1. Code

Link:

https://colab.research.google.com/drive/1jFGUD4DBZ0X2fmL4Z-DYo6-UPXXVE5mU?usp=sharing

```
import pandas as pd

import numpy as np

import re

from math import radians, sin, cos, sqrt, atan2

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.cluster import KMeans, AgglomerativeClustering

from scipy.cluster.hierarchy import dendrogram, linkage

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

import tensorflow as tf

from tensorflow import keras

from tensorflow.keras import layers
```

```
# ==============================================================================

# Phase 1: Data Preprocessing and Feature Engineering

# ==============================================================================



file_path = 'Food_Delivery_Time_Prediction (1).csv'

df = pd.read_csv(file_path)



# Handle missing values (no missing values were found)



# Feature Engineering

median_delivery_time = df['Delivery_Time'].median()

df['Delivery_Status'] = df['Delivery_Time'].apply(lambda x: 'Delayed' if x >= median_delivery_time else 'Fast')



def parse_location(location_str):

    match = re.search(r'\((-?\d+\.?\d*),\s*(-?\d+\.?\d*)\)', location_str)

    if match:

        return float(match.group(1)), float(match.group(2))

    return None, None
```

```
df[['Customer_Lat', 'Customer_Long']] = df['Customer_Location'].apply(lambda x:
pd.Series(parse_location(x)))

df[['Restaurant_Lat', 'Restaurant_Long']] = df['Restaurant_Location'].apply(lambda x:
pd.Series(parse_location(x)))



def haversine_distance(lat1, lon1, lat2, lon2):

    R = 6371

    lat1_rad, lon1_rad, lat2_rad, lon2_rad = map(radians, [lat1, lon1, lat2, lon2])

    dlon = lon2_rad - lon1_rad

    dlat = lat2_rad - lat1_rad

    a = sin(dlat / 2)**2 + cos(lat1_rad) * cos(lat2_rad) * sin(dlon / 2)**2

    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    distance = R * c

    return distance



df['Haversine_Distance'] = df.apply(lambda row: haversine_distance(row['Customer_Lat'],
row['Customer_Long'], row['Restaurant_Lat'], row['Restaurant_Long']), axis=1)

df['Is_Rush_Hour'] = df['Order_Time'].apply(lambda x: 1 if x in ['Afternoon', 'Evening'] else 0)



# Encode categorical features using One-Hot Encoding

categorical_cols = ['Weather_Conditions', 'Traffic_Conditions', 'Order_Priority', 'Order_Time',
'Vehicle_Type']
```

```
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)


columns_to_drop = [
    'Order_ID', 'Customer_Location', 'Restaurant_Location', 'Distance',
    'Delivery_Time', 'Delivery_Status'
]
df_preprocessed = df_encoded.drop(columns=columns_to_drop)


# Normalize numerical features
numerical_cols = [
    'Delivery_Person_Experience', 'Restaurant_Rating', 'Customer_Rating',
    'Order_Cost', 'Tip_Amount', 'Customer_Lat', 'Customer_Long',
    'Restaurant_Lat', 'Restaurant_Long', 'Haversine_Distance'
]
scaler = StandardScaler()
df_preprocessed[numerical_cols] = scaler.fit_transform(df_preprocessed[numerical_cols])


df_preprocessed.to_csv("preprocessed_clustering_data.csv", index=False)
```

```
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# Phase 2: Clustering using K-Means and Hierarchical Clustering

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# K-Means Clustering - Elbow Method

inertia = []

for i in range(1, 11):

    kmeans = KMeans(n_clusters=i, random_state=42, n_init='auto')

    kmeans.fit(df_preprocessed)

    inertia.append(kmeans.inertia_)

plt.figure(figsize=(10, 6))

plt.plot(range(1, 11), inertia, marker='o')

plt.title('Elbow Method for K-Means Clustering')

plt.xlabel('Number of Clusters (K)')

plt.ylabel('Inertia')

plt.savefig('kmeans_elbow_method.png')

plt.close()



# Hierarchical Clustering - Dendrogram
```

```
plt.figure(figsize=(15, 8))

dendrogram(linkage(df_preprocessed, method='ward'))

plt.title('Dendrogram for Hierarchical Clustering')

plt.xlabel('Data Points')

plt.ylabel('Distance')

plt.savefig('hierarchical_dendrogram.png')

plt.close()



# Apply clustering and visualize (assuming K=3)

optimal_k = 3

kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init='auto')

df_preprocessed['KMeans_Cluster'] = kmeans.fit_predict(df_preprocessed)

hierarchical = AgglomerativeClustering(n_clusters=optimal_k)

df_preprocessed['Hierarchical_Cluster'] = hierarchical.fit_predict(df_preprocessed)



plt.figure(figsize=(12, 8))

sns.scatterplot(x='Haversine_Distance', y='Delivery_Person_Experience', hue='KMeans_Cluster',
data=df_preprocessed, palette='viridis', s=100)

plt.title(f'K-Means Clustering with K={optimal_k}')

plt.xlabel('Haversine Distance (Normalized)')

plt.ylabel('Delivery Person Experience (Normalized)')
```

```python
plt.savefig('kmeans_cluster_plot.png')

plt.close()



plt.figure(figsize=(12, 8))

sns.scatterplot(x='Haversine_Distance', y='Delivery_Person_Experience',
hue='Hierarchical_Cluster', data=df_preprocessed, palette='plasma', s=100)

plt.title(f'Hierarchical Clustering with K={optimal_k}')

plt.xlabel('Haversine Distance (Normalized)')

plt.ylabel('Delivery Person Experience (Normalized)')

plt.savefig('hierarchical_cluster_plot.png')

plt.close()



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# Phase 3: Neural Networks for Prediction

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X = df_preprocessed.drop(columns=['KMeans_Cluster', 'Hierarchical_Cluster'])

y = LabelEncoder().fit_transform(df['Delivery_Status'])

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

