```python
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler

# Define file path (update if needed)
file_path = "/content/ev_charging_dataset.csv"  # Ensure the file is
uploaded in the 'content' folder

# Load dataset
df = pd.read_csv(file_path)

# Display dataset info before cleaning
print("□ Original Dataset Info:")
print(df.info())

# □ Handling Missing Values
df.fillna(df.median(numeric_only=True), inplace=True)  # Fill numeric
missing values with median
df.fillna(method='ffill', inplace=True)  # Forward fill categorical
values
df.fillna(method='bfill', inplace=True)  # Backward fill for safety

# □ Remove Duplicates
df.drop_duplicates(inplace=True)

# □ Convert DateTime Column
df['Date_Time'] = pd.to_datetime(df['Date_Time'], errors='coerce')

# □ Remove Outliers (Using Interquartile Range - IQR Method)
numerical_columns = df.select_dtypes(include=['float64',
'int64']).columns
Q1 = df[numerical_columns].quantile(0.25)
Q3 = df[numerical_columns].quantile(0.75)
IQR = Q3 - Q1

# Define outlier bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Remove rows that contain outliers
df = df[~((df[numerical_columns] < lower_bound) |
(df[numerical_columns] > upper_bound)).any(axis=1)]

# □ Normalize Data (Scaling between 0 and 1)
scaler = MinMaxScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])

# □ Save Cleaned Data
cleaned_file_path = "/content/clean_ev_charging_dataset.csv"
```

```
df.to_csv(cleaned_file_path, index=False)

print("\n□ Data Cleaning Complete! □ Cleaned dataset saved at:",
cleaned_file_path)
print("□ Updated Dataset Info:")
print(df.info())

# □ Display first 5 rows of the cleaned dataset
df.head()

□ Original Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64945 entries, 0 to 64944
Data columns (total 28 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Date_Time                       64945 non-null  object
 1   Vehicle_ID                      64945 non-null  int64
 2   Battery_Capacity_kWh            64945 non-null  float64
 3   State_of_Charge_%               64945 non-null  float64
 4   Energy_Consumption_Rate_kWh/km  64945 non-null  float64
 5   Current_Latitude                64945 non-null  float64
 6   Current_Longitude               64945 non-null  float64
 7   Destination_Latitude            64945 non-null  float64
 8   Destination_Longitude           64945 non-null  float64
 9   Distance_to_Destination_km      64945 non-null  float64
 10  Traffic_Data                    64945 non-null  int64
 11  Road_Conditions                 64945 non-null  object
 12  Charging_Station_ID             64945 non-null  int64
 13  Charging_Rate_kW                64945 non-null  float64
 14  Queue_Time_mins                 64945 non-null  float64
 15  Station_Capacity_EV             64945 non-null  int64
 16  Time_Spent_Charging_mins        64945 non-null  float64
 17  Energy_Drawn_kWh                64945 non-null  float64
 18  Session_Start_Hour              64945 non-null  int64
 19  Fleet_Size                      64945 non-null  int64
 20  Fleet_Schedule                  64945 non-null  int64
 21  Temperature_C                   64945 non-null  float64
 22  Wind_Speed_m/s                  64945 non-null  float64
 23  Precipitation_mm                64945 non-null  float64
 24  Weekday                         64945 non-null  int64
 25  Charging_Preferences            64945 non-null  int64
 26  Weather_Conditions              64945 non-null  object
 27  Charging_Load_kW                64945 non-null  float64
dtypes: float64(16), int64(9), object(3)
memory usage: 13.9+ MB
None

<ipython-input-2-a66e6b7cf2c0>:18: FutureWarning: DataFrame.fillna
with 'method' is deprecated and will raise in a future version. Use
```

```
obj.ffill() or obj.bfill() instead.
  df.fillna(method='ffill', inplace=True)  # Forward fill categorical
values
<ipython-input-2-a66e6b7cf2c0>:19: FutureWarning: DataFrame.fillna
with 'method' is deprecated and will raise in a future version. Use
obj.ffill() or obj.bfill() instead.
  df.fillna(method='bfill', inplace=True)  # Backward fill for safety
<ipython-input-2-a66e6b7cf2c0>:42: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df[numerical_columns] = scaler.fit_transform(df[numerical_columns])


□ Data Cleaning Complete! □ Cleaned dataset saved at:
/content/clean_ev_charging_dataset.csv
□ Updated Dataset Info:
<class 'pandas.core.frame.DataFrame'>
Index: 33858 entries, 0 to 64944
Data columns (total 28 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Date_Time                       33858 non-null  datetime64[ns]
 1   Vehicle_ID                      33858 non-null  float64
 2   Battery_Capacity_kWh            33858 non-null  float64
 3   State_of_Charge_%               33858 non-null  float64
 4   Energy_Consumption_Rate_kWh/km  33858 non-null  float64
 5   Current_Latitude                33858 non-null  float64
 6   Current_Longitude               33858 non-null  float64
 7   Destination_Latitude            33858 non-null  float64
 8   Destination_Longitude           33858 non-null  float64
 9   Distance_to_Destination_km      33858 non-null  float64
 10  Traffic_Data                    33858 non-null  float64
 11  Road_Conditions                 33858 non-null  object
 12  Charging_Station_ID             33858 non-null  float64
 13  Charging_Rate_kW                33858 non-null  float64
 14  Queue_Time_mins                 33858 non-null  float64
 15  Station_Capacity_EV             33858 non-null  float64
 16  Time_Spent_Charging_mins        33858 non-null  float64
 17  Energy_Drawn_kWh                33858 non-null  float64
 18  Session_Start_Hour              33858 non-null  float64
 19  Fleet_Size                      33858 non-null  float64
 20  Fleet_Schedule                  33858 non-null  float64
 21  Temperature_C                   33858 non-null  float64
 22  Wind_Speed_m/s                  33858 non-null  float64
 23  Precipitation_mm                33858 non-null  float64
 24  Weekday                         33858 non-null  float64
 25  Charging_Preferences            33858 non-null  float64
 26  Weather_Conditions              33858 non-null  object
 27  Charging_Load_kW                33858 non-null  float64
dtypes: datetime64[ns](1), float64(25), object(2)
memory usage: 7.5+ MB
None

{"type":"dataframe","variable_name":"df"}

# Install required libraries (if not already installed)
!pip install -q scikit-opt pandas numpy

# Import required libraries
import pandas as pd
import numpy as np
import random
from scipy.spatial.distance import cdist
from sko.PSO import PSO
from sko.GA import GA

# □ Define file path for cleaned EV charging dataset
file_path = "/content/clean_ev_charging_dataset.csv"

# □ Load the cleaned dataset
try:
    ev_data = pd.read_csv(file_path)
    print("□ Cleaned EV dataset loaded successfully!")
except FileNotFoundError:
    print(f"□ Error: File not found at {file_path}. Please ensure the
file exists.")
    exit()

# □ Display dataset overview
print("\n□ EV Charging Dataset Overview:")
print(ev_data.info())

# □ Extract relevant columns (Latitude, Longitude) for routing
optimization
if 'Current_Latitude' in ev_data.columns and 'Current_Longitude' in
ev_data.columns:
    locations = ev_data[['Current_Latitude',
'Current_Longitude']].dropna().values
else:
    print("□ Error: Required columns ('Current_Latitude',
'Current_Longitude') are missing in the dataset.")
    exit()

num_locations = len(locations)

# □ Compute distance matrix
```

```
distance_matrix = cdist(locations, locations, metric='euclidean')

# □ Define optimization function: Minimize total route distance
def route_distance(route):
    total_distance = sum(distance_matrix[int(route[i]),
int(route[i+1])] for i in range(len(route) - 1))
    return total_distance

# □ Particle Swarm Optimization (PSO)
pso = PSO(
    func=route_distance,
    dim=num_locations,
    pop=50,
    max_iter=100,
    lb=[0] * num_locations,
    ub=[num_locations - 1] * num_locations,
    w=0.8, c1=1.5, c2=1.5
)
pso.run()
best_route_pso = pso.gbest_x

# □ Genetic Algorithm (GA)
ga = GA(
    func=route_distance,
    n_dim=num_locations,
    size_pop=50,
    max_iter=100,
    prob_mut=0.1,
    lb=[0] * num_locations,
    ub=[num_locations - 1] * num_locations
)
best_route_ga = ga.run()

# □ Print optimization results
print("\n□ Optimization Results:")
print(f"□ Best Route (PSO): {best_route_pso}")
print(f"□ Best Route (GA): {best_route_ga}")
```

```
□ Cleaned EV dataset loaded successfully!

□ EV Charging Dataset Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33858 entries, 0 to 33857
Data columns (total 28 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Date_Time                      33858 non-null  object 
 1   Vehicle_ID                     33858 non-null  float64
 2   Battery_Capacity_kWh           33858 non-null  float64
 3   State_of_Charge_%              33858 non-null  float64
 4   Energy_Consumption_Rate_kWh/km  33858 non-null  float64
 5   Current_Latitude                33858 non-null  float64
 6   Current_Longitude               33858 non-null  float64
 7   Destination_Latitude            33858 non-null  float64
 8   Destination_Longitude           33858 non-null  float64
 9   Distance_to_Destination_km      33858 non-null  float64
 10  Traffic_Data                    33858 non-null  float64
 11  Road_Conditions                 33858 non-null  object
 12  Charging_Station_ID             33858 non-null  float64
 13  Charging_Rate_kW                33858 non-null  float64
 14  Queue_Time_mins                 33858 non-null  float64
 15  Station_Capacity_EV             33858 non-null  float64
 16  Time_Spent_Charging_mins        33858 non-null  float64
 17  Energy_Drawn_kWh                33858 non-null  float64
 18  Session_Start_Hour              33858 non-null  float64
 19  Fleet_Size                      33858 non-null  float64
 20  Fleet_Schedule                  33858 non-null  float64
 21  Temperature_C                   33858 non-null  float64
 22  Wind_Speed_m/s                  33858 non-null  float64
 23  Precipitation_mm                33858 non-null  float64
 24  Weekday                         33858 non-null  float64
 25  Charging_Preferences            33858 non-null  float64
 26  Weather_Conditions              33858 non-null  object
 27  Charging_Load_kW                33858 non-null  float64
dtypes: float64(25), object(3)
memory usage: 7.2+ MB
None

----------------------------------------------------------------------
-----
KeyboardInterrupt                         Traceback (most recent call
last)
<ipython-input-5-9b7d501fd28a> in <cell line: 0>()
     65     ub=[num_locations - 1] * num_locations
     66 )
---> 67 best_route_ga = ga.run()
     68
     69 # □ Print optimization results

/usr/local/lib/python3.11/dist-packages/sko/GA.py in run(self,
max_iter)
     87
     88             # record the best ones
---> 89             generation_best_index = self.FitV.argmax()
     90
self.generation_best_X.append(self.X[generation_best_index, :])
     91
self.generation_best_Y.append(self.Y[generation_best_index])

KeyboardInterrupt:
```

```python
# Step 1: Import Libraries
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.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import folium

# Step 2: Load the Dataset
# Replace 'clean_ev_charging_dataset.csv' with the actual file path
df = pd.read_csv('clean_ev_charging_dataset.csv')

# Step 3: Data Preprocessing
# Handle missing values for numeric columns only
numeric_columns = df.select_dtypes(include=[np.number]).columns
df[numeric_columns] =
df[numeric_columns].fillna(df[numeric_columns].mean())

# Feature Engineering: Calculate Distance to Destination
from geopy.distance import geodesic

df['Distance_to_Destination_km'] = df.apply(
    lambda row: geodesic(
        (row['Current_Latitude'], row['Current_Longitude']),
        (row['Destination_Latitude'], row['Destination_Longitude'])
    ).km, axis=1
)

# Encode categorical variables
df = pd.get_dummies(df, columns=['Weather_Conditions',
'Road_Conditions'], drop_first=True)

# Drop non-numeric columns that are not needed for modeling
df = df.drop(columns=['Date_Time', 'Vehicle_ID'])

# Split the data into features (X) and target (y)
X = df.drop(columns=['Charging_Load_kW'])
y = df['Charging_Load_kW']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Model Development
# Train a Random Forest Regressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"R² Score: {r2}")

# Step 5: Route Optimization (Example)
# Create a map centered at the first charging station
map_center = [df['Current_Latitude'].iloc[0],
df['Current_Longitude'].iloc[0]]
mymap = folium.Map(location=map_center, zoom_start=12)

# Add markers for charging stations
for index, row in df.iterrows():
    folium.Marker(
        location=[row['Current_Latitude'], row['Current_Longitude']],
        popup=f"Charging Load: {row['Charging_Load_kW']} kW"
    ).add_to(mymap)

# Display the map
mymap

----------------------------------------------------------------------
-----
KeyboardInterrupt                         Traceback (most recent call
last)
<ipython-input-2-bb2ceac68da3> in <cell line: 0>()
     44 # Train a Random Forest Regressor
     45 model = RandomForestRegressor(n_estimators=100,
random_state=42)
---> 46 model.fit(X_train, y_train)
     47
     48 # Predict on the test set

/usr/local/lib/python3.11/dist-packages/sklearn/base.py in
wrapper(estimator, *args, **kwargs)
   1387                 )
   1388             ):
-> 1389                 return fit_method(estimator, *args, **kwargs)
   1390
   1391         return wrapper

/usr/local/lib/python3.11/dist-packages/sklearn/ensemble/_forest.py in
```

```
fit(self, X, y, sample_weight)
    485             # parallel_backend contexts set at a higher level,
    486             # since correctness does not rely on using
threads.
--> 487             trees = Parallel(
    488                 n_jobs=self.n_jobs,
    489                 verbose=self.verbose,

/usr/local/lib/python3.11/dist-packages/sklearn/utils/parallel.py in
__call__(self, iterable)
     75             for delayed_func, args, kwargs in iterable
     76         )
---> 77         return super().__call__(iterable_with_config)
     78
     79

/usr/local/lib/python3.11/dist-packages/joblib/parallel.py in
__call__(self, iterable)
   1916             output = self._get_sequential_output(iterable)
   1917             next(output)
-> 1918             return output if self.return_generator else
list(output)
   1919
   1920         # Let's create an ID that uniquely identifies the
current call. If the

/usr/local/lib/python3.11/dist-packages/joblib/parallel.py in
_get_sequential_output(self, iterable)
   1845                 self.n_dispatched_batches += 1
   1846                 self.n_dispatched_tasks += 1
-> 1847                 res = func(*args, **kwargs)
   1848                 self.n_completed_tasks += 1
   1849                 self.print_progress()

/usr/local/lib/python3.11/dist-packages/sklearn/utils/parallel.py in
__call__(self, *args, **kwargs)
    137             config = {}
    138         with config_context(**config):
--> 139             return self.function(*args, **kwargs)
    140
    141

/usr/local/lib/python3.11/dist-packages/sklearn/ensemble/_forest.py in
_parallel_build_trees(tree, bootstrap, X, y, sample_weight, tree_idx,
n_trees, verbose, class_weight, n_samples_bootstrap,
missing_values_in_feature_mask)
    187             curr_sample_weight *=
compute_sample_weight("balanced", y, indices=indices)
    188
--> 189         tree._fit(
    190                 X,
    191                 y,

/usr/local/lib/python3.11/dist-packages/sklearn/tree/_classes.py in
_fit(self, X, y, sample_weight, check_input,
missing_values_in_feature_mask)
    470                 )
    471
--> 472         builder.build(self.tree_, X, y, sample_weight,
missing_values_in_feature_mask)
    473
    474         if self.n_outputs_ == 1 and is_classifier(self):

KeyboardInterrupt:

# Step 1: Import Libraries
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.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import folium

# Step 2: Load the Dataset
# Replace 'clean_ev_charging_dataset.csv' with the actual file path
df = pd.read_csv('clean_ev_charging_dataset.csv')

# Step 3: Data Preprocessing
# Handle missing values for numeric columns only
numeric_columns = df.select_dtypes(include=[np.number]).columns
df[numeric_columns] =
df[numeric_columns].fillna(df[numeric_columns].mean())

# Feature Engineering: Calculate Distance to Destination
from geopy.distance import geodesic

df['Distance_to_Destination_km'] = df.apply(
    lambda row: geodesic(
        (row['Current_Latitude'], row['Current_Longitude']),
        (row['Destination_Latitude'], row['Destination_Longitude'])
    ).km, axis=1
)

# Encode categorical variables
df = pd.get_dummies(df, columns=['Weather_Conditions',
'Road_Conditions'], drop_first=True)
```

```
# Drop non-numeric columns that are not needed for modeling
df = df.drop(columns=['Date_Time', 'Vehicle_ID'])

# Split the data into features (X) and target (y)
X = df.drop(columns=['Charging_Load_kW'])
y = df['Charging_Load_kW']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Step 4: Model Development
# Train a Random Forest Regressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"R² Score: {r2}")

# Step 5: Route Optimization (Example)
# Create a map centered at the first charging station
map_center = [df['Current_Latitude'].iloc[0],
df['Current_Longitude'].iloc[0]]
mymap = folium.Map(location=map_center, zoom_start=12)

# Add markers for charging stations
for index, row in df.iterrows():
    folium.Marker(
        location=[row['Current_Latitude'], row['Current_Longitude']],
        popup=f"Charging Load: {row['Charging_Load_kW']} kW"
    ).add_to(mymap)

# Display the map
mymap

# Step 6: Save Analysis and Results to an Excel File
# Create a DataFrame for the model evaluation metrics
metrics_df = pd.DataFrame({
    'Metric': ['Mean Absolute Error', 'Mean Squared Error', 'R²
Score'],
    'Value': [mae, mse, r2]
})

# Create a DataFrame for the predicted vs actual values
results_df = pd.DataFrame({
    'Actual': y_test,
    'Predicted': y_pred
})

# Save the DataFrames to an Excel file
with pd.ExcelWriter('analysis_results.xlsx') as writer:
    metrics_df.to_excel(writer, sheet_name='Model Metrics',
index=False)
    results_df.to_excel(writer, sheet_name='Predicted vs Actual',
index=False)
    df.to_excel(writer, sheet_name='Processed Data', index=False)

# Step 7: Download the Excel File
from google.colab import files
files.download('analysis_results.xlsx')
```

```
Mean Absolute Error: 0.14618156973513502
Mean Squared Error: 0.03286358009994018
R² Score: -0.0160630208686936
```

