Objective :

The goal is to predict whether food delivery will be fast or delayed based on features like customer location, restaurant location, weather conditions, traffic conditions, and more. This task is a binary classification problem where the model will predict delivery status: "Fast" or "Delayed."

Phase 1
Data Preprocessing

(2 steps)

Step 1 - Data Import and Cleaning

In [396…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, label_binarize
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDispla
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
```

In [397…

```
data=pd.read_csv('Food_Delivery_Time_prediction.csv')
d=data.copy()
d.head()
```

Out[397…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Traffic
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	Rainy	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	Cloudy	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	Snowy	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	Cloudy	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	Rainy	

In [398…

```
d.isnull().sum()
```

Out[398…

```
Order_ID                      0
Customer_Location             0
Restaurant_Location           0
Distance                      0
Weather_Conditions            0
Traffic_Conditions            0
Delivery_Person_Experience    0
Order_Priority                0
Order_Time                    0
Vehicle_Type                  0
Restaurant_Rating             0
Customer_Rating               0
Delivery_Time                 0
Order_Cost                    0
Tip_Amount                    0
dtype: int64
```

Null values do not exist in any column

Now checking for incorrect data

In [399…

```
#drop duplicate and empty rows of Order_ID column
d.dropna(subset=['Order_ID'])
d.drop_duplicates(subset='Order_ID', keep='first')
# drop incorrect data for Order_ID column
d.drop(d[ d['Order_ID'].str.match(r'^ORD\d{4}$')==False ].index, inplace=True)
# here if inplace=True not used then the changes will not be applied to the origina

#drop rows with null values in Customer_Location column
d.dropna(subset=['Customer_Location'], inplace=True)

#drop rows with null values in Restaurant_Location column
d.dropna(subset=['Restaurant_Location'], inplace=True)

# # distance values all greater than 0
# d.loc[d['Distance']<=0,'Distance']=np.mean(d[d['Distance']>0]['Distance'])

# fill null values in Weather_Conditions with 'Sunny'
# Weather_Conditions values should be one of the following
d['Weather_Conditions'].fillna('Sunny')
valid_weather_conditions = ['Sunny', 'Rainy', 'Snowy', 'Cloudy']
d.loc[~d['Weather_Conditions'].isin(valid_weather_conditions), 'Weather_Conditions'

# fill null values in Traffic_Conditions with 'Medium'
# Traffic_Conditions values should be one of the following
d['Traffic_Conditions'].fillna('Medium')
valid_traffic_conditions = ['Low', 'Medium', 'High']
d.loc[~d['Traffic_Conditions'].isin(valid_traffic_conditions), 'Traffic_Condisions'

# # Deliver_Person_Experience values should be positive and non-zero
# d.loc[d['Delivery_Person_Experience']<=0,'Delivery_Person_Experience']=np.mean(d.

# fill null values in Order_Priority with 'Medium'
# Order_Priority values should be one of the following
```

```
d['Order_Priority'].fillna('Medium')
valid_order_priority = ['Low', 'Medium', 'High']
d.loc[~d['Order_Priority'].isin(valid_order_priority), 'Order_Priority'] = 'Medium'

# fill null values in Order_Time with 'Night'
# Order_Time values should be one of the following
d['Order_Time'].fillna('Night')
valid_order_time = ['Afternoon', 'Night', 'Evening', 'Morning']
d.loc[~d['Order_Time'].isin(valid_order_time), 'Order_Time'] = 'Night'

# fill null values in Vehicle_Type with 'Bike'
# Vehicle_Type values should be one of the following
d['Vehicle_Type'].fillna('Bike')
valid_vehicle_type = ['Car', 'Bike', 'Bicycle']
d.loc[~d['Vehicle_Type'].isin(valid_vehicle_type), 'Vehicle_Type'] = 'Bike'
```

In [400…

```
d
```

Out[400…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Tra
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	Rainy	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	Cloudy	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	Snowy	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	Cloudy	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	Rainy	
...	...	...	...	...	...	
195	ORD0196	(17.910045, 81.56199)	(18.098924, 87.896124)	23.82	Cloudy	
196	ORD0197	(21.66459, 82.226635)	(16.892341, 80.554716)	6.09	Snowy	
197	ORD0198	(14.575401, 82.55641)	(13.625369, 82.418092)	20.61	Snowy	
198	ORD0199	(12.094497, 82.893369)	(19.135509, 86.659978)	24.06	Rainy	
199	ORD0200	(19.360304, 84.132424)	(20.941636, 77.01334)	9.18	Snowy	

200 rows × 16 columns

In [401…

```
# Setting numeric values to column Weather_Conditions
weather_map = {'Sunny': 0, 'Rainy': 1, 'Snowy': 2, 'Cloudy': 3}
```

```
d['Weather_Conditions'] = d['Weather_Conditions'].map(weather_map)

# Setting numeric values to column Traffic_Conditions
traffic_map = {'Low': 0, 'Medium': 1, 'High': 2}
d['Traffic_Conditions'] = d['Traffic_Conditions'].map(traffic_map)

# Setting numeric values to column Vehicle_Type
vehicle_type_map = {'Bicycle': 0, 'Bike': 1, 'Car': 2}
d['Vehicle_Type'] = d['Vehicle_Type'].map(vehicle_type_map)
```

In [402…

```
d
```

Out[402…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Traf
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	1	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	3	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	2	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	3	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	1	
...	...	...	...	...	...	
195	ORD0196	(17.910045, 81.56199)	(18.098924, 87.896124)	23.82	3	
196	ORD0197	(21.66459, 82.226635)	(16.892341, 80.554716)	6.09	2	
197	ORD0198	(14.575401, 82.55641)	(13.625369, 82.418092)	20.61	2	
198	ORD0199	(12.094497, 82.893369)	(19.135509, 86.659978)	24.06	1	
199	ORD0200	(19.360304, 84.132424)	(20.941636, 77.01334)	9.18	2	

200 rows × 16 columns

In [403…