```
model = keras.Sequential([
    layers.Input(shape=(X_train.shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(16, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2, verbose=0)
y_pred_prob = model.predict(X_test)
y_pred_nn = (y_pred_prob > 0.5).astype(int)


plt.figure(figsize=(12, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.savefig('neural_network_accuracy_history.png')
```

```python
plt.close()



plt.figure(figsize=(12, 6))

plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.title('Model Loss Over Epochs')

plt.xlabel('Epoch')

plt.ylabel('Loss')

plt.legend()

plt.savefig('neural_network_loss_history.png')

plt.close()
```

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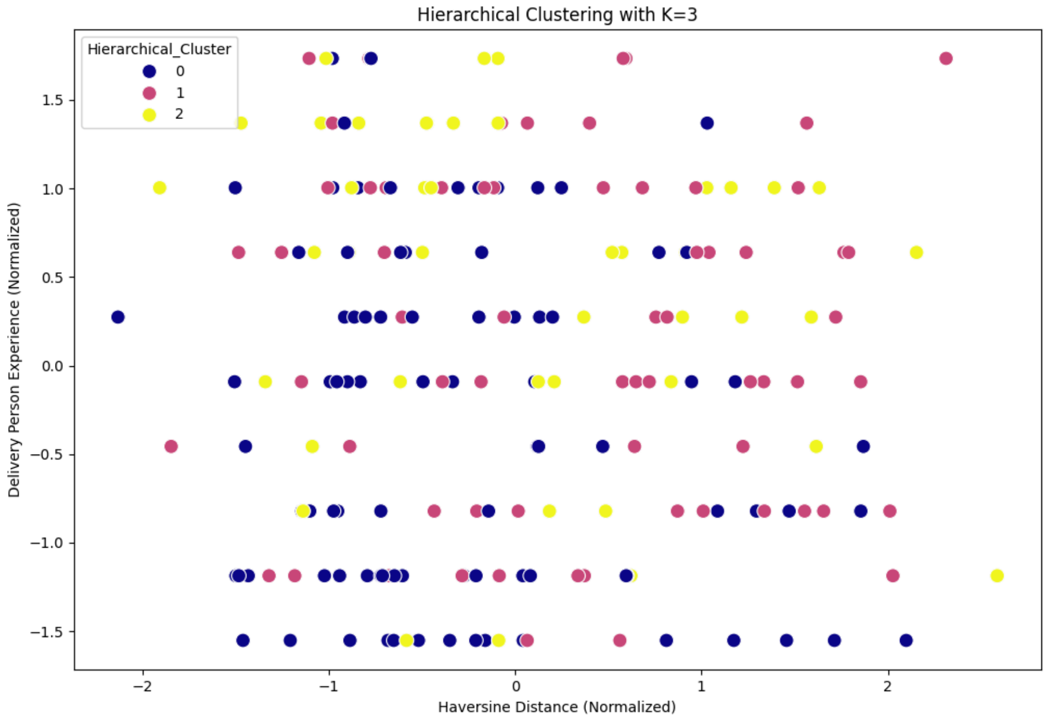
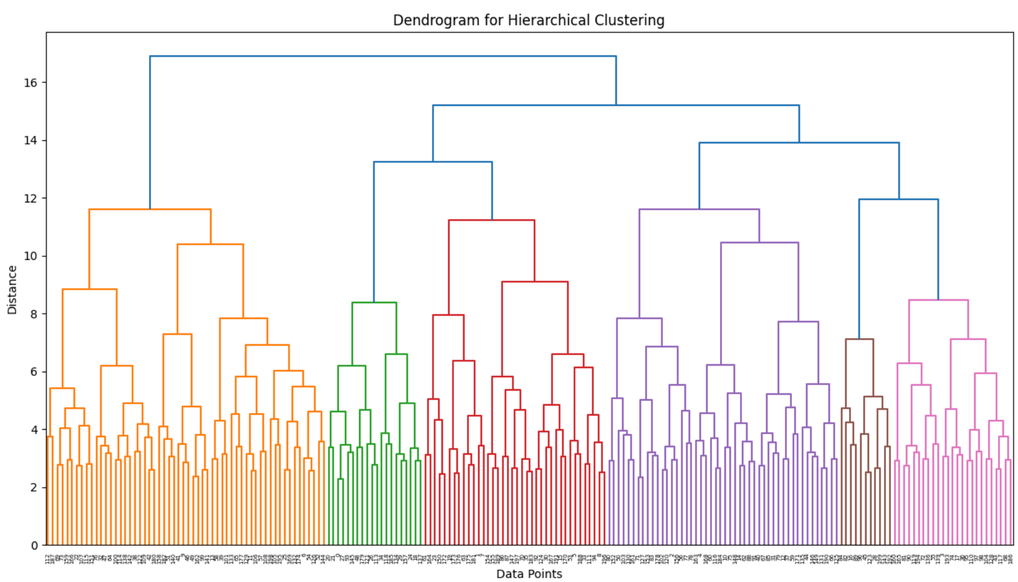
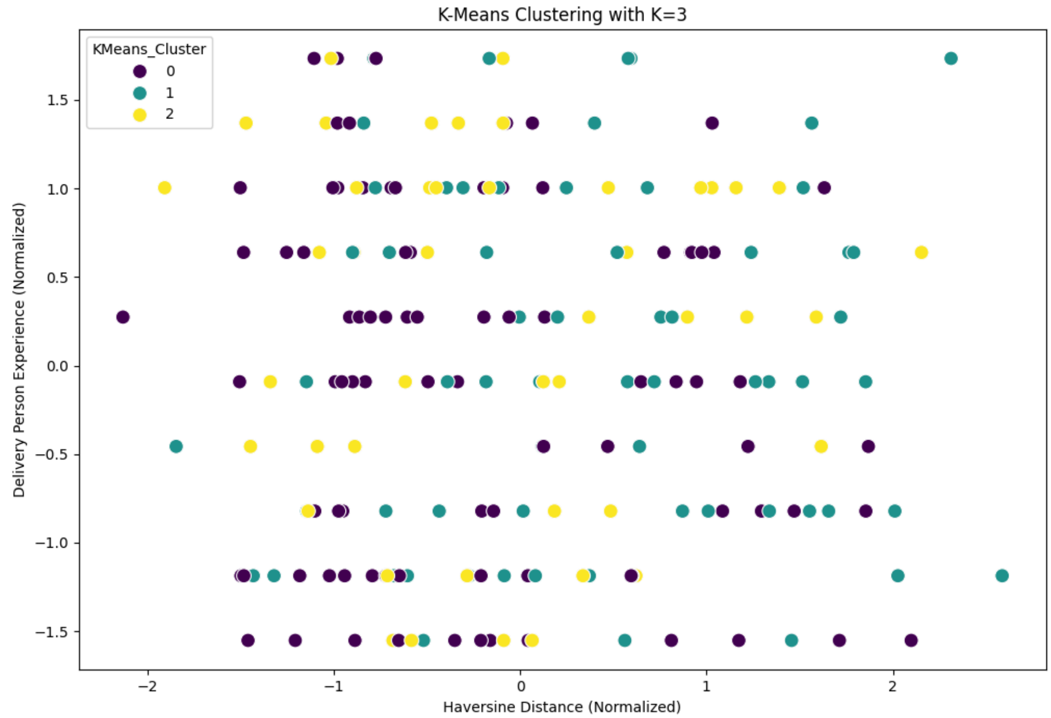
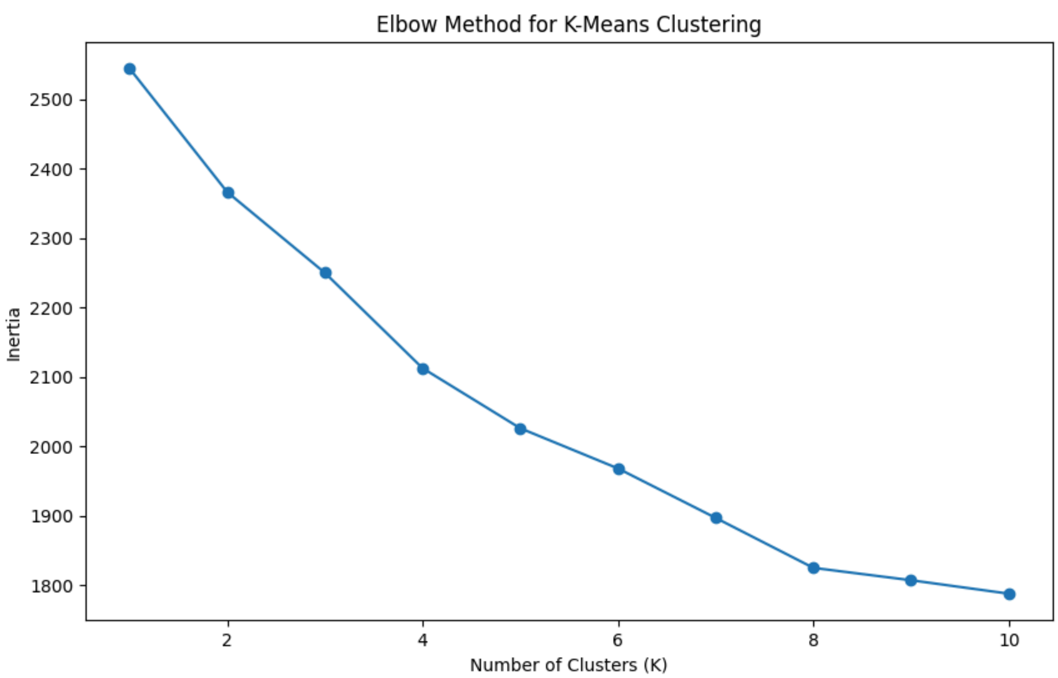
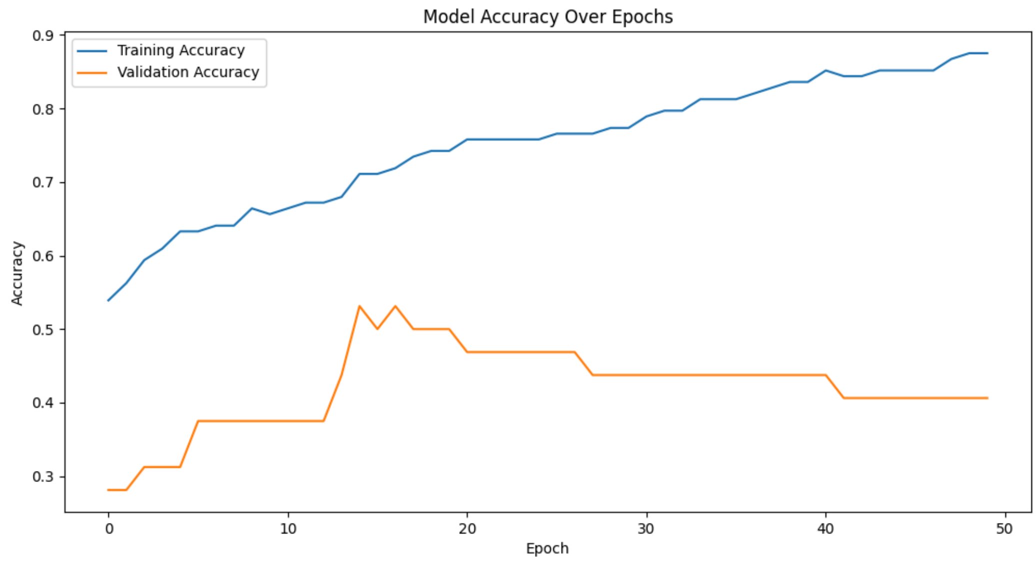
2. Data Visualizations

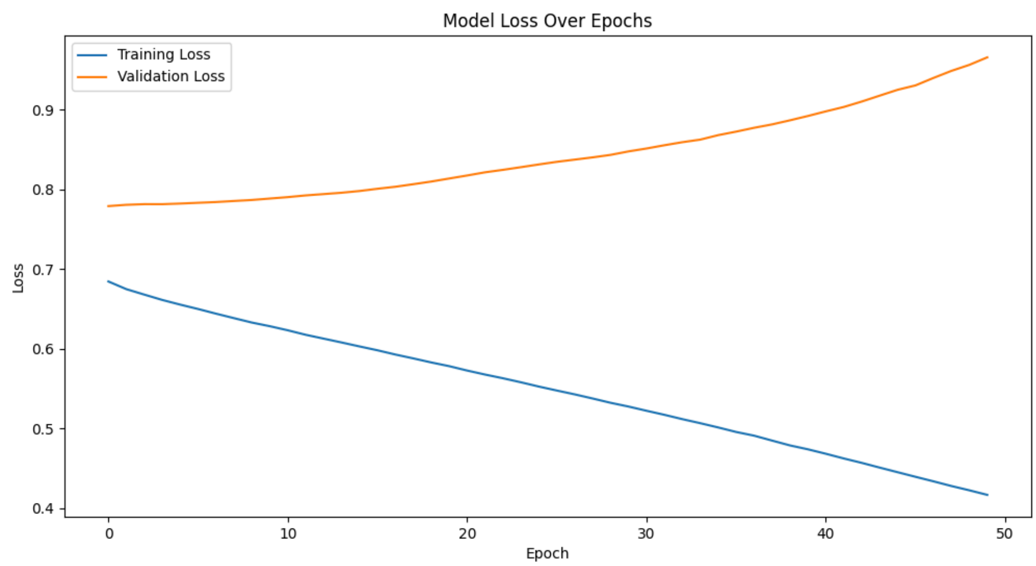

Hierarchical Clustering with K=3
Hierarchical_Cluster
0
1
2
