_watson

dw_test = durbin_watson(residuals)
print(f'Durbin-Watson statistic: {dw_test}')
```

```
Durbin-Watson statistic: 2.0075369541681964
```

Step 2: Model Training

In [211…
```
X = df.drop(columns=["Delivery_Time_min"])
y = df["Delivery_Time_min"]
```

In [212…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
#num_features_sel = ["Distance_km", "Preparation_Time_min"]
```

In [213…
```
scaler = StandardScaler()
X_train[num_features] = scaler.fit_transform(X_train[num_features])
X_test[num_features] = scaler.transform(X_test[num_features])
```

In [214…
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[214…

```
LinearRegression()
```

In [215…

```
y_pred = model.predict(X_test)
```

In [216…

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error (MAE): {mae}")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"R² Score: {r2}")
```

```
Mean Absolute Error (MAE): 6.409567456930308
Mean Squared Error (MSE): 86.59952495732139
Root Mean Squared Error (RMSE): 9.305886575567177
R² Score: 0.806795374246895
```

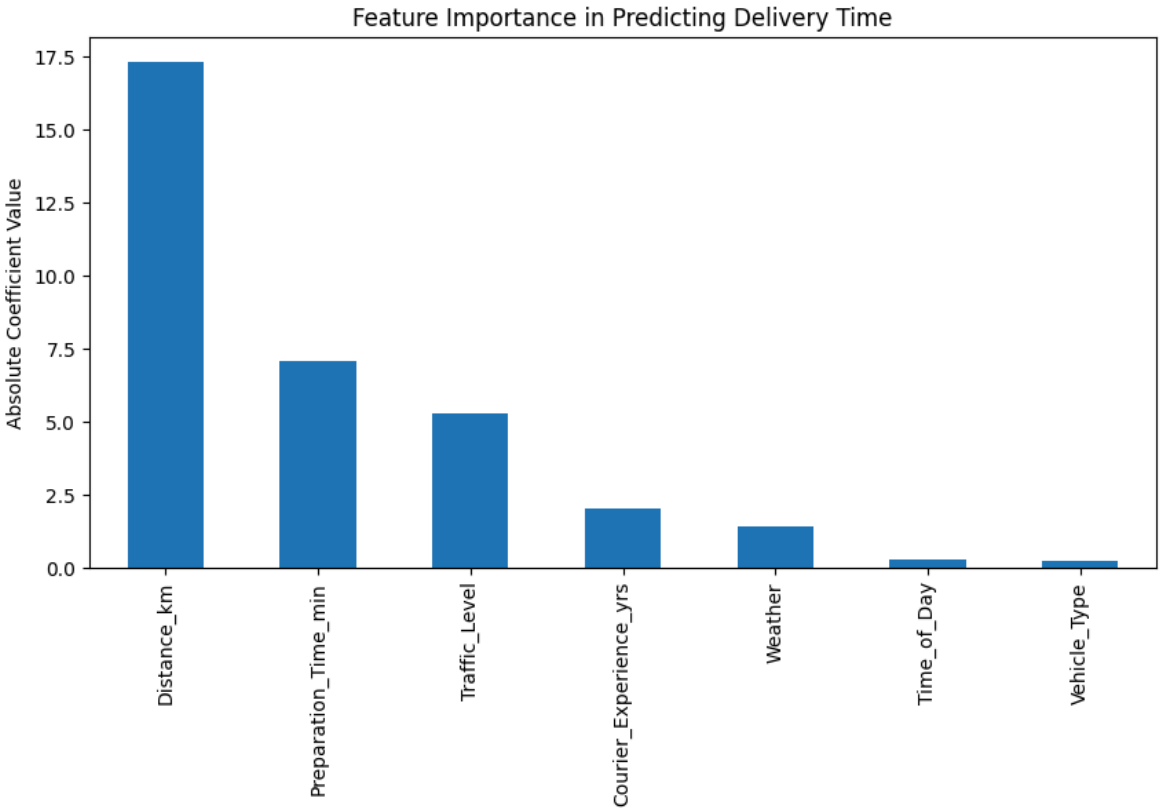
In [217…

```
plt.scatter(y_test, y_pred, alpha=0.5)
plt.xlabel("Actual Delivery Time")
plt.ylabel("Predicted Delivery Time")
plt.title("Actual vs Predicted Delivery Time")
plt.plot([y.min(), y.max()], [y.min(), y.max()], "r--")
plt.show()
```

In [218…

```
feature_importance = pd.Series(abs(model.coef_), index=X.columns)
feature_importance.sort_values(ascending=False).plot(kind="bar", figsize=(10, 5)
plt.title("Feature Importance in Predicting Delivery Time")
```

```
plt.ylabel("Absolute Coefficient Value")
plt.show()
```



Conclusion

- In the **scatter plot**, most points follow an **upward trend**, meaning that as the **actual delivery time increases, the predicted time also increases**.
- The **red dashed line (ideal fit line)** further supports this, as a **strong positive correlation** would align points closely along this diagonal.
- The **R^2 score of 0.807** indicates that the model captures a significant portion of this positive relationship.

In [ ]: