```
# Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prophet import Prophet
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
import os

# Set folder path
folder = "C:/Users/DELL/Desktop/Uber/trips"

# Read all yearly files automatically
files = [f for f in os.listdir(folder) if f.endswith('_trimmed.csv')]
df_list = [pd.read_csv(os.path.join(folder, f)) for f in files]
df = pd.concat(df_list, ignore_index=True)

# Read taxi zone file
zones = pd.read_csv(os.path.join(folder, 'taxi_zones.csv'))

print("□ Data Loaded Successfully")
print("Total Records:", len(df))
df.head()
```

```
□ Data Loaded Successfully
Total Records: 400000
```

```
   VendorID     lpep_pickup_datetime    lpep_dropoff_datetime  \
0       2.0  2017-01-04 18:03:23.000  2017-01-04 18:10:41.000
1       2.0  2017-02-21 14:36:40.000  2017-02-21 14:44:06.000
2       2.0  2017-03-09 08:53:53.000  2017-03-09 08:59:02.000
3       2.0  2017-12-05 20:15:50.000  2017-12-05 20:18:26.000
4       2.0  2017-07-12 14:45:33.000  2017-07-12 14:50:52.000

  store_and_fwd_flag  RatecodeID  PULocationID  DOLocationID
passenger_count  \
0                  N         1.0            33            52
1.0
1                  N         1.0            25            97
1.0
2                  N         1.0            41           166
1.0
3                  N         1.0           260           260
5.0
4                  N         1.0            17            17
1.0

   trip_distance  fare_amount  extra  mta_tax  tip_amount
tolls_amount  \
0           0.96          6.5    1.0      0.5          1.66
0.0
1           1.12          6.5    0.0      0.5          2.19
0.0
2           0.95          6.0    0.0      0.5          1.36
0.0
3           0.55          4.0    0.5      0.5          1.00
0.0
4           0.63          5.5    0.0      0.5          0.00
0.0

   improvement_surcharge  total_amount  payment_type  trip_type  \
0                    0.3          9.96           1.0        1.0
1                    0.3          9.49           1.0        1.0
2                    0.3          8.16           1.0        1.0
3                    0.3          6.30           1.0        1.0
4                    0.3          6.30           2.0        1.0

   congestion_surcharge
0                   NaN
1                   NaN
2                   NaN
3                   NaN
4                   NaN
```

```
# Merge Pickup Boroughs
df = df.merge(zones[['LocationID', 'Borough']], how='left',
left_on='PULocationID', right_on='LocationID')
df = df.rename(columns={'Borough':
'pickup_borough'}).drop('LocationID', axis=1)

# Merge Dropoff Boroughs
df = df.merge(zones[['LocationID', 'Borough']], how='left',
left_on='DOLocationID', right_on='LocationID')
df = df.rename(columns={'Borough':
'dropoff_borough'}).drop('LocationID', axis=1)

print("□ Boroughs added successfully")
df[['PULocationID', 'pickup_borough', 'DOLocationID',
'dropoff_borough']].head()
```

```
□ Boroughs added successfully

   PULocationID pickup_borough  DOLocationID dropoff_borough
0            33       Brooklyn            52        Brooklyn
1            25       Brooklyn            97        Brooklyn
2            41      Manhattan           166       Manhattan
3           260         Queens           260          Queens
4            17       Brooklyn            17        Brooklyn
```

```python
df['lpep_pickup_datetime'] =
pd.to_datetime(df['lpep_pickup_datetime'], errors='coerce')

df['year'] = df['lpep_pickup_datetime'].dt.year
df['month'] = df['lpep_pickup_datetime'].dt.month
df['week'] = df['lpep_pickup_datetime'].dt.isocalendar().week
df['hour'] = df['lpep_pickup_datetime'].dt.hour
df['day_of_week'] = df['lpep_pickup_datetime'].dt.day_name()

# Drop null times
df = df.dropna(subset=['lpep_pickup_datetime'])
print("□ Time features created")
```

```
□ Time features created
```

