```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

from sklearn.preprocessing import MinMaxScaler


city_stats_df =
pd.read_csv('/content/drive/MyDrive/Project/Datasets/MSW_Waste_59_Citi
es.csv')
waste_df =
pd.read_csv('/content/drive/MyDrive/Project/Datasets/Waste_Management_
and_Recycling_India.csv')
new_pop_df =
pd.read_csv('/content/drive/MyDrive/Project/Datasets/cities_r2.csv')
# Your new population dataset
sdg_df =
pd.read_csv('/content/drive/MyDrive/Project/Datasets/Data_SDG_India_In
dex_2020-21.csv')
population_df =
pd.read_csv('/content/drive/MyDrive/Project/Datasets/Area_Population_D
ensity_and_Population_2011_Census.csv')


# Save raw datasets before preprocessing
waste_df.to_csv('/content/drive/MyDrive/Project/Dataset/backup_waste_r
aw.csv', index=False)
population_df.to_csv('/content/drive/MyDrive/Project/Dataset/backup_po
pulation_raw.csv', index=False)
city_stats_df.to_csv('/content/drive/MyDrive/Project/Dataset/backup_ci
ty_stats_raw.csv', index=False)
new_pop_df.to_csv('/content/drive/MyDrive/Project/Dataset/backup_new_p
op_raw.csv', index=False)
sdg_df.to_csv('/content/drive/MyDrive/Project/Dataset/backup_sdg_raw.c
sv', index=False)



# Optionally display heads to verify in notebook
print("Raw waste_df snapshot:")
print(waste_df.head())
```

```
Raw waste_df snapshot:
  City/District    Waste Type  Waste Generated (Tons/Day)  Recycling
Rate (%)  \
0        Mumbai       Plastic                        6610
68
1        Mumbai       Organic                        1181
56
2        Mumbai       E-Waste                        8162
53
3        Mumbai  Construction                        8929
56
4        Mumbai     Hazardous                        5032
44

   Population Density (People/km²)  Municipal Efficiency Score (1-10)
\
0                            11191                                  9

1                            11191                                  5

2                            11191                                  8

3                            11191                                  5

4                            11191                                  7


  Disposal Method  Cost of Waste Management (₹/Ton)  \
0      Composting                              3056
1      Composting                              2778
2    Incineration                              3390
3        Landfill                              1498
4       Recycling                              2221

   Awareness Campaigns Count    Landfill Name Landfill Location (Lat,
Long)  \
0                         14  Mumbai Landfill              22.4265,
77.4931
1                         12  Mumbai Landfill              22.4265,
77.4931
2                         13  Mumbai Landfill              22.4265,
77.4931
3                         14  Mumbai Landfill              22.4265,
77.4931
4                         16  Mumbai Landfill              22.4265,
77.4931

   Landfill Capacity (Tons)  Year
0                     45575  2019
1                     45575  2019
2                     45575  2019
```

```
3                     45575  2019
4                     45575  2019
```

```
print(new_pop_df.columns)
```

```
Index(['name_of_city', 'state_code', 'state_name', 'dist_code',
       'population_total', 'population_male', 'population_female',
       '0-6_population_total', '0-6_population_male', '0-
6_population_female',
       'literates_total', 'literates_male', 'literates_female',
'sex_ratio',
       'child_sex_ratio', 'effective_literacy_rate_total',
       'effective_literacy_rate_male',
'effective_literacy_rate_female',
       'location', 'total_graduates', 'male_graduates',
'female_graduates'],
      dtype='object')
```

```
print(city_stats_df.columns)
```

```
Index(['City', 'Population_2001', 'Area_sq_km', 'Waste_TPD',
       'Waste_kg_per_capita_per_day'],
      dtype='object')
```

```
print(waste_df.columns)
```

```
Index(['City/District', 'Waste Type', 'Waste Generated (Tons/Day)',
       'Recycling Rate (%)', 'Population Density (People/km²)',
       'Municipal Efficiency Score (1-10)', 'Disposal Method',
       'Cost of Waste Management (₹/Ton)', 'Awareness Campaigns
Count',
       'Landfill Name', 'Landfill Location (Lat, Long)',
       'Landfill Capacity (Tons)', 'Year'],
      dtype='object')
```

```
print(population_df.columns)
```

```
Index(['District', 'Geograpical Area (Sq.Kms)', 'Population Density',
'Male',
       'Female', ' Total', 'Percentage Share to Total Population',
'Rank'],
      dtype='object')
```

```
print(sdg_df.columns)
```

```
Index(['Category', 'State/UT', 'SDG 1', 'SDG 2', 'SDG 3', 'SDG 4',
'SDG 5',
       'SDG 6', 'SDG 7', 'SDG 8', 'SDG 9', 'SDG 10', 'SDG 11', 'SDG
12',
```

```
       'SDG 13', 'SDG 15', 'SDG 16', 'Composite Score', 'Rank'],
      dtype='object')
```

```python
# Preprocessing for merging
# Rename columns for consistency before merging
city_stats_df.rename(columns={'City': 'City_Name'}, inplace=True)
waste_df.rename(columns={'City/District': 'City_Name', 'Population
Density (People/km²)': 'Population Density'}, inplace=True)
population_df.rename(columns={
    'District': 'City_Name',
    ' Total': 'Total_Population',
    'Population Density (per sq.km)': 'Population Density',
    'Geographical Area (Sq.Kms)': 'Geographical_Area'
}, inplace=True)
new_pop_df.rename(columns={
    'name_of_city': 'City_Name',
    'state_name': 'State',
    'population_total': 'Total_Population'
}, inplace=True)
sdg_df.rename(columns={'State/UT': 'State'}, inplace=True)

# Strip and standardize city/state names
for df_ in [city_stats_df, waste_df, population_df, new_pop_df]:
    df_['City_Name'] = df_['City_Name'].str.strip().str.title()
sdg_df['State'] = sdg_df['State'].str.strip().str.title()

# Manually map city to state (ensure full mapping)
city_to_state = {
    'Mumbai': 'Maharashtra', 'Delhi': 'Delhi', 'Bengaluru':
'Karnataka', 'Chennai': 'Tamil Nadu',
    'Kolkata': 'West Bengal', 'Hyderabad': 'Telangana', 'Pune':
'Maharashtra', 'Ahmedabad': 'Gujarat',
    'Jaipur': 'Rajasthan', 'Lucknow': 'Uttar Pradesh', 'Surat':
'Gujarat', 'Kanpur': 'Uttar Pradesh',
    'Nagpur': 'Maharashtra', 'Patna': 'Bihar', 'Bhopal': 'Madhya
Pradesh', 'Thiruvananthapuram': 'Kerala',
    'Indore': 'Madhya Pradesh', 'Vadodara': 'Gujarat', 'Guwahati':
'Assam', 'Coimbatore': 'Tamil Nadu',
    'Ranchi': 'Jharkhand', 'Amritsar': 'Punjab', 'Jodhpur':
'Rajasthan', 'Varanasi': 'Uttar Pradesh',
    'Ludhiana': 'Punjab', 'Agra': 'Uttar Pradesh', 'Meerut': 'Uttar
Pradesh', 'Nashik': 'Maharashtra',
    'Rajkot': 'Gujarat', 'Madurai': 'Tamil Nadu', 'Jabalpur': 'Madhya
Pradesh', 'Allahabad': 'Uttar Pradesh',
    'Visakhapatnam': 'Andhra Pradesh', 'Gwalior': 'Madhya Pradesh'
}
waste_df['State'] = waste_df['City_Name'].map(city_to_state)
```

```
# Fix known city name typos before merging
waste_df['City_Name'] = waste_df['City_Name'].replace({
    'New Delhi': 'Delhi',
    'Thiruvanathapuram': 'Thiruvananthapuram',
    'Vishakhapatnam': 'Visakhapatnam',
    'Mysore': 'Mysuru'
})




# Merge datasets stepwise
merged_df = waste_df.merge(city_stats_df, on='City_Name', how='left')
merged_df = merged_df.merge(new_pop_df[['City_Name', 'State',
'Total_Population']], on=['City_Name', 'State'], how='left')
merged_df = merged_df.merge(sdg_df[['State', 'SDG 12', 'Composite
Score']], on='State', how='left')

# Fallback: use Population_2001 from city_stats_df if still missing
still_missing_pop = merged_df['Total_Population'].isna()
fallback_pop_map = city_stats_df.set_index('City_Name')
['Population_2001'].to_dict()
merged_df.loc[still_missing_pop, 'Total_Population'] =
merged_df.loc[still_missing_pop, 'City_Name'].map(fallback_pop_map)

manual_pop_map = {
    'Mumbai': 11978450,
    'Bengaluru': 6490131,
    'Thiruvananthapuram': 752490,
    'Visakhapatnam': 982904,
    'Jodhpur': 856034,
    'Gwalior':826919
}
merged_df.loc[merged_df['City_Name'].isin(manual_pop_map.keys()),
'Population_2001'] = \
    merged_df['City_Name'].map(manual_pop_map)

# Fill missing Geographical Area and Population Density from
city_stats_df
area_map = city_stats_df.set_index('City_Name')
['Area_sq_km'].to_dict()
pop_2001_map = city_stats_df.set_index('City_Name')
['Population_2001'].to_dict()

# Fill missing area
merged_df['Area_sq_km'] =
merged_df['Area_sq_km'].fillna(merged_df['City_Name'].map(area_map))

# Calculate population density where missing: population_2001 /
area_sq_km
```

```
merged_df['Population Density'] = merged_df['Population
Density'].fillna(
    merged_df['City_Name'].map(pop_2001_map) /
merged_df['City_Name'].map(area_map)
)

# Diagnostics: Print missing data counts
print("Missing Geographical Area:",
merged_df[merged_df['Area_sq_km'].isna()]['City_Name'].unique())
print("Missing Population Density:", merged_df[merged_df['Population
Density'].isna()]['City_Name'].unique())
print("Missing Total Population:",
merged_df[merged_df['Total_Population'].isna()]['City_Name'].unique())
print("Missing Waste Generated:", merged_df[merged_df['Waste Generated
(Tons/Day)'].isna()]['City_Name'].unique())
print("States with missing SDG 12:", merged_df[merged_df['SDG
12'].isna()]['State'].unique())



# Feature engineering
merged_df['Waste_per_capita'] = merged_df['Waste Generated
(Tons/Day)'] * 1000 / merged_df['Population_2001']
merged_df['Recycling_Efficiency'] = merged_df['Recycling Rate (%)'] /
100
merged_df['Circular_Score'] = (
    merged_df['Recycling Rate (%)'] +
    merged_df['Municipal Efficiency Score (1-10)'] * 10 +
    merged_df['SDG 12']
) / 3

# Normalize features for modeling
features_to_scale = ['Waste_per_capita', 'Recycling_Efficiency',
'Circular_Score', 'Population Density']
scaler = MinMaxScaler()
merged_df[features_to_scale] =
scaler.fit_transform(merged_df[features_to_scale])

# Preview final dataframe
print(merged_df.head())
```

```
Missing Geographical Area: ['Mumbai' 'Bengaluru' 'Thiruvananthapuram'
'Jodhpur' 'Visakhapatnam'
 'Gwalior']
Missing Population Density: []
Missing Total Population: ['Mumbai' 'Bengaluru' 'Thiruvananthapuram'
'Jodhpur' 'Visakhapatnam'
 'Gwalior']
Missing Waste Generated: []
States with missing SDG 12: []
```

```
  City_Name    Waste Type  Waste Generated (Tons/Day)  Recycling Rate
(%)  \
0    Mumbai       Plastic                        6610
68
1    Mumbai       Organic                        1181
56
2    Mumbai       E-Waste                        8162
53
3    Mumbai  Construction                        8929
56
4    Mumbai     Hazardous                        5032
44

   Population Density  Municipal Efficiency Score (1-10) Disposal
Method  \
0            0.408167                                  9
Composting
1            0.408167                                  5
Composting
2            0.408167                                  8
Incineration
3            0.408167                                  5
Landfill
4            0.408167                                  7
Recycling

   Cost of Waste Management (₹/Ton)  Awareness Campaigns Count  \
0                              3056                         14
1                              2778                         12
2                              3390                         13
3                              1498                         14
4                              2221                         16

     Landfill Name  ... Population_2001  Area_sq_km  Waste_TPD  \
0  Mumbai Landfill  ...      11978450.0         NaN        NaN
1  Mumbai Landfill  ...      11978450.0         NaN        NaN
2  Mumbai Landfill  ...      11978450.0         NaN        NaN
3  Mumbai Landfill  ...      11978450.0         NaN        NaN
4  Mumbai Landfill  ...      11978450.0         NaN        NaN

  Waste_kg_per_capita_per_day  Total_Population  SDG 12  Composite
Score  \
0                         NaN               NaN      82
70
1                         NaN               NaN      82
70
2                         NaN               NaN      82
70
3                         NaN               NaN      82
70
```

```
4                               NaN                 NaN      82
70

   Waste_per_capita  Recycling_Efficiency  Circular_Score
0          0.039189              0.690909        0.808824
1          0.002015              0.472727        0.426471
2          0.049817              0.418182        0.625000
3          0.055069              0.472727        0.426471
4          0.028384              0.254545        0.485294

[5 rows x 24 columns]
```

```python
# ... after all processing steps

# Save the final cleaned and processed dataset to CSV
merged_df.to_csv('/content/drive/MyDrive/Project/Datasets/merged_final_dataset.csv', index=False)
print("Merged dataset saved successfully.")
```

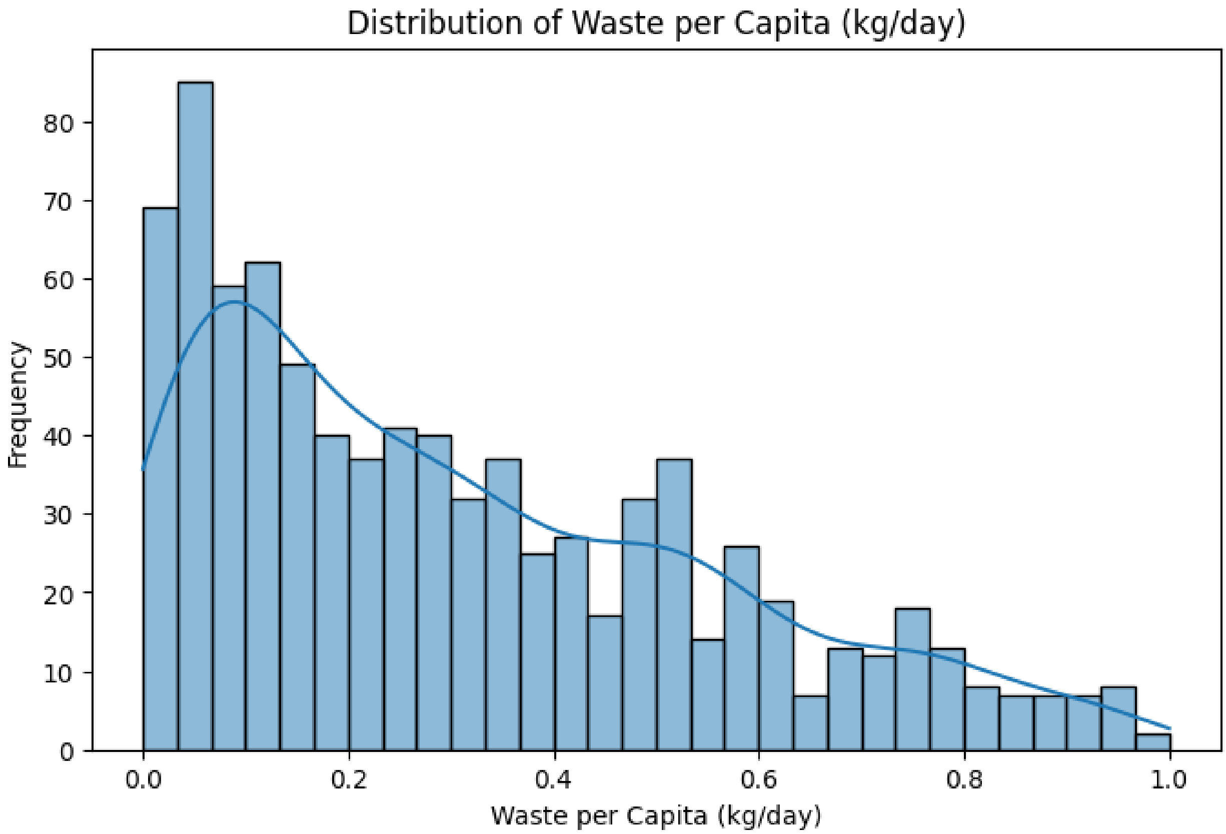
```
Merged dataset saved successfully.
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# 1. Summary statistics
print("Summary statistics:")
print(merged_df.describe())

# 2. Distribution of Waste per Capita
plt.figure(figsize=(8,5))
sns.histplot(merged_df['Waste_per_capita'], bins=30, kde=True)
plt.title('Distribution of Waste per Capita (kg/day)')
plt.xlabel('Waste per Capita (kg/day)')
plt.ylabel('Frequency')
plt.show()
```

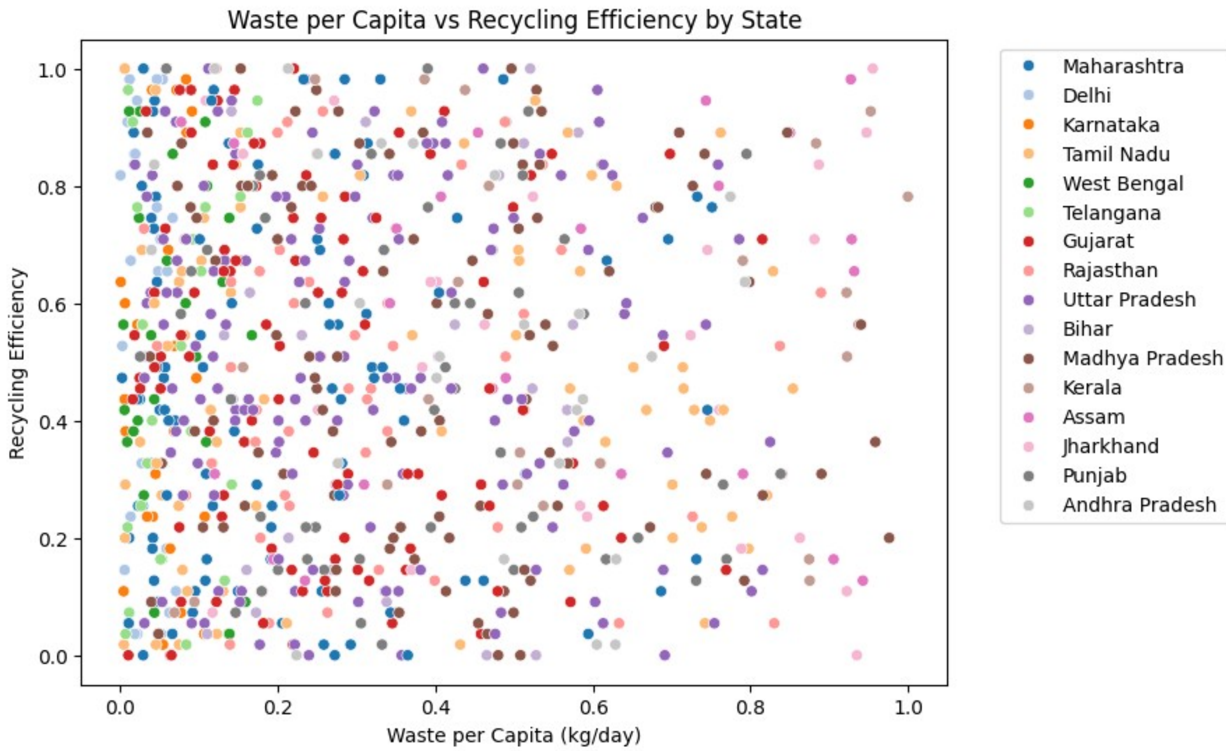
```
Summary statistics:
       Waste Generated (Tons/Day)  Recycling Rate (%)  Population
Density  \
count                  850.000000          850.000000
850.000000
mean                  5262.249412           57.076471
0.514113
std                   2786.984735           16.129994
0.305622
min                    511.000000           30.000000
0.000000
25%                   2865.750000           43.000000
```

```
0.257731
50%                5283.000000          56.000000
0.472162
75%                7757.250000          71.000000
0.772088
max                9980.000000          85.000000
1.000000

       Municipal Efficiency Score (1-10)  Cost of Waste Management
(₹/Ton)  \
count                         850.000000
850.000000
mean                            7.400000
2778.458824
std                             1.722162
1276.325630
min                             5.000000
503.000000
25%                             6.000000
1647.500000
50%                             7.000000
2853.000000
75%                             9.000000
3855.000000
max                            10.000000
4999.000000

       Awareness Campaigns Count  Landfill Capacity (Tons)
Year  \
count                 850.000000                850.000000
850.000000
mean                    9.904706              58934.617647
2021.000000
std                     6.070772              19413.627292
1.415046
min                     0.000000              22690.000000
2019.000000
25%                     5.000000              45575.000000
2020.000000
50%                    10.000000              61038.500000
2021.000000
75%                    15.000000              71127.000000
2022.000000
max                    20.000000              98646.000000
2023.000000

       Population_2001   Area_sq_km    Waste_TPD
Waste_kg_per_capita_per_day  \
count     8.500000e+02   700.000000   700.000000
700.000000
```

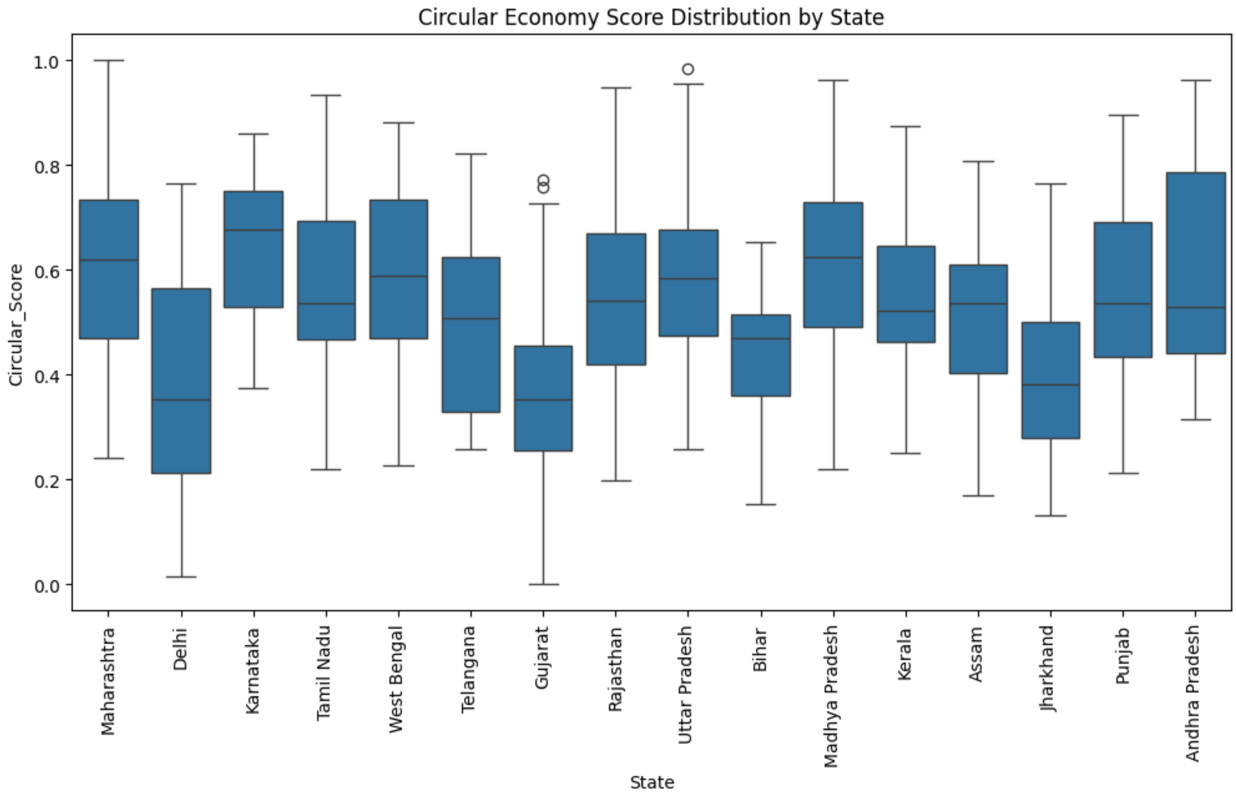
```
mean      2.394508e+06   229.071429   975.357143
0.396429
std       2.555171e+06   259.234585  1188.270892
0.130620
min       7.524900e+05    52.000000   166.000000
0.190000
25%       9.668620e+05   110.750000   408.000000
0.265000
50%       1.336336e+06   171.500000   520.500000
0.395000
75%       2.538473e+06   241.000000  1025.000000
0.512500
max       1.197845e+07  1483.000000  5922.000000
0.620000

       Total_Population       SDG 12  Composite Score  Waste_per_capita
\
count      7.000000e+02  850.000000       850.000000        850.000000

mean       2.125940e+06   72.294118        65.441176          0.308621

std        1.905892e+06   11.381409         5.945330          0.247007

min        8.098950e+05   50.000000        52.000000          0.000000

25%        9.734138e+05   66.000000        60.000000          0.098794

50%        1.382456e+06   78.000000        68.000000          0.250968

75%        2.459994e+06   79.000000        70.000000          0.484880

max        1.030645e+07   89.000000        75.000000          1.000000


       Recycling_Efficiency  Circular_Score
count            850.000000      850.000000
mean               0.492299        0.539490
std                0.293273        0.191454
min                0.000000        0.000000
25%                0.236364        0.404412
50%                0.472727        0.536765
75%                0.745455        0.676471
max                1.000000        1.000000
```



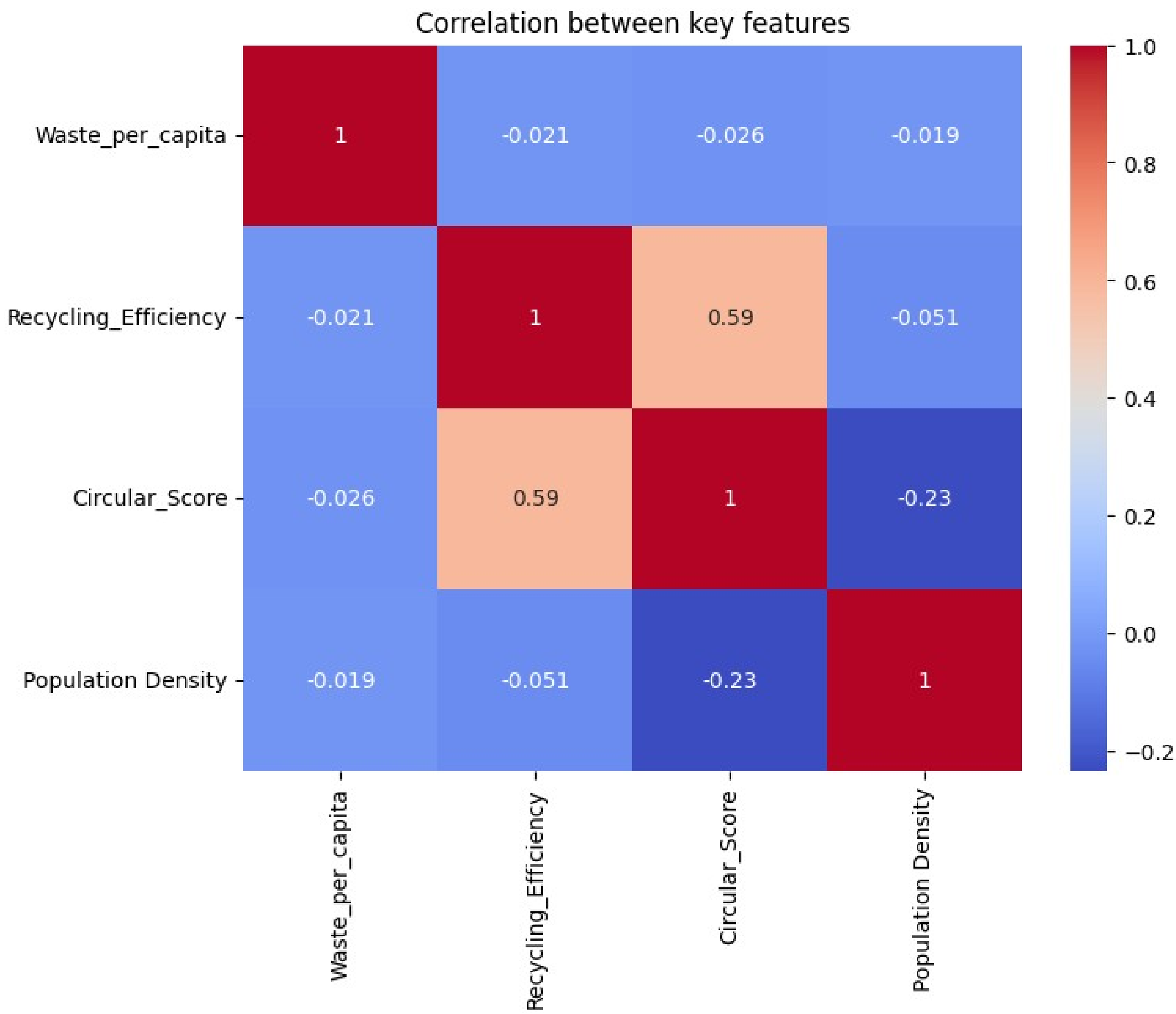

```
# 3. Scatter plot: Waste per Capita vs Recycling Efficiency (colored
by State)
plt.figure(figsize=(8,6))
sns.scatterplot(data=merged_df, x='Waste_per_capita',
y='Recycling_Efficiency', hue='State', palette='tab20')
plt.title('Waste per Capita vs Recycling Efficiency by State')
plt.xlabel('Waste per Capita (kg/day)')
plt.ylabel('Recycling Efficiency')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```