```
# Standardization
s=StandardScaler()
d['Distance_Scaled'] = s.fit_transform(d[['Distance']])
d['Delivery_Time_Scaled'] = s.fit_transform(d[['Delivery_Time']])
# StandardScaler().fit_transform() expects a 2D array or DataFrame, but you passed
# So pass a DataFrame with double brackets d[['Distance']]
```

In [404…
```
d
```

Out[404…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Tra
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	1	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	3	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	2	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	3	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	1	
...	...	...	...	...	...	
195	ORD0196	(17.910045, 81.56199)	(18.098924, 87.896124)	23.82	3	
196	ORD0197	(21.66459, 82.226635)	(16.892341, 80.554716)	6.09	2	
197	ORD0198	(14.575401, 82.55641)	(13.625369, 82.418092)	20.61	2	
198	ORD0199	(12.094497, 82.893369)	(19.135509, 86.659978)	24.06	1	
199	ORD0200	(19.360304, 84.132424)	(20.941636, 77.01334)	9.18	2	

200 rows × 18 columns

Step 2 - Feature Engineering

In [405…
```
def haversine_formula(coords_array1, coords_array2):
    lat1 = coords_array1[:,0]
    lon1 = coords_array1[:,1]
    lat2 = coords_array2[:,0]
    lon2 = coords_array2[:,1]
    # Convert decimal degrees to radians
    lat1=np.radians(lat1)
    lon1=np.radians(lon1)
    lat2=np.radians(lat2)
    lon2=np.radians(lon2)
    # Haversine formula
    lat_diff = lat2 - lat1
    lon_diff = lon2 - lon1
    a = np.sin(lat_diff/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(lon_diff/2)**2
    c = 2 * np.asin(np.sqrt(a))
```

```
    r = 6371  # Radius of earth in km
    return c * r

def parse_location(loc_str):
    # Remove parentheses and split by comma
    lat, lon = loc_str.strip("()").split(",")
    return float(lat), float(lon)

coords_array1 = d['Customer_Location'].apply(parse_location).tolist()
coords_array1 = np.array(coords_array1)

coords_array2 = d['Restaurant_Location'].apply(parse_location).tolist()
coords_array2 = np.array(coords_array2)

d['Calculated_Distance'] = haversine_formula(coords_array1, coords_array2)
```

In [406…

```
d[['Calculated_Distance']]
```

Out[406…

	Calculated_Distance
0	775.651198
1	1042.385597
2	476.220706
3	389.912629
4	806.505886
...	...
195	670.130652
196	558.891202
197	106.686689
198	880.580093
199	763.581776

200 rows × 1 columns

In [407…

```
d
```

Out[407…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Traf
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	1	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	3	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	2	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	3	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	1	
...	...	...	...	...	...	
195	ORD0196	(17.910045, 81.56199)	(18.098924, 87.896124)	23.82	3	
196	ORD0197	(21.66459, 82.226635)	(16.892341, 80.554716)	6.09	2	
197	ORD0198	(14.575401, 82.55641)	(13.625369, 82.418092)	20.61	2	
198	ORD0199	(12.094497, 82.893369)	(19.135509, 86.659978)	24.06	1	
199	ORD0200	(19.360304, 84.132424)	(20.941636, 77.01334)	9.18	2	

200 rows × 19 columns

In [408…

```
delivery_time_mean = np.mean(d['Delivery_Time'])
print(delivery_time_mean)
```

```
70.49494999999999
```

In [409…

```
d['Delivery_Time_Binary'] = np.where(d['Delivery_Time'] > delivery_time_mean, 1, 0)
# 1 for delivery time greater than mean (Delayed), 0 for less than or equal to mean
```

In [410…

```
d
```

Out[410…

	Order_ID	Customer_Location	Restaurant_Location	Distance	Weather_Conditions	Traf
0	ORD0001	(17.030479, 79.743077)	(12.358515, 85.100083)	1.57	1	
1	ORD0002	(15.398319, 86.639122)	(14.174874, 77.025606)	21.32	3	
2	ORD0003	(15.687342, 83.888808)	(19.594748, 82.048482)	6.95	2	
3	ORD0004	(20.415599, 78.046984)	(16.915906, 78.278698)	13.79	3	
4	ORD0005	(14.786904, 78.706532)	(15.206038, 86.203182)	6.72	1	
...	...	...	...	...	...	
195	ORD0196	(17.910045, 81.56199)	(18.098924, 87.896124)	23.82	3	
196	ORD0197	(21.66459, 82.226635)	(16.892341, 80.554716)	6.09	2	
197	ORD0198	(14.575401, 82.55641)	(13.625369, 82.418092)	20.61	2	
198	ORD0199	(12.094497, 82.893369)	(19.135509, 86.659978)	24.06	1	
199	ORD0200	(19.360304, 84.132424)	(20.941636, 77.01334)	9.18	2	

200 rows × 20 columns

Phase 2
Classification using Naive Bayes, K-Nearest Neighbors, and Decision Tree

contains 3 steps

Step 3 - Naive Bayes Classifier

In [411…

```
x=d[['Distance_Scaled', 'Weather_Conditions', 'Traffic_Conditions', 'Vehicle_Type',
y=d['Delivery_Time_Binary']
```

In [412…

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_sta
```

In [413…

```
gnb = GaussianNB()
gnb.fit(x_train, y_train)
```

Out[413…

▾ GaussianNB

▶ Parameters

In [414…

```
y_pred_gnb = gnb.predict(x_test)
y_pred_gnb
```

Out[414…

```
array([0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1,
       0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1])
```

In [415…

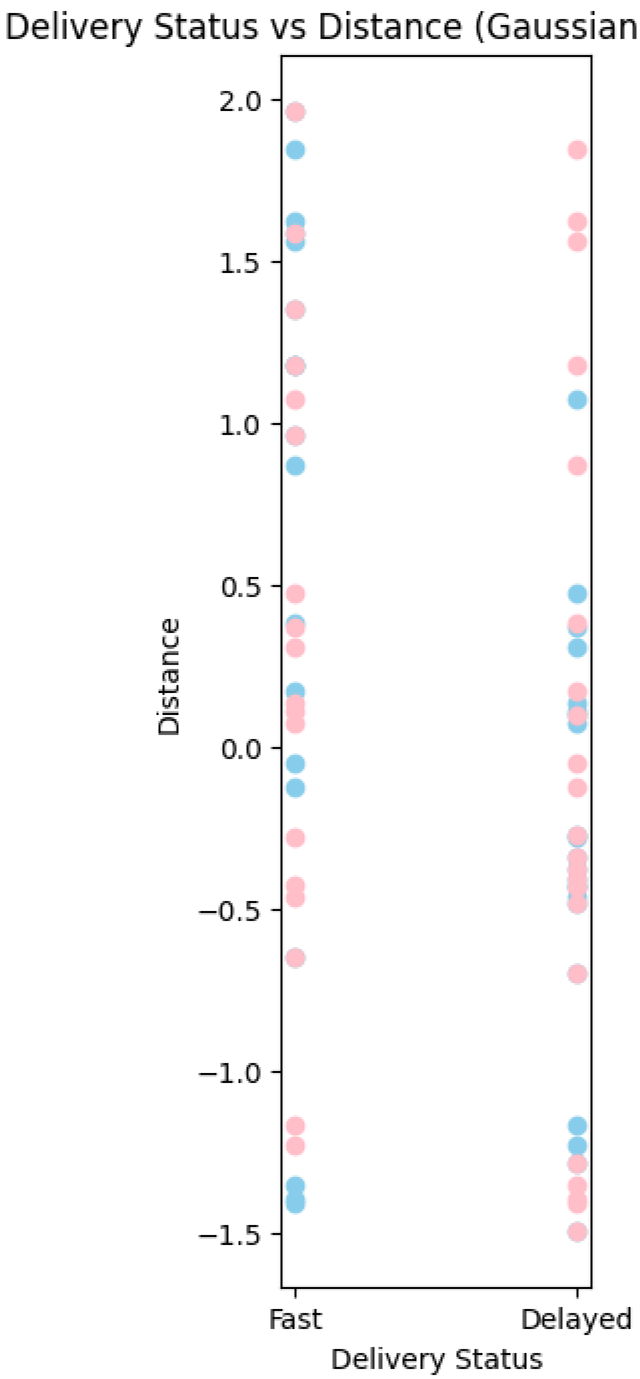
```
label_map = {0: 'Fast', 1: 'Delayed'}
y_test_labels = [label_map[label] for label in y_test]
```

In [416…

```
label_map = {0: 'Fast', 1: 'Delayed'}
y_pred_labels_gnb = [label_map[label] for label in y_pred_gnb]
```

In [417…

```
plt.figure(figsize=(2,8))
plt.scatter(y_pred_labels_gnb, x_test['Distance_Scaled'], color='skyblue', label='P
plt.scatter(y_test_labels, x_test['Distance_Scaled'], color='pink', label='Actual S
plt.xlabel('Delivery Status')
plt.ylabel('Distance')
plt.title('Delivery Status vs Distance (Gaussian Naive Bayes)')
plt.legend
plt.show()
```



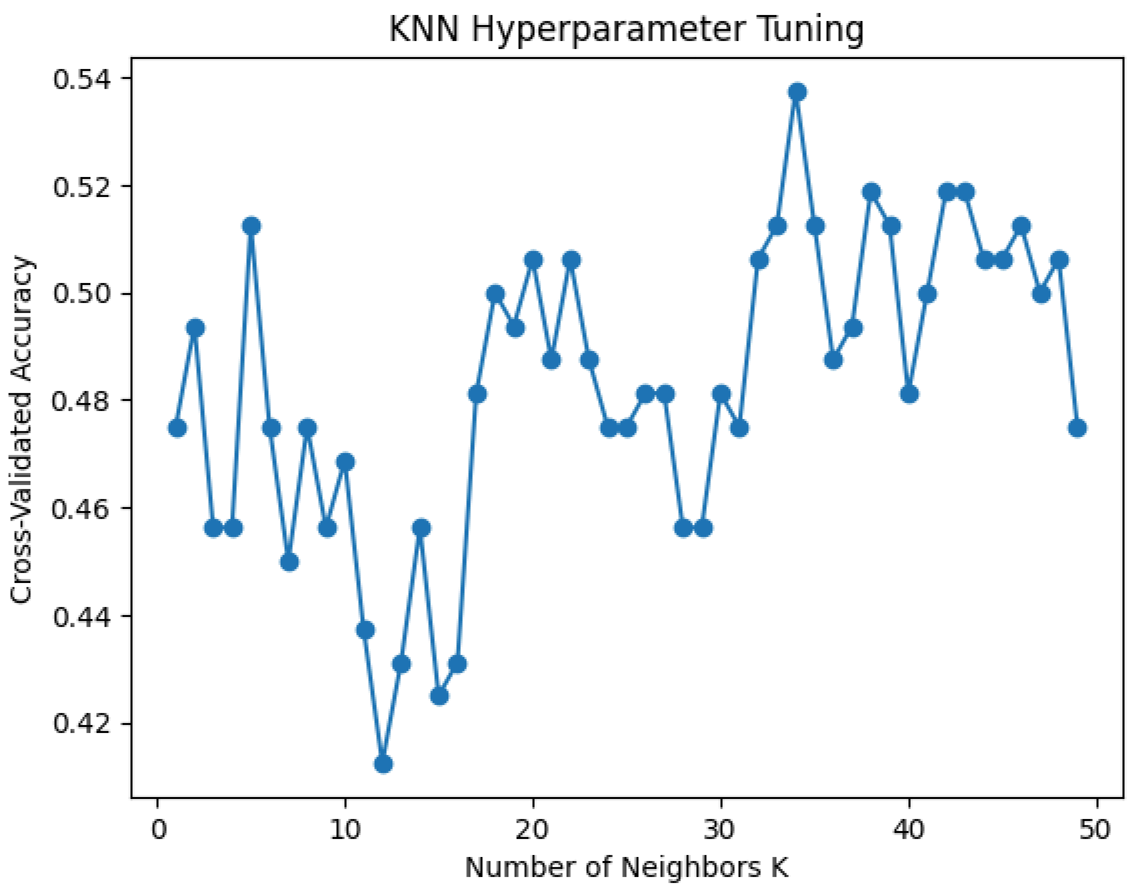
Step 4 - K-Nearest Neighbors (KNN)

In [418…

```
k_range = range(1, 50)
cv_scores = []

for k in k_range:
    knn_cv = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn_cv, x_train, y_train, cv=5, scoring='accuracy')
    cv_scores.append(scores.mean())

optimal_k = k_range[cv_scores.index(max(cv_scores))]
print("")
print(f"Optimal number of neighbors (K): {optimal_k}")
```

```
print("")

plt.plot(k_range, cv_scores, marker='o')
plt.xlabel('Number of Neighbors K')
plt.ylabel('Cross-Validated Accuracy')
plt.title('KNN Hyperparameter Tuning')
plt.show()
```

```
Optimal number of neighbors (K): 34
```



In [419…

```
knn = KNeighborsClassifier(n_neighbors=optimal_k)
knn.fit(x_train, y_train)
```

Out[419…

```
▾ KNeighborsClassifier
▶ Parameters
```

In [420…

```
y_pred_knn = knn.predict(x_test)
y_pred_knn
```

Out[420…

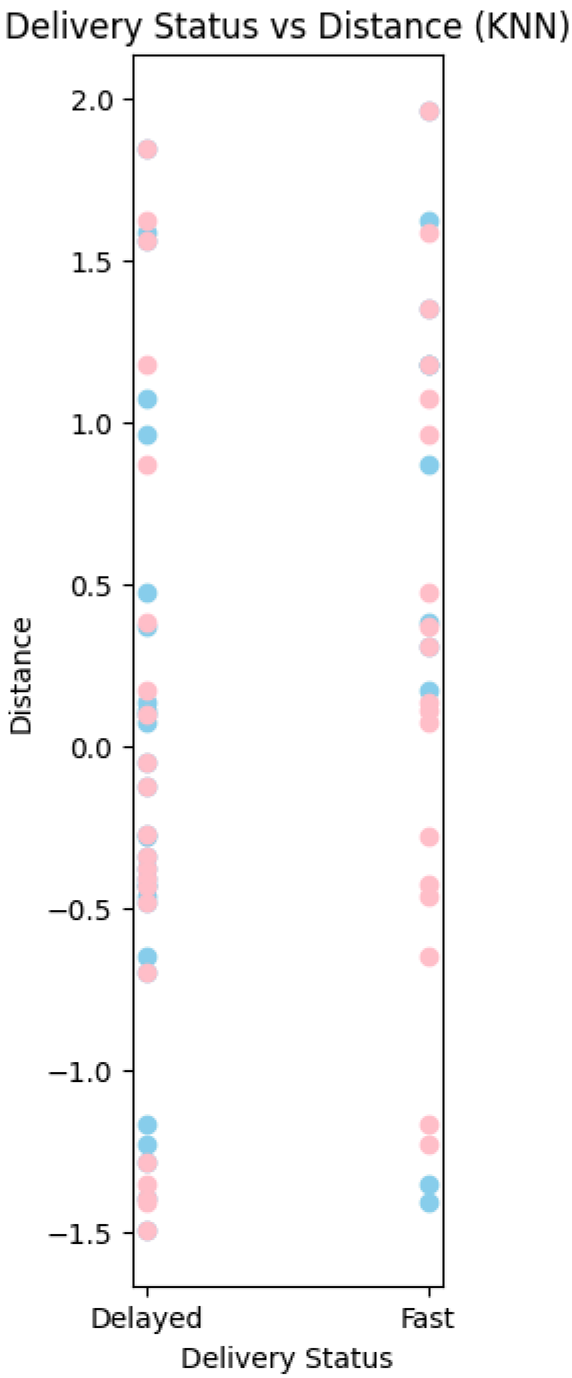
```
array([1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1])
```

In [421…

```
label_map = {0: 'Fast', 1: 'Delayed'}
y_pred_labels_knn = [label_map[label] for label in y_pred_knn]
```

In [422…

```
plt.figure(figsize=(2,8))
plt.scatter(y_pred_labels_knn, x_test['Distance_Scaled'], color='skyblue', label='P
plt.scatter(y_test_labels, x_test['Distance_Scaled'], color='pink', label='Actual S
plt.xlabel('Delivery Status')
plt.ylabel('Distance')
plt.title('Delivery Status vs Distance (KNN)')
plt.legend
plt.show()
```



Step 5 - Decision Tree

In [445…

```
# Define parameter grid for pruning
param_grid = {
    'max_depth': [2, 3, 4, 5, 6, 8, 10, None],
    'min_samples_split': [2, 5, 10, 20]
}
```

In [446…

```
dt_grid = DecisionTreeClassifier(random_state=42)
grid_search = GridSearchCV(dt_grid, param_grid, cv=5, scoring='accuracy')
grid_search.fit(x_train, y_train)

print("Best parameters:", grid_search.best_params_)
print("Best cross-validated accuracy:", grid_search.best_score_)
```

```
Best parameters: {'max_depth': 10, 'min_samples_split': 20}
Best cross-validated accuracy: 0.51875
```

In [447…

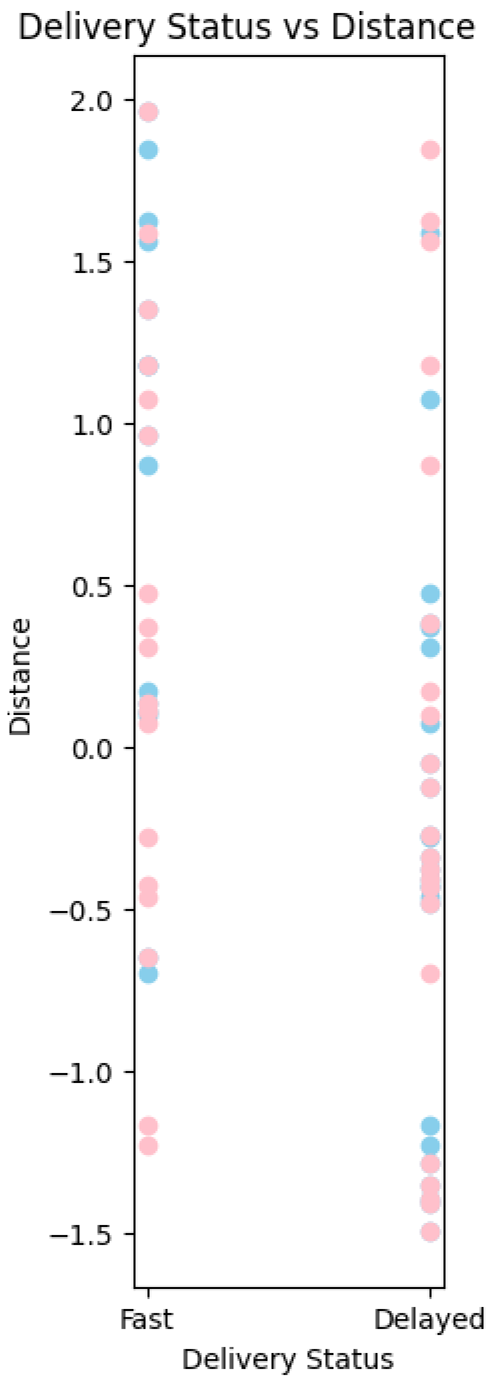
```
# Fit and evaluate pruned tree
dt_pruned = DecisionTreeClassifier(random_state=42, **grid_search.best_params_)
dt_pruned.fit(x_train, y_train)

y_pred_dt = dt_pruned.predict(x_test)
```

In [448…

```
label_map = {0: 'Fast', 1: 'Delayed'}
y_pred_labels_dt = [label_map[label] for label in y_pred_dt]
```

In [449…

```
plt.figure(figsize=(2,8))
plt.scatter(y_pred_labels_dt, x_test['Distance_Scaled'], color='skyblue', label='Pr
plt.scatter(y_test_labels, x_test['Distance_Scaled'], color='pink', label='Actual S
plt.xlabel('Delivery Status')
plt.ylabel('Distance')
plt.title('Delivery Status vs Distance (DT)')
plt.legend
plt.show()
```



Phase 3
Reporting and Insights

(2 steps)