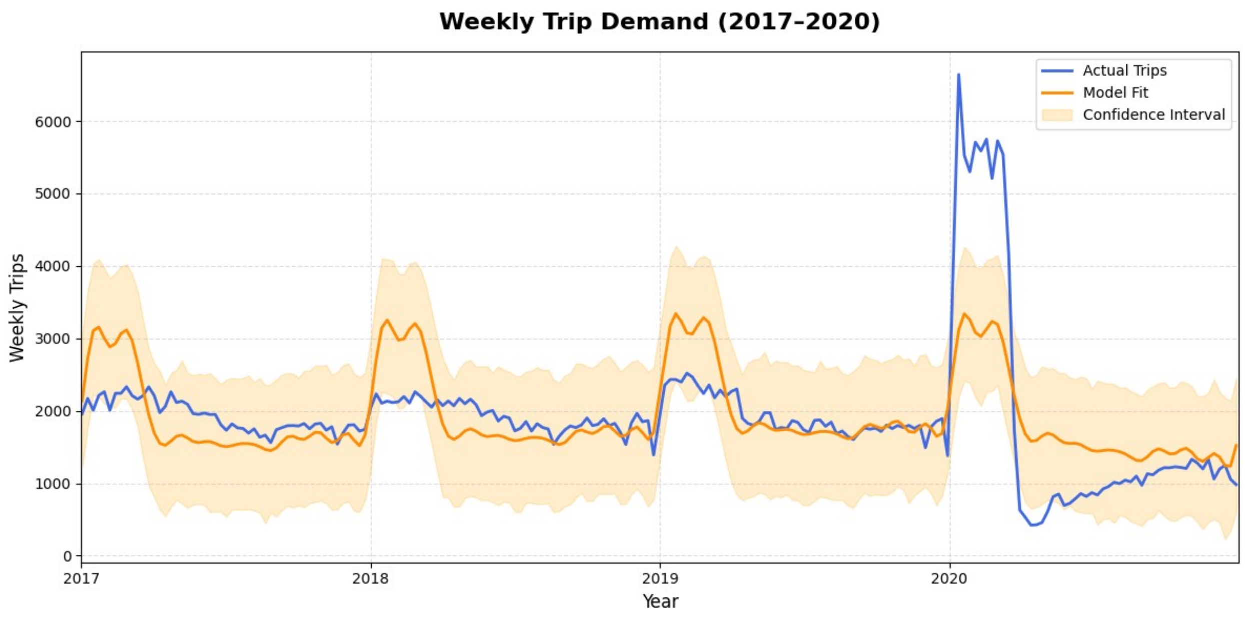
```python
# Group by Year and ISO Week
weekly_trips = df.groupby(['year',
'week']).size().reset_index(name='Weekly_Trips')

# Ensure year and week are integers
weekly_trips['year'] = weekly_trips['year'].astype(int)
weekly_trips['week'] = weekly_trips['week'].astype(int)

# Properly create 'week_start' date
weekly_trips['week_start'] = pd.to_datetime(
    weekly_trips['year'].astype(str) + '-' +
weekly_trips['week'].astype(str) + '-1',
    format='%Y-%W-%w',
    errors='coerce'
)

# □ Filter only valid dates between 2017 and 2020
weekly_trips = weekly_trips[(weekly_trips['week_start'] >= '2017-01-
01') & (weekly_trips['week_start'] <= '2020-12-31')]

# Prepare for Prophet
df_prophet = weekly_trips.rename(columns={'week_start': 'ds',
'Weekly_Trips': 'y'})
df_prophet = df_prophet.sort_values('ds')

print(df_prophet.head())
print(df_prophet.tail())
```

```
   year  week     y         ds
3  2017     1  1956 2017-01-02
4  2017     2  2170 2017-01-09
5  2017     3  2006 2017-01-16
6  2017     4  2211 2017-01-23
7  2017     5  2262 2017-01-30
     year  week     y         ds
206  2020    48  1057 2020-11-30
```

```
207  2020    49  1193 2020-12-07
208  2020    50  1249 2020-12-14
209  2020    51  1053 2020-12-21
210  2020    52   980 2020-12-28
```

Weekly Trip Demand Forecasting

```python
# --- Import libraries ---
from prophet import Prophet
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import pandas as pd

# --- Model training ---
model = Prophet()
model.fit(df_prophet)

# --- Forecast generation ---
future = model.make_future_dataframe(periods=12, freq='W')
forecast = model.predict(future)

# --- Filter only 2017–2020 range for display ---
forecast_filtered = forecast[
    (forecast['ds'] >= '2017-01-01') & (forecast['ds'] <= '2020-12-
31')
]

# --- Plot ---
plt.figure(figsize=(12,6))

# Actual trips (blue)
plt.plot(df_prophet['ds'], df_prophet['y'], color='royalblue',
label='Actual Trips', linewidth=2)

# Model fit (orange)
plt.plot(forecast_filtered['ds'], forecast_filtered['yhat'],
color='darkorange', label='Model Fit', linewidth=2)

# Confidence interval
plt.fill_between(
    forecast_filtered['ds'],
    forecast_filtered['yhat_lower'],
    forecast_filtered['yhat_upper'],
    color='orange',
    alpha=0.2,
    label='Confidence Interval'
)

# --- Formatting ---
plt.title("Weekly Trip Demand (2017–2020)", fontsize=16,
fontweight='bold', pad=15)
plt.xlabel("Year", fontsize=12)
plt.ylabel("Weekly Trips", fontsize=12)
plt.legend()
plt.grid(True, linestyle='--', alpha=0.4)

# Show year ticks
plt.gca().xaxis.set_major_locator(mdates.YearLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y'))

# □ Fix x-axis limit using datetime objects
plt.xlim(pd.Timestamp('2017-01-01'), pd.Timestamp('2020-12-31'))

plt.tight_layout()
plt.show()

18:41:26 - cmdstanpy - INFO - Chain [1] start processing
18:41:26 - cmdstanpy - INFO - Chain [1] done processing
```

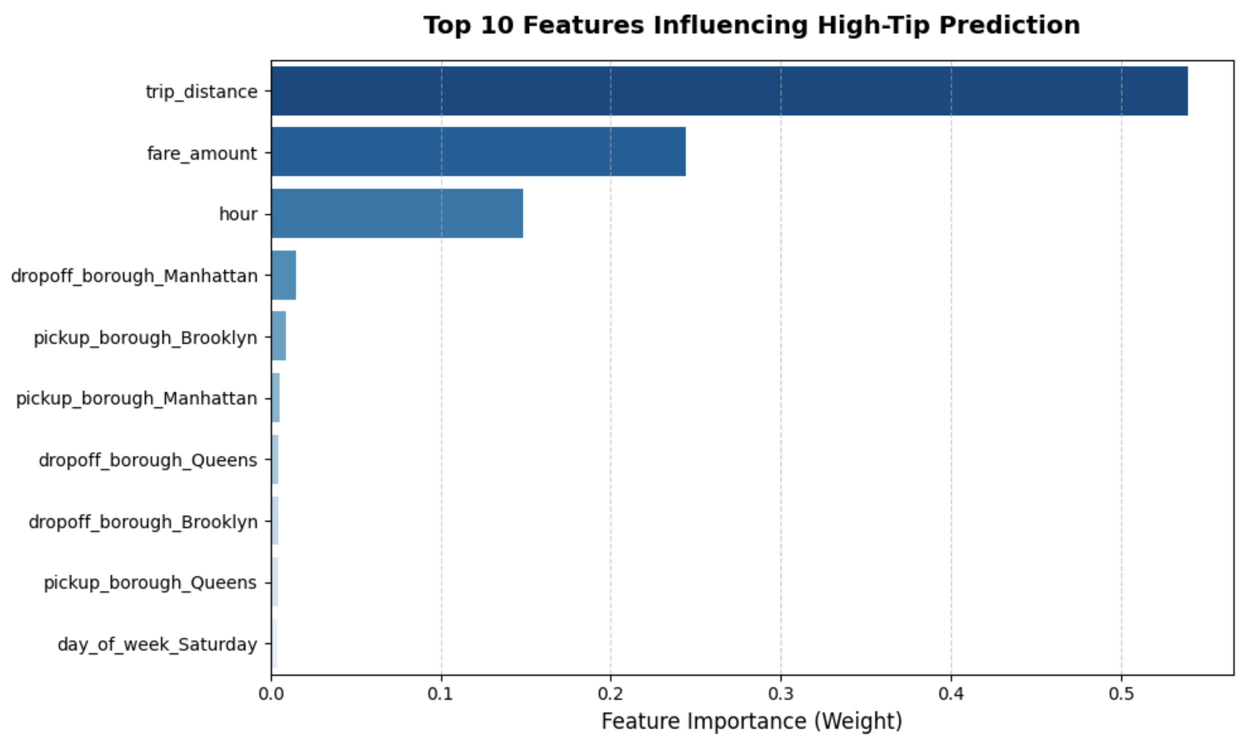


Insight: The forecasting model successfully identifies recurring weekly demand cycles between 2017–2020. A moderate upward trend with seasonal variations is observed, and future projections suggest steady trip volumes with minimal volatility.