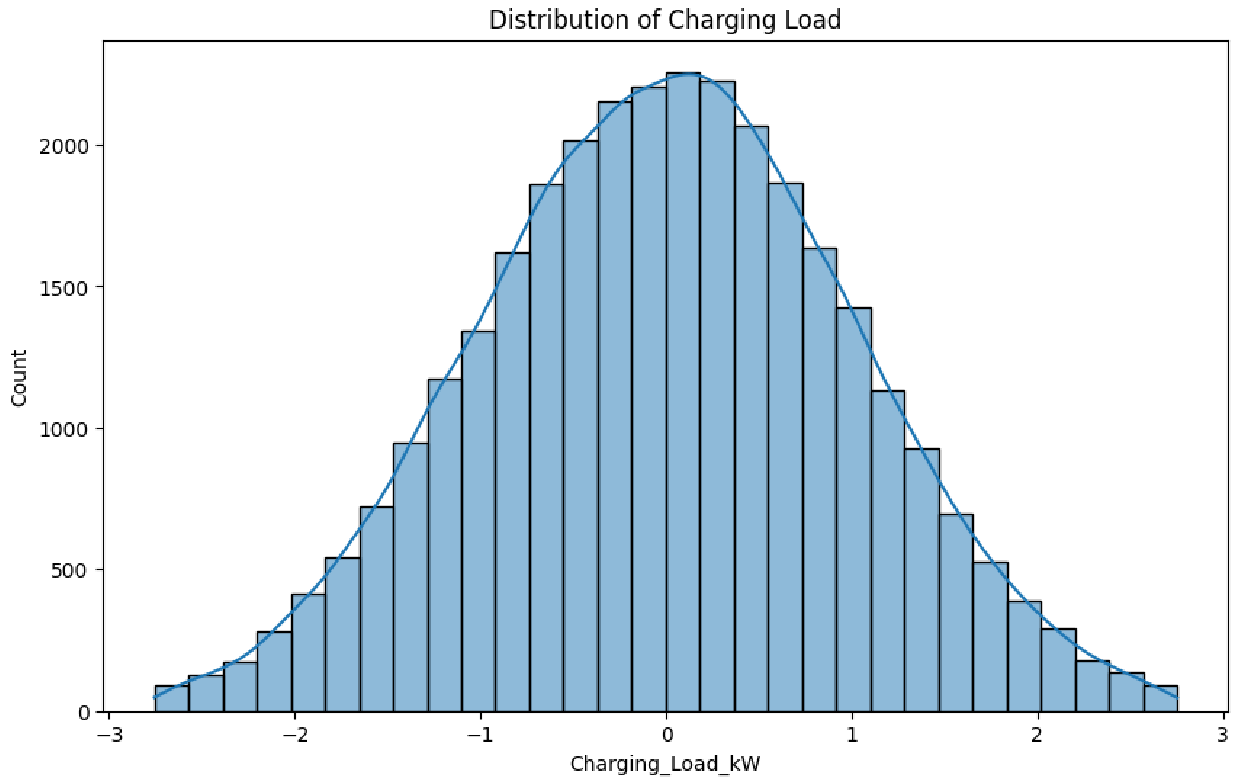
```
<IPython.core.display.Javascript object>
```

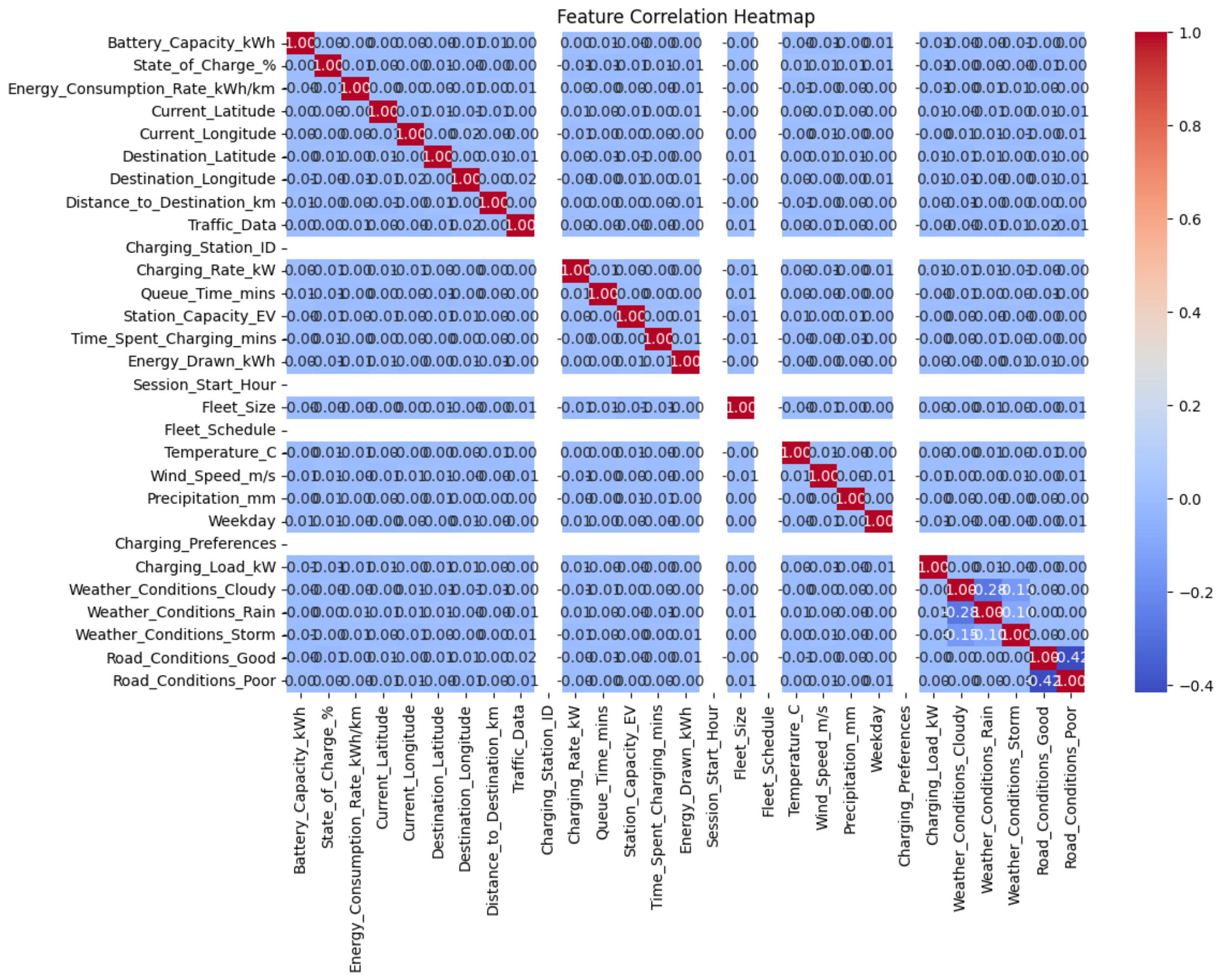
```
<IPython.core.display.Javascript object>
```

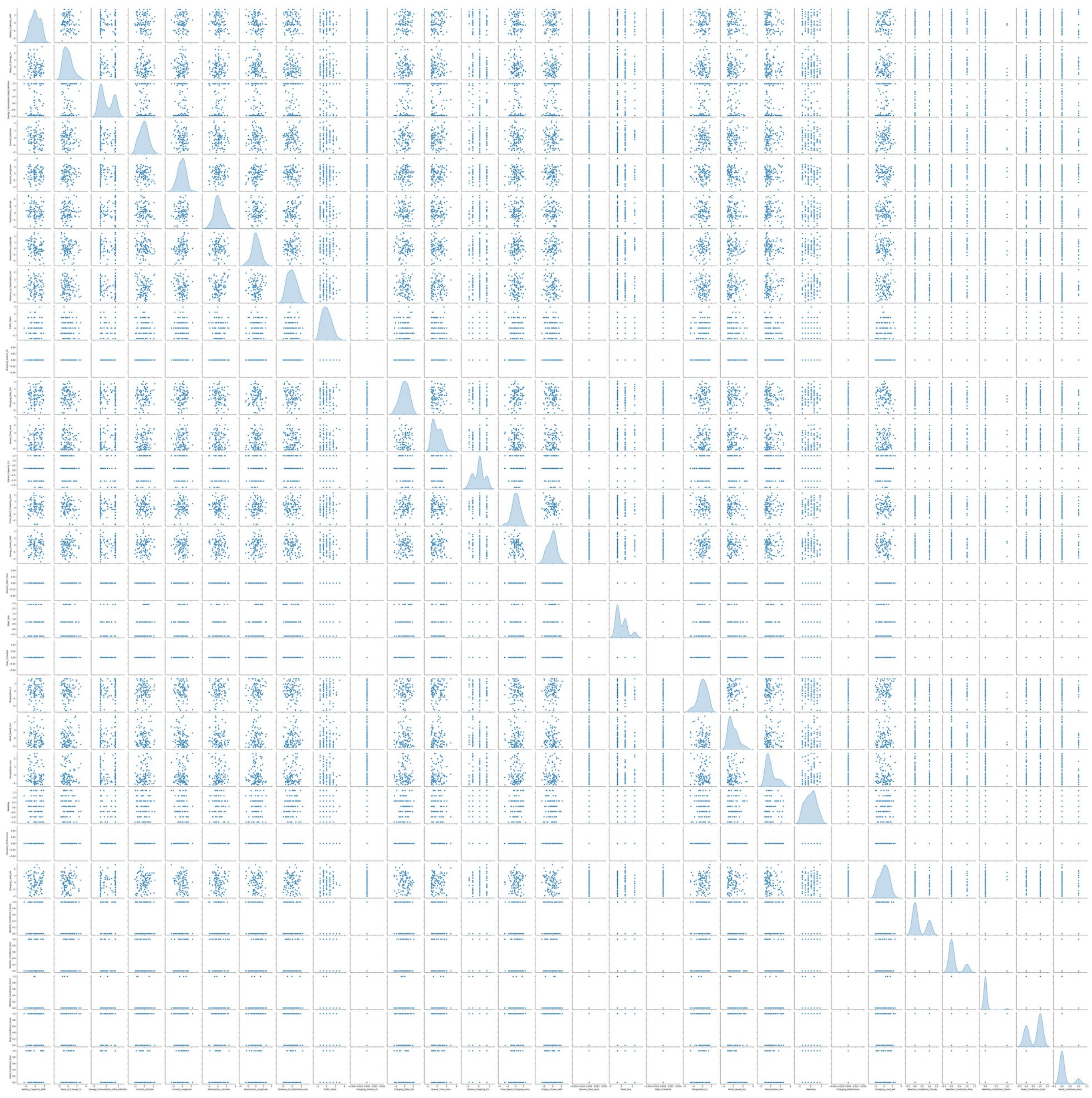
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