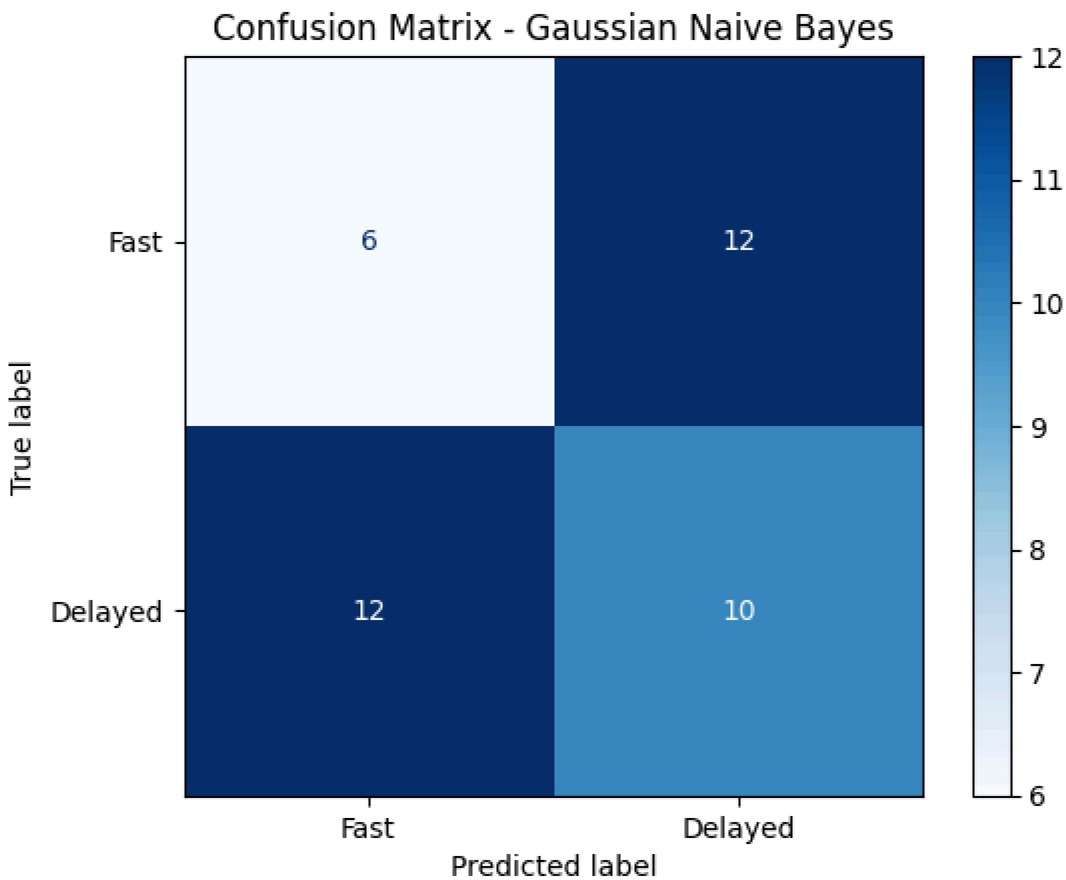
Step 6 - Model Comparison

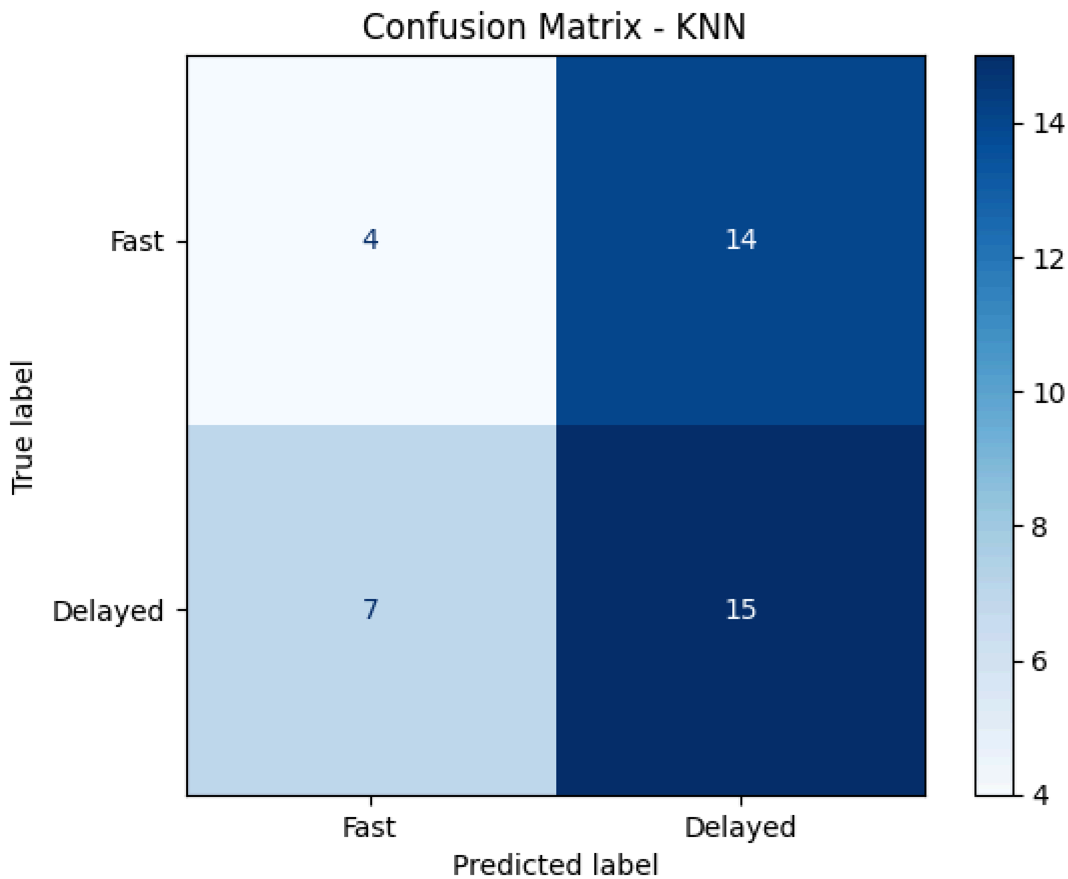
In [450…

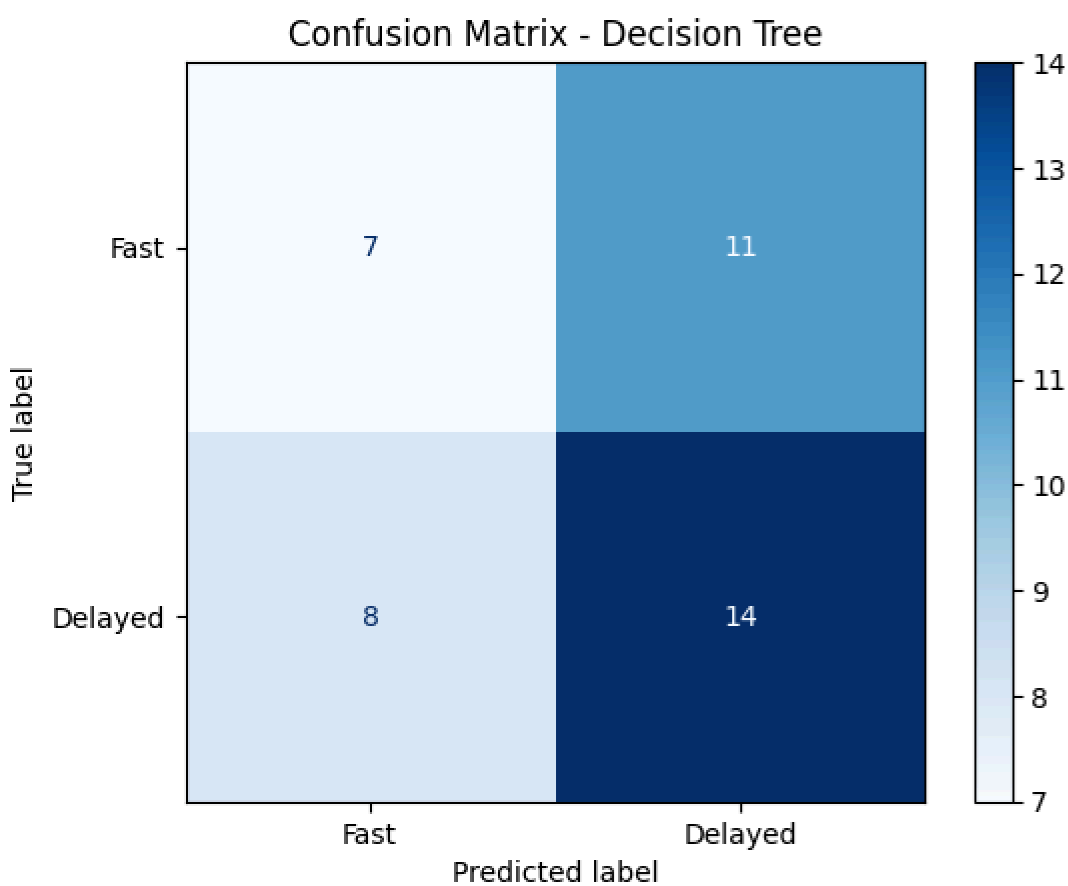
```
# Naive Bayes
accuracy_gnb = accuracy_score(y_test, y_pred_gnb)
print("Accuracy gnb : ", accuracy_gnb)
precision_gnb = precision_score(y_test, y_pred_gnb)
```

```
print("Precision gnb : ", precision_gnb)
recall_gnb = recall_score(y_test, y_pred_gnb)
print("Recall gnb : ", recall_gnb)
f1_score_gnb = f1_score(y_test, y_pred_gnb)
print("F1 Score gnb : ", f1_score_gnb)

# KNN
print("")
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print("Accuracy knn : ", accuracy_knn)
precision_knn = precision_score(y_test, y_pred_knn)
print("Precision knn : ", precision_knn)
recall_knn = recall_score(y_test, y_pred_knn)
print("Recall knn : ", recall_knn)
f1_score_knn = f1_score(y_test, y_pred_knn)
print("F1 Score knn : ", f1_score_knn)

# Decision Tree
print("")
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print("Accuracy dt : ", accuracy_dt)
precision_dt = precision_score(y_test, y_pred_dt)
print("Precision dt : ", precision_dt)
recall_dt = recall_score(y_test, y_pred_dt)
print("Recall dt : ", recall_dt)
f1_score_dt = f1_score(y_test, y_pred_dt)
print("F1 Score dt : ", f1_score_dt)

cm_gnb = confusion_matrix(y_test, y_pred_gnb)
disp_gnb = ConfusionMatrixDisplay(confusion_matrix=cm_gnb, display_labels=['Fast',
disp_gnb.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix - Gaussian Naive Bayes')
plt.show()