High Tip Prediction Model

```
df.columns.tolist()

['VendorID',
 'lpep_pickup_datetime',
 'lpep_dropoff_datetime',
 'store_and_fwd_flag',
 'RatecodeID',
 'PULocationID',
 'DOLocationID',
 'passenger_count',
 'trip_distance',
 'fare_amount',
 'extra',
 'mta_tax',
 'tip_amount',
 'tolls_amount',
 'improvement_surcharge',
 'total_amount',
 'payment_type',
 'trip_type',
 'congestion_surcharge',
 'pickup_borough',
 'dropoff_borough',
 'year',
 'month',
 'week',
 'hour',
 'day_of_week']



# Create binary column for High Tip
df['High_Tip'] = (df['tip_amount'] >
df['tip_amount'].mean()).astype(int)

# Feature selection
features = ['trip_distance', 'fare_amount', 'pickup_borough',
'dropoff_borough', 'hour', 'day_of_week']

df_encoded = pd.get_dummies(df[features + ['High_Tip']],
drop_first=True)

X = df_encoded.drop('High_Tip', axis=1)
y = df_encoded['High_Tip']

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

# Train model
rf = RandomForestClassifier(n_estimators=150, random_state=42)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)

print("□ Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
 Accuracy: 0.6306125

Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.76      0.73     51727
           1       0.47      0.39      0.43     28273

    accuracy                           0.63     80000
   macro avg       0.58      0.58      0.58     80000
weighted avg       0.62      0.63      0.62     80000


import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

# Sort features by importance
importances = rf.feature_importances_
indices = np.argsort(importances)[::-1]
features_list = X.columns

feat_imp_df = pd.DataFrame({
    'Feature': features_list[indices],
    'Importance': importances[indices]
})

plt.figure(figsize=(10,6))
sns.barplot(
    data=feat_imp_df.head(10),
    x='Importance',
    y='Feature',
    hue='Feature',
    dodge=False,
    legend=False,
    palette='Blues_r'
)

plt.title("Top 10 Features Influencing High-Tip Prediction",
fontsize=14, weight='bold', pad=15)
plt.xlabel("Feature Importance (Weight)", fontsize=12)
plt.ylabel("")
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



Route-Based Revenue Forecast

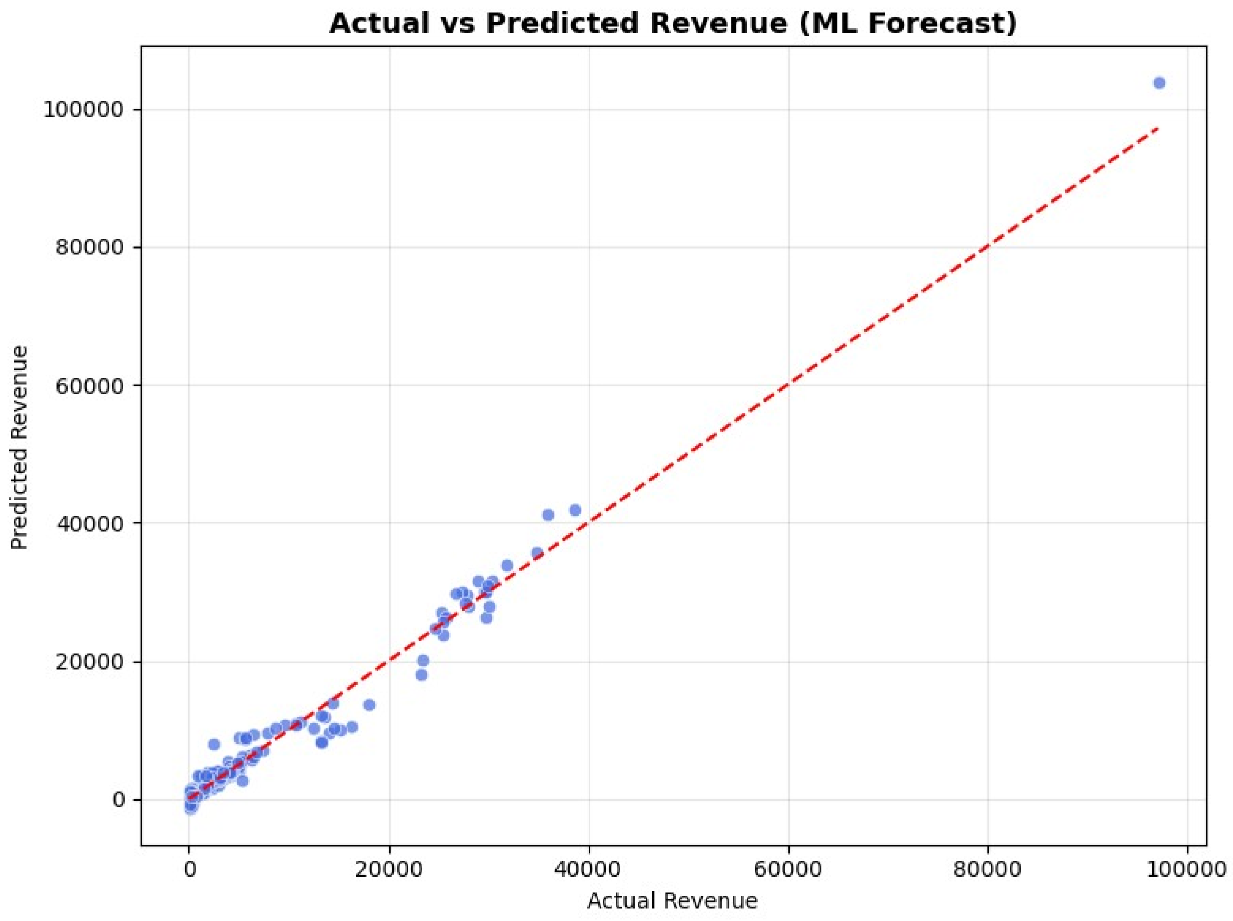
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, r2_score

# --- Step 1: Prepare dataset ---
# Keep only relevant years
df = df[(df['lpep_pickup_datetime'].dt.year >= 2017) &
(df['lpep_pickup_datetime'].dt.year <= 2020)]

# Create route name
df['route'] = df['pickup_borough'] + " → " + df['dropoff_borough']

# Create month column
df['month'] =
df['lpep_pickup_datetime'].dt.to_period('M').dt.to_timestamp()

# Aggregate revenue per route per month
monthly_route = df.groupby(['route', 'month']).agg(
    total_revenue=('total_amount', 'sum'),
    total_trips=('total_amount', 'count'),
    avg_fare=('fare_amount', 'mean'),
    avg_distance=('trip_distance', 'mean')