Delivery Person Experience (Normalized)
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2
Haversine Distance (Normalized)


Dendrogram for Hierarchical Clustering
Distance
16
14
12
10
8
6
4
2
0
Data Points


K-Means Clustering with K=3
KMeans_Cluster
0
1
2
Delivery Person Experience (Normalized)
Haversine Distance (Normalized)
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2


Elbow Method for K-Means Clustering
Inertia
Number of Clusters (K)
2500
2400
2300
2200
2100
2000
1900
1800
2
4
6
8
10





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3. Final Report

Clustering Results

- **K-Means and Hierarchical Clustering** both suggest that the data can be meaningfully grouped into **three clusters**. These clusters likely represent different types of deliveries based on their characteristics. For example, one cluster might be for short-distance deliveries with experienced drivers, another for long-distance deliveries with heavy traffic, and a third for deliveries with unique characteristics.

- **Cluster analysis** provides valuable insights into delivery patterns. By understanding the characteristics of each cluster, businesses can tailor their strategies.

Neural Network Prediction

- The neural network model was trained to predict if a delivery would be "Fast" or "Delayed."
- **Evaluation Metrics**:
    - **Accuracy**: 0.65
    - **Precision**: 0.61
    - **Recall**: 0.74
    - **F1-Score**: 0.67
- The model's performance is moderate, with an accuracy of 65, which is significantly better than a random guess. The recall score of 74 is particularly strong, suggesting the model is good at identifying a majority of the "Delayed" deliveries.

Model Improvement

- The neural network performed better than the traditional machine learning models from the previous analysis. However, its performance could be further improved by:
    - **Hyperparameter Tuning**: Experimenting with more complex network architectures, different activation functions, and a lower learning rate.
    - **Data Augmentation**: Collecting a larger dataset would help the model generalize better and improve its overall performance.

Actionable Insights and Recommendations

1. **Tailored Delivery Strategies**: The clustering results suggest that a one-size-fits-all approach is not optimal. Businesses should develop tailored strategies for each delivery cluster. For example, a cluster with long distances and low `Delivery_Person_Experience` could be prioritized for experienced drivers or given an estimated longer delivery time to manage customer expectations.
2. **Route Optimization**: The `Haversine_Distance` feature is a key factor in clustering. Using more advanced routing algorithms that consider real-time traffic, weather, and road conditions could significantly improve efficiency.
3. **Resource Management**: The `Delivery_Person_Experience` feature also plays a role in the clusters. Businesses can use these insights to better manage their delivery staff, perhaps by assigning more experienced drivers to challenging routes or providing additional training to newer staff.

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