cm_knn = confusion_matrix(y_test, y_pred_knn)
disp_knn = ConfusionMatrixDisplay(confusion_matrix=cm_knn, display_labels=['Fast',
disp_knn.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix - KNN')
plt.show()

cm_dt = confusion_matrix(y_test, y_pred_dt)
disp_dt = ConfusionMatrixDisplay(confusion_matrix=cm_dt, display_labels=['Fast', 'D
disp_dt.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix - Decision Tree')
plt.show()
```

```
Accuracy gnb :  0.4
Precision gnb :  0.45454545454545453
Recall gnb :  0.45454545454545453
F1 Score gnb :  0.45454545454545453

Accuracy knn :  0.475
Precision knn :  0.5172413793103449
Recall knn :  0.6818181818181818
F1 Score knn :  0.5882352941176471

Accuracy dt :  0.525
Precision dt :  0.56
Recall dt :  0.6363636363636364
F1 Score dt :  0.5957446808510638
```




Confusion Matrix - KNN
True label
Predicted label
Fast
Delayed
Fast
Delayed
4
14
7
15
14
12
10
8
6
4


Confusion Matrix - Decision Tree
True label
Predicted label
Fast
Delayed
Fast
Delayed
7
11
8
14
14
13
12
11
10
9
8
7

In [451…

```
cr_gnb = classification_report(y_test, y_pred_gnb, target_names=['Delayed', 'Fast']
cr_knn = classification_report(y_test, y_pred_knn, target_names=['Delayed', 'Fast']
cr_dt = classification_report(y_test, y_pred_dt, target_names=['Delayed', 'Fast'])

print("Gaussian Naive Bayes Classification Report:\n", cr_gnb)
print("")
print("")
print("KNN Classification Report:\n", cr_knn)
print("")
print("")
print("Decision Tree Classification Report:\n", cr_dt)
```