).reset_index()

print(monthly_route.head())
```

```
            route      month  total_revenue  total_trips   avg_fare  \
0  Bronx → Bronx 2017-01-01        2715.92          241   9.841909
1  Bronx → Bronx 2017-02-01        2874.64          276   9.215580
2  Bronx → Bronx 2017-03-01        4264.67          364  10.381319
3  Bronx → Bronx 2017-04-01        3091.79          270  10.195556
4  Bronx → Bronx 2017-05-01        2664.08          237   9.905105

   avg_distance
0      2.044689
1      1.823007
2      2.147418
3      2.057407
4      1.981983

# Extract time features
monthly_route['year'] = monthly_route['month'].dt.year
monthly_route['month_num'] = monthly_route['month'].dt.month
monthly_route['is_year_start'] =
monthly_route['month'].dt.is_year_start.astype(int)

# Sort for lag features
monthly_route = monthly_route.sort_values(['route', 'month'])

# Lag (previous month revenue) — helps model learn trends
monthly_route['prev_month_revenue'] = monthly_route.groupby('route')
['total_revenue'].shift(1)
monthly_route['revenue_growth'] = (
    monthly_route['total_revenue'] -
monthly_route['prev_month_revenue']
) / monthly_route['prev_month_revenue']

# Drop NaN from first months
monthly_route.dropna(inplace=True)

#  ROUTE-BASED REVENUE FORECASTING


import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score


# 1 FEATURE SELECTION & ENCODING


# Features used for model training
features = [
    'total_trips', 'avg_fare', 'avg_distance',
    'year', 'month_num', 'is_year_start',
    'prev_month_revenue', 'revenue_growth'
]

# □ Ensure monthly_route exists
if 'monthly_route' not in locals():
    raise ValueError("monthly_route DataFrame not found. Please create
it before running this code.")

# □ Select only Top 20 routes to avoid MemoryError from one-hot
encoding
top_routes = monthly_route['route'].value_counts().head(20).index
monthly_route_small =
monthly_route[monthly_route['route'].isin(top_routes)].copy()

# □ One-hot encode routes safely
monthly_route_encoded = pd.get_dummies(monthly_route_small,
columns=['route'], drop_first=True)

# □ Build X and y
X = monthly_route_encoded[features + [col for col in
monthly_route_encoded.columns if col.startswith('route_')]]
y = monthly_route_encoded['total_revenue']


# 2 CLEAN FEATURE MATRIX SAFELY

X = X.copy()
X.replace([np.inf, -np.inf], np.nan, inplace=True)
X.fillna(0, inplace=True)
y = y.replace([np.inf, -np.inf], np.nan).fillna(0)


# 3 TRAIN-TEST SPLIT & MODEL TRAINING

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

lr = LinearRegression()
lr.fit(X_train, y_train)

# Predictions
y_pred = lr.predict(X_test)


# 4 EVALUATION

mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

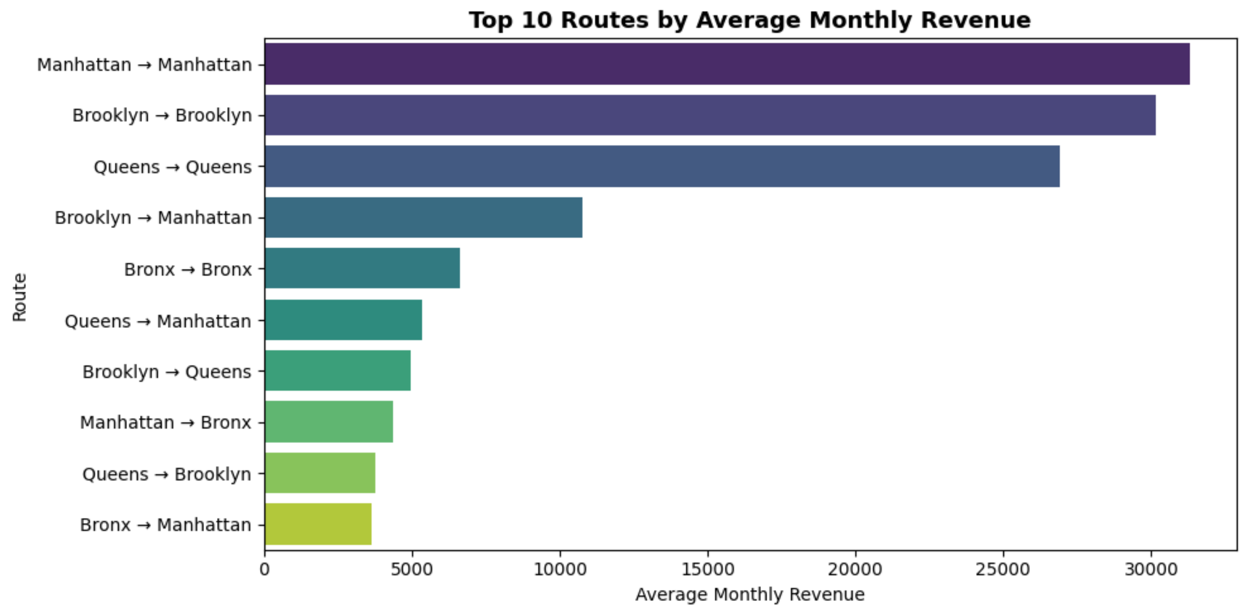
```
print("□ Model Performance:")
print(f"   • Mean Absolute Error (MAE): {mae:.2f}")
print(f"   • R² Score: {r2:.2f}")