```python
# 4. Boxplot of Circular Score by State
plt.figure(figsize=(12,6))
sns.boxplot(data=merged_df, x='State', y='Circular_Score')
plt.xticks(rotation=90)
plt.title('Circular Economy Score Distribution by State')
plt.show()
```




```python
# 5. Correlation heatmap for key features
plt.figure(figsize=(8,6))
corr = merged_df[['Waste_per_capita', 'Recycling_Efficiency',
'Circular_Score', 'Population Density']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation between key features')
plt.show()
```




```python
# 6. Interactive Plotly scatter: Waste per Capita vs Circular Score
colored by SDG 12
fig = px.scatter(
    merged_df,
    x='Waste_per_capita',
    y='Circular_Score',
    color='SDG 12',
    hover_name='City_Name',
    title='Waste per Capita vs Circular Economy Score by SDG 12'
)
fig.show()

import tensorflow as tf
from tensorflow.keras import Input
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.preprocessing import MinMaxScaler
```

```
import numpy as np

cities = merged_df['City_Name'].unique()
results = {}

for city in cities:
    city_data = merged_df[merged_df['City_Name'] ==
city].sort_values(by='Year')
    if city_data['Year'].nunique() < 5:
        print(f"□ Not enough data to forecast for {city}")
        continue

    time_series = city_data[['Year', 'Waste Generated
(Tons/Day)']].dropna()
    if len(time_series) < 4:  # at least window size + 1 data points
        print(f"□ Not enough data points for {city}")
        continue

    scaler = MinMaxScaler()
    waste_scaled = scaler.fit_transform(time_series[['Waste Generated
(Tons/Day)']])

    def create_sequences(data, window_size=3):
        X, y = [], []
        for i in range(len(data) - window_size):
            X.append(data[i:i+window_size])
            y.append(data[i+window_size])
        return np.array(X), np.array(y)

    X, y = create_sequences(waste_scaled, window_size=3)
    X = X.reshape((X.shape[0], X.shape[1], 1))

    model = Sequential([
    Input(shape=(X.shape[1], 1)),  # <-- Add Input layer explicitly
here
    LSTM(64, activation='relu'),
    Dropout(0.2),
    Dense(1)
])
    model.compile(optimizer='adam', loss='mse')
    model.fit(X, y, epochs=100, verbose=0)

    last_sequence = waste_scaled[-3:].reshape((1, 3, 1))
    next_prediction = model.predict(last_sequence)
    next_tpd = scaler.inverse_transform(next_prediction)[0][0]

    results[city] = next_tpd
    print(f"□ Forecasted Waste for {city} (next year): {next_tpd:.2f}
Tons/Day")
```