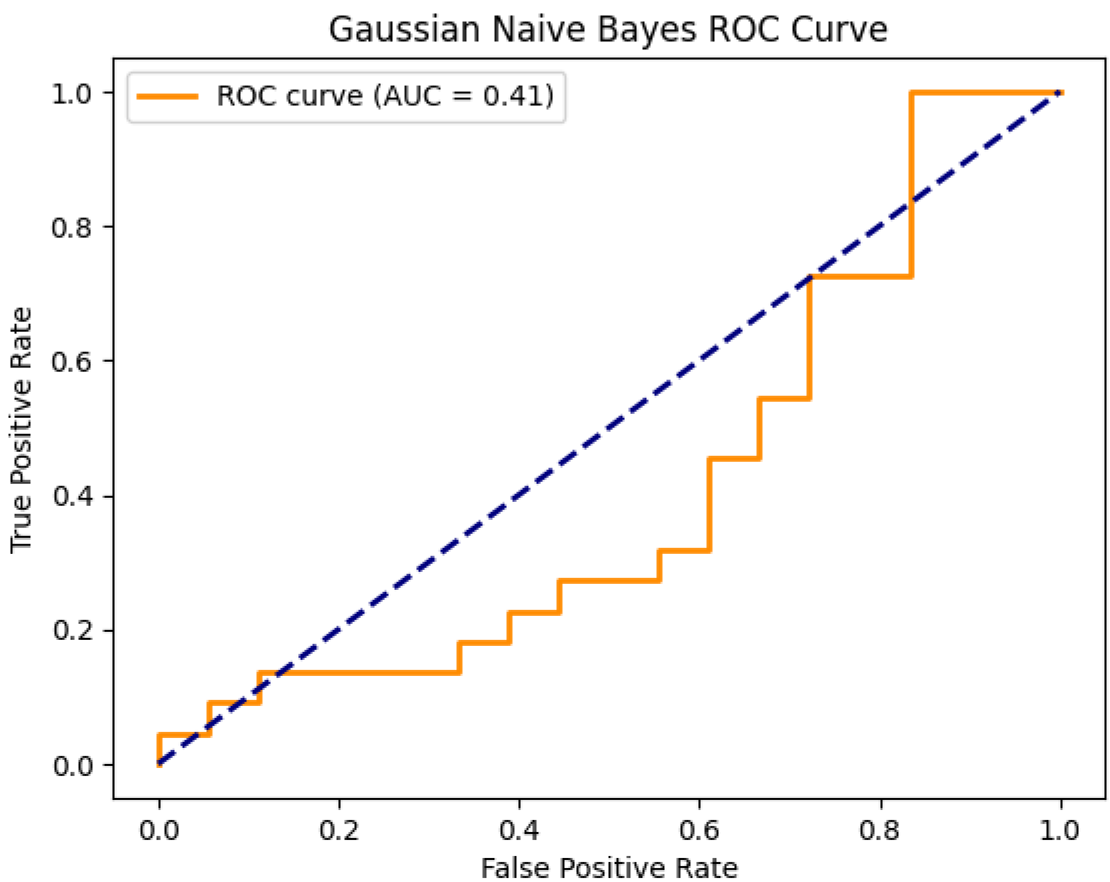
```
Gaussian Naive Bayes Classification Report:
               precision    recall  f1-score   support

     Delayed       0.33      0.33      0.33        18
        Fast       0.45      0.45      0.45        22

    accuracy                           0.40        40
   macro avg       0.39      0.39      0.39        40
weighted avg       0.40      0.40      0.40        40



KNN Classification Report:
               precision    recall  f1-score   support

     Delayed       0.36      0.22      0.28        18
        Fast       0.52      0.68      0.59        22

    accuracy                           0.47        40
   macro avg       0.44      0.45      0.43        40
weighted avg       0.45      0.47      0.45        40



Decision Tree Classification Report:
               precision    recall  f1-score   support

     Delayed       0.47      0.39      0.42        18
        Fast       0.56      0.64      0.60        22

    accuracy                           0.53        40
   macro avg       0.51      0.51      0.51        40
weighted avg       0.52      0.53      0.52        40
```

ROC wants a 1D array

In [452…

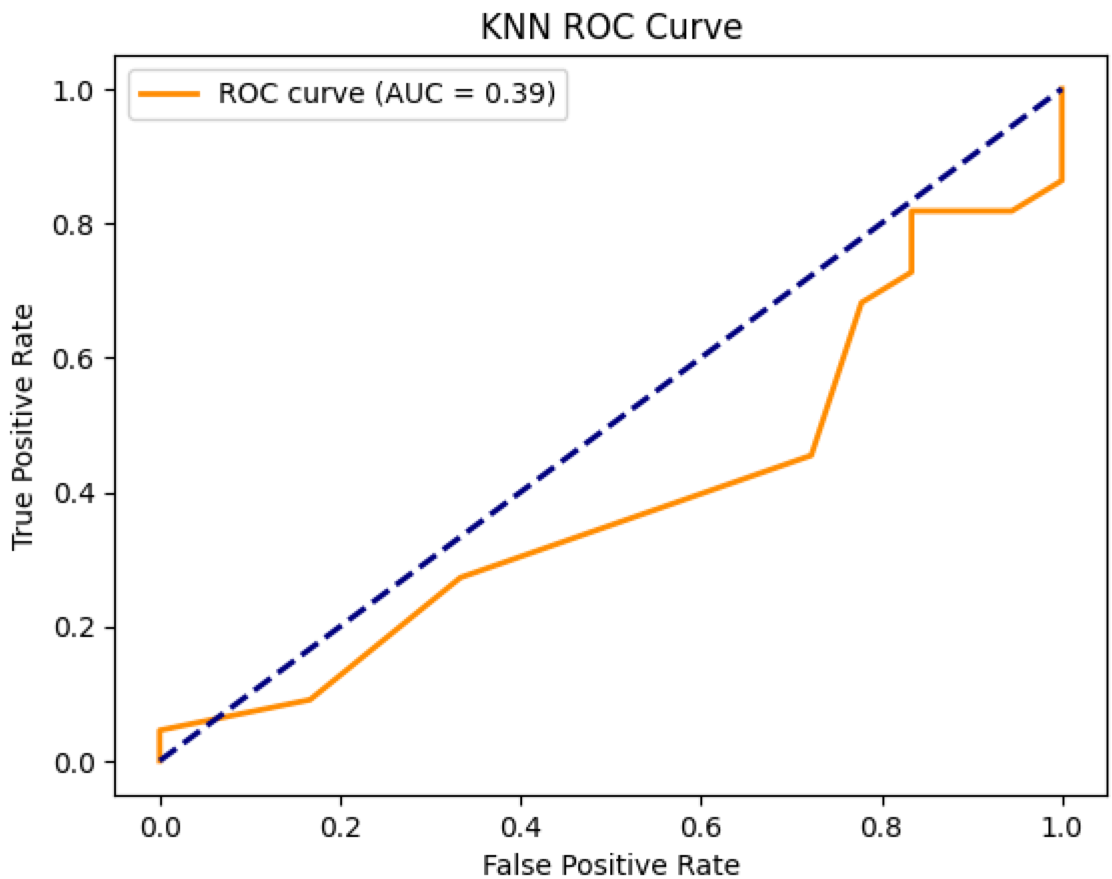
```
lb = label_binarize(y_test, classes=[0, 1])

y_test_bin = y_test.values
y_pred_prob = gnb.predict_proba(x_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test_bin, y_pred_prob)
```

```
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f}
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Gaussian Naive Bayes ROC Curve')
plt.legend()
plt.show()
```