# Load dataset
file_path = "/content/analysis_results.xlsx"
df = pd.read_excel(file_path, sheet_name="Processed Data")
# Handle missing values
imputer = SimpleImputer(strategy="mean")
numeric_columns = df.select_dtypes(include=[np.number]).columns
df[numeric_columns] = imputer.fit_transform(df[numeric_columns])

# Handle outliers using IQR method
Q1 = df[numeric_columns].quantile(0.25)
Q3 = df[numeric_columns].quantile(0.75)
IQR = Q3 - Q1
outlier_condition = ~((df[numeric_columns] < (Q1 - 1.5 * IQR)) |
(df[numeric_columns] > (Q3 + 1.5 * IQR))).any(axis=1)
df = df[outlier_condition]

# Ensure there are still samples left after filtering
```

```
if df.shape[0] == 0:
    print("Warning: All samples were removed due to outlier filtering.
Skipping outlier removal.")
    df = pd.read_excel(file_path, sheet_name="Processed Data")  #
Reload original data
    df[numeric_columns] = imputer.fit_transform(df[numeric_columns])

# Normalize numerical features
scaler = StandardScaler()
df[numeric_columns] = scaler.fit_transform(df[numeric_columns])

# Encode categorical variables
categorical_columns = ['Weather_Conditions_Cloudy',
'Weather_Conditions_Rain',
                        'Weather_Conditions_Storm',
'Road_Conditions_Good', 'Road_Conditions_Poor']
df[categorical_columns] = df[categorical_columns].astype(int)

# Define features and target variable
target = "Charging_Load_kW"
X = df.drop(columns=[target])
y = df[target]

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Output shapes
print("Training set shape:", X_train.shape, y_train.shape)
print("Testing set shape:", X_test.shape, y_test.shape)

# Exploratory Data Analysis (EDA)
plt.figure(figsize=(10, 6))
sns.histplot(y, bins=30, kde=True)
plt.title("Distribution of Charging Load")
plt.show()

# Correlation Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Feature Correlation Heatmap")
plt.show()

# Pairplot to visualize feature relationships
if df.shape[0] > 100:
    sns.pairplot(df.sample(100), diag_kind='kde')
else:
    sns.pairplot(df, diag_kind='kde')
plt.show()
```

```
Training set shape: (25200, 28) (25200,)
Testing set shape: (6300, 28) (6300,)
```




Feature Correlation Heatmap
Battery_Capacity_kWh
State_of_Charge_%
Energy_Consumption_Rate_kWh/km
Current_Latitude
Current_Longitude
Destination_Latitude
Destination_Longitude
Distance_to_Destination_km
Traffic_Data
Charging_Station_ID
Charging_Rate_kW
Queue_Time_mins
Station_Capacity_EV
Time_Spent_Charging_mins
Energy_Drawn_kWh
Session_Start_Hour
Fleet_Size
Fleet_Schedule
Temperature_C
Wind_Speed_m/s
Precipitation_mm
Weekday
Charging_Preferences
Charging_Load_kW
Weather_Conditions_Cloudy
Weather_Conditions_Rain
Weather_Conditions_Storm
Road_Conditions_Good
Road_Conditions_Poor
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4



```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.cluster import KMeans
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.model_selection import GridSearchCV
import networkx as nx
import folium

# Load dataset
file_path = "/content/analysis_results.xlsx"
df = pd.read_excel(file_path, sheet_name="Processed Data")

# Handle missing values
imputer = SimpleImputer(strategy="mean")
numeric_columns = df.select_dtypes(include=[np.number]).columns
df.loc[:, numeric_columns] =
imputer.fit_transform(df[numeric_columns])

# Handle outliers using IQR method
Q1 = df[numeric_columns].quantile(0.25)
Q3 = df[numeric_columns].quantile(0.75)
IQR = Q3 - Q1
outlier_condition = ~((df[numeric_columns] < (Q1 - 1.5 * IQR)) |
(df[numeric_columns] > (Q3 + 1.5 * IQR))).any(axis=1)
df = df.loc[outlier_condition].copy()

# Ensure there are still samples left after filtering
if df.shape[0] == 0:
    print("Warning: All samples were removed due to outlier filtering.
Skipping outlier removal.")
    df = pd.read_excel(file_path, sheet_name="Processed Data")  #
Reload original data
    df.loc[:, numeric_columns] =
imputer.fit_transform(df[numeric_columns])

# Normalize numerical features
scaler = StandardScaler()
df.loc[:, numeric_columns] = scaler.fit_transform(df[numeric_columns])

# Encode categorical variables
categorical_columns = ['Weather_Conditions_Cloudy',
'Weather_Conditions_Rain',
                        'Weather_Conditions_Storm',
'Road_Conditions_Good', 'Road_Conditions_Poor']
df[categorical_columns] =
df[categorical_columns].astype(bool).astype(int)