```python
# Optional: convert results dict to DataFrame for saving or analysis
import pandas as pd
forecast_df = pd.DataFrame(list(results.items()),
columns=['City_Name', 'Forecasted_Waste_TonsPerDay'])
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 274ms/step
□ Forecasted Waste for Mumbai (next year): 6061.08 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 183ms/step
□ Forecasted Waste for Delhi (next year): 5556.22 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 294ms/step
□ Forecasted Waste for Bengaluru (next year): 4719.50 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 177ms/step
□ Forecasted Waste for Chennai (next year): 4512.31 Tons/Day
```

```
WARNING:tensorflow:5 out of the last 5 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_dist
ributed at 0x780264067ce0> triggered tf.function retracing. Tracing is
expensive and the excessive number of tracings could be due to (1)
creating @tf.function repeatedly in a loop, (2) passing tensors with
different shapes, (3) passing Python objects instead of tensors. For
(1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid
unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
□ Forecasted Waste for Kolkata (next year): 4047.00 Tons/Day
```

```
WARNING:tensorflow:6 out of the last 6 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_dist
ributed at 0x780260433a60> triggered tf.function retracing. Tracing is
expensive and the excessive number of tracings could be due to (1)
creating @tf.function repeatedly in a loop, (2) passing tensors with
different shapes, (3) passing Python objects instead of tensors. For
(1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid
unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 196ms/step
□ Forecasted Waste for Hyderabad (next year): 3579.45 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 185ms/step
□ Forecasted Waste for Pune (next year): 5819.08 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 268ms/step
□ Forecasted Waste for Ahmedabad (next year): 4958.43 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step
```

```
 Forecasted Waste for Jaipur (next year): 5233.23 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 196ms/step
 Forecasted Waste for Lucknow (next year): 5555.64 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 175ms/step
 Forecasted Waste for Surat (next year): 5803.92 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 174ms/step
 Forecasted Waste for Kanpur (next year): 5005.38 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 182ms/step
 Forecasted Waste for Nagpur (next year): 4669.88 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 204ms/step
 Forecasted Waste for Patna (next year): 4496.56 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 197ms/step
 Forecasted Waste for Bhopal (next year): 5612.57 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 262ms/step
 Forecasted Waste for Thiruvananthapuram (next year): 3841.90
Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 176ms/step
 Forecasted Waste for Indore (next year): 4557.53 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 198ms/step
 Forecasted Waste for Vadodara (next year): 5984.08 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 168ms/step
 Forecasted Waste for Guwahati (next year): 4982.79 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 201ms/step
 Forecasted Waste for Coimbatore (next year): 5278.44 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 180ms/step
 Forecasted Waste for Ranchi (next year): 4551.01 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 185ms/step
 Forecasted Waste for Amritsar (next year): 5056.85 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 181ms/step
 Forecasted Waste for Jodhpur (next year): 3397.81 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step
 Forecasted Waste for Varanasi (next year): 4042.34 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step
 Forecasted Waste for Ludhiana (next year): 3623.85 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 192ms/step
 Forecasted Waste for Agra (next year): 5122.79 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 181ms/step
 Forecasted Waste for Meerut (next year): 3929.37 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 264ms/step
 Forecasted Waste for Nashik (next year): 4979.12 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 170ms/step
 Forecasted Waste for Rajkot (next year): 5012.54 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 178ms/step
 Forecasted Waste for Madurai (next year): 2276.50 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 172ms/step
 Forecasted Waste for Jabalpur (next year): 5631.14 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 186ms/step
 Forecasted Waste for Allahabad (next year): 5778.92 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 186ms/step
```

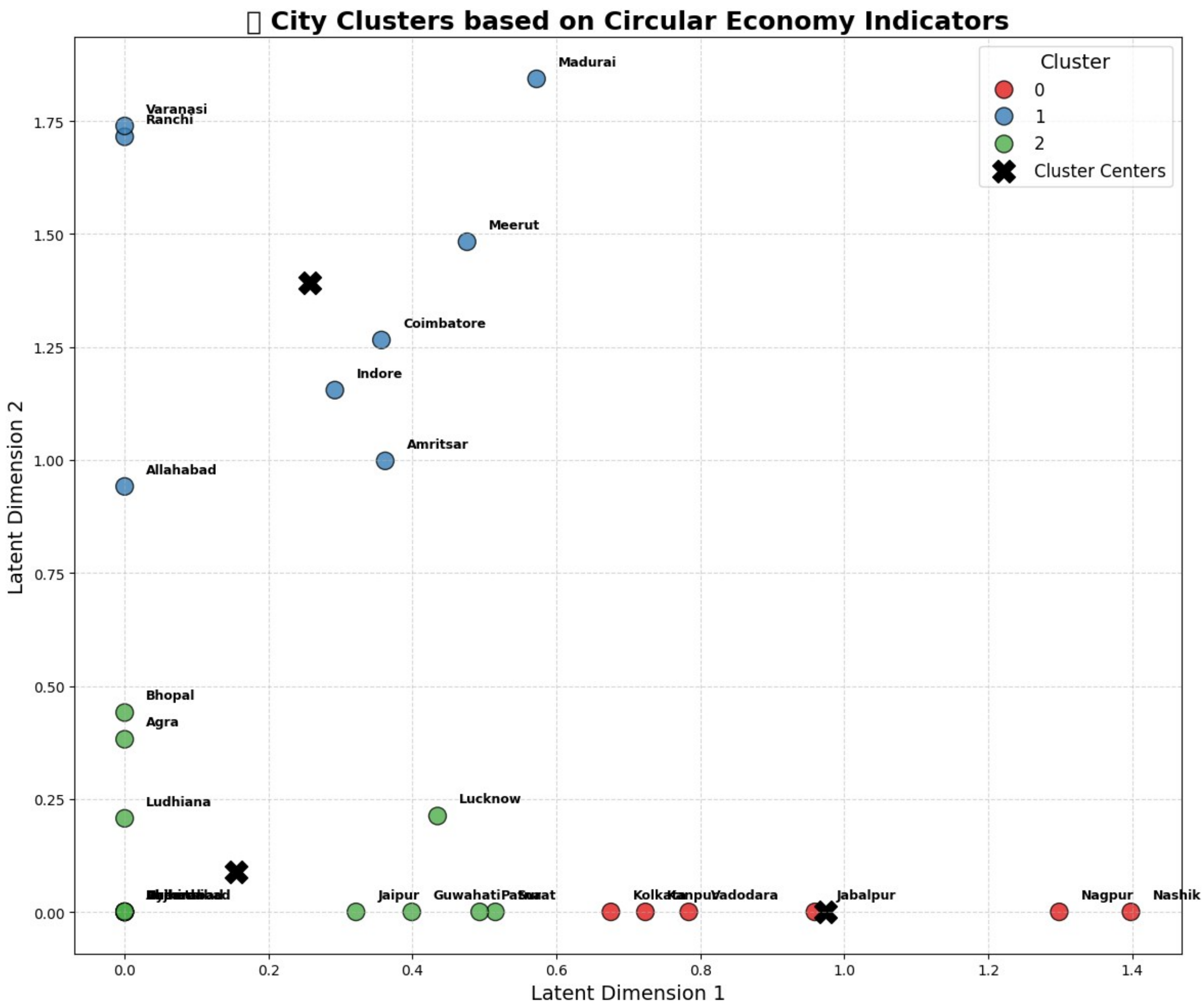
```
 Forecasted Waste for Visakhapatnam (next year): 5474.69 Tons/Day
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 190ms/step
 Forecasted Waste for Gwalior (next year): 5837.37 Tons/Day
```