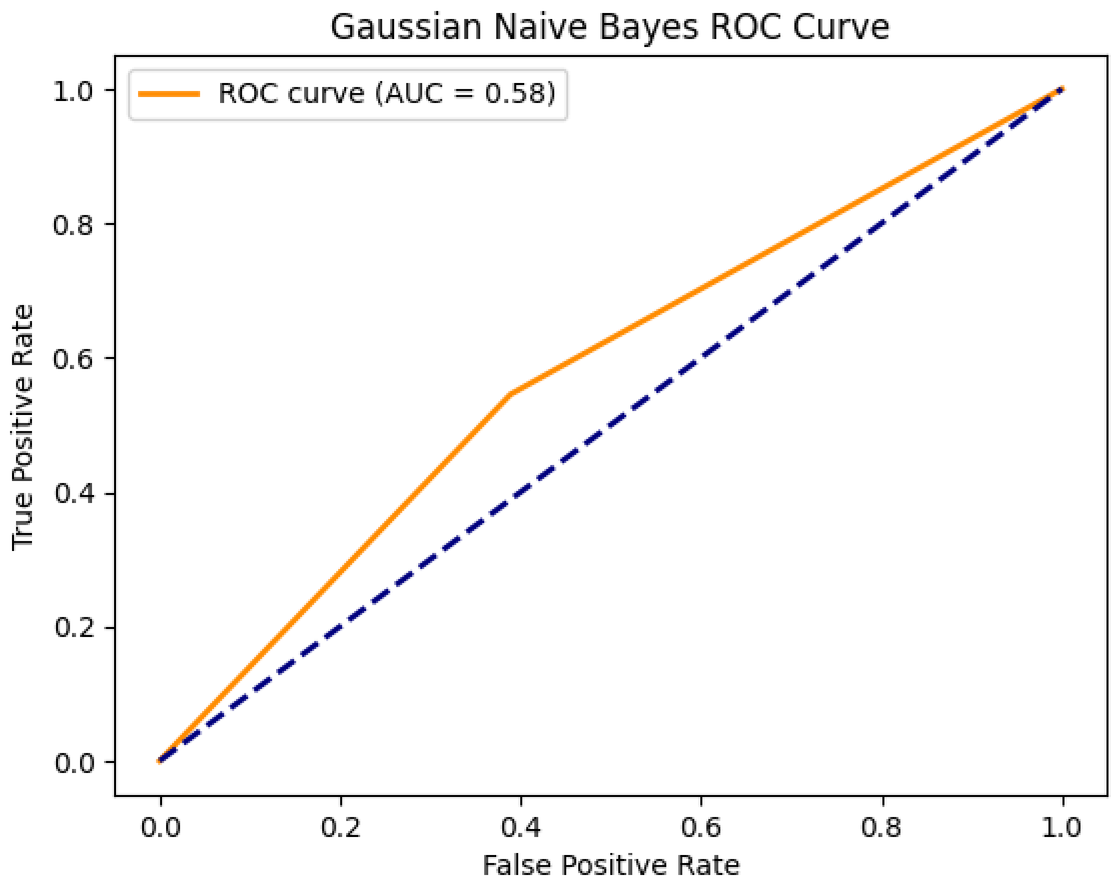
In [453…

```
lb = label_binarize(y_test, classes=[0, 1])
y_test_bin = y_test.values
y_pred_prob = knn.predict_proba(x_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test_bin, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f}
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('KNN ROC Curve')
plt.legend()
plt.show()
```



In [454…

```
lb = label_binarize(y_test, classes=[0, 1])

y_test_bin = y_test.values
y_pred_prob = dt.predict_proba(x_test)[:, 1]

fpr, tpr, thresholds = roc_curve(y_test_bin, y_pred_prob)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f}
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Gaussian Naive Bayes ROC Curve')
plt.legend()
plt.show()
```



Step 7 - Actionable Insights

In [456…

```
insights = """
Strengths and Weaknesses:

- Gaussian Naive Bayes (GNB):
    Strengths: Simple, fast, and works well with small datasets. Easy to implement
    Weaknesses: Assumes feature independence and Gaussian distribution, which may n

- K-Nearest Neighbors (KNN):
    Strengths: Non-parametric, can capture complex relationships, and performs reas
    Weaknesses: Sensitive to feature scaling, less interpretable, and computational

- Decision Tree (DT):
    Strengths: Highest accuracy (0.53) and F1 score (0.60). Provides clear interpre
    Weaknesses: Can overfit if not pruned, and performance may vary with small chan

Recommendation:

Based on the results, the Decision Tree classifier is recommended for this task. It
"""

print(insights)
```

```
Strengths and Weaknesses:

- Gaussian Naive Bayes (GNB):
    Strengths: Simple, fast, and works well with small datasets. Easy to implement a
nd interpret.
    Weaknesses: Assumes feature independence and Gaussian distribution, which may no
t hold for this dataset. Lower accuracy (0.40) and F1 score (0.45) indicate underper
formance.

- K-Nearest Neighbors (KNN):
    Strengths: Non-parametric, can capture complex relationships, and performs reaso
nably well (accuracy: 0.48, F1: 0.59). No strong assumptions about data distributio
n.
    Weaknesses: Sensitive to feature scaling, less interpretable, and computationall
y expensive for large datasets.

- Decision Tree (DT):
    Strengths: Highest accuracy (0.53) and F1 score (0.60). Provides clear interpret
ability and can handle feature interactions. Pruning helps prevent overfitting.
    Weaknesses: Can overfit if not pruned, and performance may vary with small chang
es in data.

Recommendation:

Based on the results, the Decision Tree classifier is recommended for this task. It
offers the best balance between predictive performance and interpretability, making
it suitable for understanding the factors influencing delivery delays and for deploy
ment in real-world scenarios.
```

Final Summary

This project focused on classifying food delivery status as either *"Fast"* or *"Delayed"* using factors such as order timing, distance, traffic conditions, and delivery experience. The pipeline included data cleaning, encoding categorical features, feature scaling, and applying classification models to predict delivery performance.

- *Data Preparation:* The dataset was cleaned and transformed by handling missing values, encoding categorical variables, scaling distance metrics, and mapping delivery outcomes to binary labels (*Fast = 0*, *Delayed = 1*).

- *Model Evaluation:*

    - **Gaussian Naive Bayes (GNB)** achieved low performance with an *accuracy of 40%* and *F1-score of 45%*, due to its strong assumptions about feature independence and normal distribution.
    - **K-Nearest Neighbors (KNN)** improved performance to an *accuracy of 48%* and *F1-score of 59%*, capturing non-linear patterns but being sensitive to feature scaling.
    - **Decision Tree (DT)** delivered the highest *accuracy of 53%* and *F1-score of 60%*, offering strong interpretability and benefiting from hyperparameter tuning

(pruning) to control overfitting.

- *Insights & Recommendations:*
  - Most features showed weak individual correlation with delivery status, indicating that delivery delays are influenced by complex interactions or unrecorded external factors.
  - Simpler models offer limited predictive power; however, Decision Trees provide actionable insights due to their explainability.

In conclusion, the Decision Tree model is the most suitable for this task, balancing interpretability and predictive performance. For better accuracy in real-world applications, future work should incorporate additional real-time variables like GPS route data, live traffic conditions, and driver behavior patterns. Furthermore, ensemble methods such as Random Forest or Gradient Boosting could be explored to improve prediction quality.