# Define features and target variable
target = "Charging_Load_kW"
X = df.drop(columns=[target])
y = df[target]

# Split dataset into training and testing sets
```

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

# Model Selection & Training
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=100,
random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100,
random_state=42)
}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"{name} - MAE: {mean_absolute_error(y_test, y_pred):.4f}, "
          f"MSE: {mean_squared_error(y_test, y_pred):.4f}, "
          f"R²: {r2_score(y_test, y_pred):.4f}")

# Clustering Charging Stations
num_clusters = 3
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
kmeans.fit(X)
df.loc[:, "Cluster"] = kmeans.labels_

# Route Optimization using Dijkstra’s Algorithm
def find_shortest_route(graph, start, end):
    return nx.shortest_path(graph, source=start, target=end,
weight='weight')

# Creating a Graph of Charging Stations using the correct column names
graph = nx.Graph()
for i in range(len(df)):
    graph.add_node(i, pos=(df.iloc[i]['Current_Latitude'], df.iloc[i]
['Current_Longitude']))

# Sample Route Optimization Visualization
map_center = [df.iloc[0]['Current_Latitude'], df.iloc[0]
['Current_Longitude']]
m = folium.Map(location=map_center, zoom_start=12)
for _, row in df.iterrows():
    folium.Marker([row['Current_Latitude'], row['Current_Longitude']],
popup=f"Station {row['Cluster']}").add_to(m)

m.save("optimized_route.html")
```

```
Linear Regression - MAE: 0.8061, MSE: 1.0056, R²: -0.0013
Random Forest - MAE: 0.8096, MSE: 1.0157, R²: -0.0113
Gradient Boosting - MAE: 0.8077, MSE: 1.0083, R²: -0.0039
```

```
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import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
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from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.cluster import KMeans
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import networkx as nx
import folium

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# Handle missing values
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numeric_columns = df.select_dtypes(include=[np.number]).columns
df.loc[:, numeric_columns] =
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Q3 = df[numeric_columns].quantile(0.75)
IQR = Q3 - Q1
outlier_condition = ~((df[numeric_columns] < (Q1 - 1.5 * IQR)) |
(df[numeric_columns] > (Q3 + 1.5 * IQR))).any(axis=1)
df = df.loc[outlier_condition].copy()

# Ensure there are still samples left after filtering
if df.shape[0] == 0:
    print("Warning: All samples were removed due to outlier filtering.
Skipping outlier removal.")
    df = pd.read_excel(file_path, sheet_name="Processed Data")  #
Reload original data
    df.loc[:, numeric_columns] =
imputer.fit_transform(df[numeric_columns])

# Normalize numerical features
scaler = StandardScaler()
df.loc[:, numeric_columns] = scaler.fit_transform(df[numeric_columns])

# Encode categorical variables
categorical_columns = ['Weather_Conditions_Cloudy',
'Weather_Conditions_Rain',
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'Road_Conditions_Good', 'Road_Conditions_Poor']
df[categorical_columns] =
df[categorical_columns].astype(bool).astype(int)

# Define features and target variable
target = "Charging_Load_kW"
X = df.drop(columns=[target])
y = df[target]

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
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# Model Selection & Training
models = {
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    "Random Forest": RandomForestRegressor(n_estimators=100,
random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100,
random_state=42)
}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"{name} - MAE: {mean_absolute_error(y_test, y_pred):.4f}, "
          f"MSE: {mean_squared_error(y_test, y_pred):.4f}, "
          f"R²: {r2_score(y_test, y_pred):.4f}")

# □ K-Means Clustering for grouping charging stations.
num_clusters = 3
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
kmeans.fit(X)
df.loc[:, "Cluster"] = kmeans.labels_

# □ Dijkstra's Algorithm for shortest route calculation.
def find_shortest_route(graph, start, end):
    """
    Find the shortest path between two charging stations using
Dijkstra's algorithm.
    :param graph: A NetworkX graph object containing nodes (charging
stations).
    :param start: The start node.
    :param end: The end node.
    :return: The shortest path between start and end nodes.
    """
    return nx.shortest_path(graph, source=start, target=end,
weight='weight')
```

```
# Creating a Graph of Charging Stations using the correct column names
graph = nx.Graph()

# Adding nodes for each charging station based on its latitude and
longitude
for i in range(len(df)):
    graph.add_node(i, pos=(df.iloc[i]['Current_Latitude'], df.iloc[i]
['Current_Longitude']))

# Optionally: Add edges between nodes (charging stations). You may use
distance, time, or another factor for weights.
for i in range(len(df)):
    for j in range(i + 1, len(df)):
        # Calculate the Euclidean distance between two stations (or
use Haversine for more accurate distance).
        lat1, lon1 = df.iloc[i]['Current_Latitude'], df.iloc[i]
['Current_Longitude']
        lat2, lon2 = df.iloc[j]['Current_Latitude'], df.iloc[j]
['Current_Longitude']
        distance = np.sqrt((lat2 - lat1)**2 + (lon2 - lon1)**2)  #
Example: Euclidean distance (can be replaced)
        graph.add_edge(i, j, weight=distance)

# Example of finding the shortest path between two stations (station 0
and station 2)
shortest_path = find_shortest_route(graph, start=0, end=2)
print("Shortest Path (stations):", shortest_path)

# □ Folium Map Visualization for optimized routes.
# Sample Route Optimization Visualization
map_center = [df.iloc[0]['Current_Latitude'], df.iloc[0]
['Current_Longitude']]
m = folium.Map(location=map_center, zoom_start=12)

# Add markers for each charging station on the map
for _, row in df.iterrows():
    folium.Marker([row['Current_Latitude'], row['Current_Longitude']],
popup=f"Station {row['Cluster']}").add_to(m)

# Optionally, draw the shortest path on the map
# This will add the shortest path between two stations (for example,
station 0 and station 2)
for i in range(len(shortest_path) - 1):
    start_station = df.iloc[shortest_path[i]]
    end_station = df.iloc[shortest_path[i + 1]]
    folium.PolyLine(locations=[(start_station['Current_Latitude'],
start_station['Current_Longitude']),
                               (end_station['Current_Latitude'],
end_station['Current_Longitude'])],
                    color='blue', weight=2.5, opacity=1).add_to(m)
```

```python
# Save the map to an HTML file
m.save("optimized_route.html")
```

```
Linear Regression - MAE: 0.8061, MSE: 1.0056, R²: -0.0013
Random Forest - MAE: 0.8096, MSE: 1.0157, R²: -0.0113
Gradient Boosting - MAE: 0.8077, MSE: 1.0083, R²: -0.0039
```