# 5 VISUALIZATION: ACTUAL vs PREDICTED

plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred, color='royalblue', alpha=0.7)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
'r--')
plt.title("Actual vs Predicted Revenue (ML Forecast)", fontsize=13,
weight='bold')
plt.xlabel("Actual Revenue")
plt.ylabel("Predicted Revenue")
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()


# 6 TOP ROUTES BY AVERAGE REVENUE

# Calculate top 10 routes by average monthly revenue
top_revenue_routes = (
    monthly_route.groupby('route')['total_revenue']
    .mean()
    .sort_values(ascending=False)
    .head(10)
)

# Convert to DataFrame for plotting
top_routes_df = top_revenue_routes.reset_index()
top_routes_df.columns = ['Route', 'Avg Monthly Revenue']

plt.figure(figsize=(10, 5))
sns.barplot(
    data=top_routes_df,
    x='Avg Monthly Revenue',
    y='Route',
    palette='viridis'
)
plt.title("Top 10 Routes by Average Monthly Revenue", fontsize=13,
weight='bold')
plt.xlabel("Average Monthly Revenue")
plt.ylabel("Route")
plt.tight_layout()
plt.show()
```

```
print("\n Top 10 Routes by Average Monthly Revenue:\n")
print(top_routes_df.to_string(index=False))
```

```
 Model Performance:
   • Mean Absolute Error (MAE): 1037.63
   • R² Score: 0.98
```



```
C:\Users\DELL\AppData\Local\Temp\ipykernel_896\4139037727.py:98:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(
```



```
 Top 10 Routes by Average Monthly Revenue:

                Route  Avg Monthly Revenue
Manhattan → Manhattan         31320.744468
  Brooklyn → Brooklyn         30156.020638
      Queens → Queens         26920.087447
 Brooklyn → Manhattan         10750.090000
        Bronx → Bronx          6614.662128
   Queens → Manhattan          5347.752979
    Brooklyn → Queens          4946.473191
    Manhattan → Bronx          4363.073617
    Queens → Brooklyn          3754.484255
    Bronx → Manhattan          3640.451915
```