```
ce_features = [
    'Recycling Rate (%)',
    'Municipal Efficiency Score (1-10)',
    'Awareness Campaigns Count',
    'Waste_TPD',  # from your dataset
    'SDG 12',
    'Waste_per_capita'
]

import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, silhouette_samples
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
import matplotlib.pyplot as plt
import seaborn as sns



# Drop duplicates so each city only once
ce_df = merged_df.drop_duplicates(subset='City_Name')

# Filter CE feature columns and drop rows with missing values
ce_data = ce_df[ce_features].dropna()

# Save city names corresponding to filtered rows
city_names = ce_df.loc[ce_data.index, 'City_Name'].values

# --- 2. Scale the features ---
scaler = StandardScaler()
X_scaled = scaler.fit_transform(ce_data)

# --- 3. Build Autoencoder for Dimensionality Reduction ---
input_dim = X_scaled.shape[1]
encoding_dim = 2  # compress to 2D for visualization

input_layer = Input(shape=(input_dim,))
encoded = Dense(5, activation='relu')(input_layer)
encoded = Dense(encoding_dim, activation='relu')(encoded)
decoded = Dense(5, activation='relu')(encoded)
decoded = Dense(input_dim, activation='linear')(decoded)

autoencoder = Model(inputs=input_layer, outputs=decoded)
encoder = Model(inputs=input_layer, outputs=encoded)
```

```
autoencoder.compile(optimizer='adam', loss='mse')

# Train autoencoder
autoencoder.fit(X_scaled, X_scaled, epochs=100, batch_size=8,
verbose=0)

# --- 4. Extract encoded features ---
X_encoded = encoder.predict(X_scaled)

# --- 5. Cluster in encoded space ---
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
clusters = kmeans.fit_predict(X_encoded)

# --- 6. Silhouette score ---
silhouette_avg = silhouette_score(X_encoded, clusters)
print(f"□ Silhouette Score (Overall Clustering Quality):
{silhouette_avg:.2f}")

# Prepare DataFrame with embeddings and cluster info
encoded_df = pd.DataFrame(X_encoded, columns=['Dim1', 'Dim2'])
encoded_df['Cluster'] = clusters
encoded_df['City'] = city_names
encoded_df['Silhouette'] = silhouette_samples(X_encoded, clusters)

# --- 7. Visualization ---
plt.figure(figsize=(12, 10))
palette = sns.color_palette("Set1", n_colors=n_clusters)

sns.scatterplot(
    data=encoded_df,
    x='Dim1',
    y='Dim2',
    hue='Cluster',
    palette=palette,
    s=150,
    alpha=0.8,
    edgecolor='black'
)

# Plot cluster centers
centers = kmeans.cluster_centers_
plt.scatter(
    centers[:, 0], centers[:, 1],
    c='black', s=250, marker='X', label='Cluster Centers'
)

# Annotate city names with small offset
for i, row in encoded_df.iterrows():
    plt.text(row['Dim1'] + 0.03, row['Dim2'] + 0.03, row['City'],
```

```
fontsize=9, weight='bold')

plt.title("🔄 City Clusters based on Circular Economy Indicators",
fontsize=18, weight='bold')
plt.xlabel("Latent Dimension 1", fontsize=14)
plt.ylabel("Latent Dimension 2", fontsize=14)
plt.legend(title='Cluster', fontsize=12, title_fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

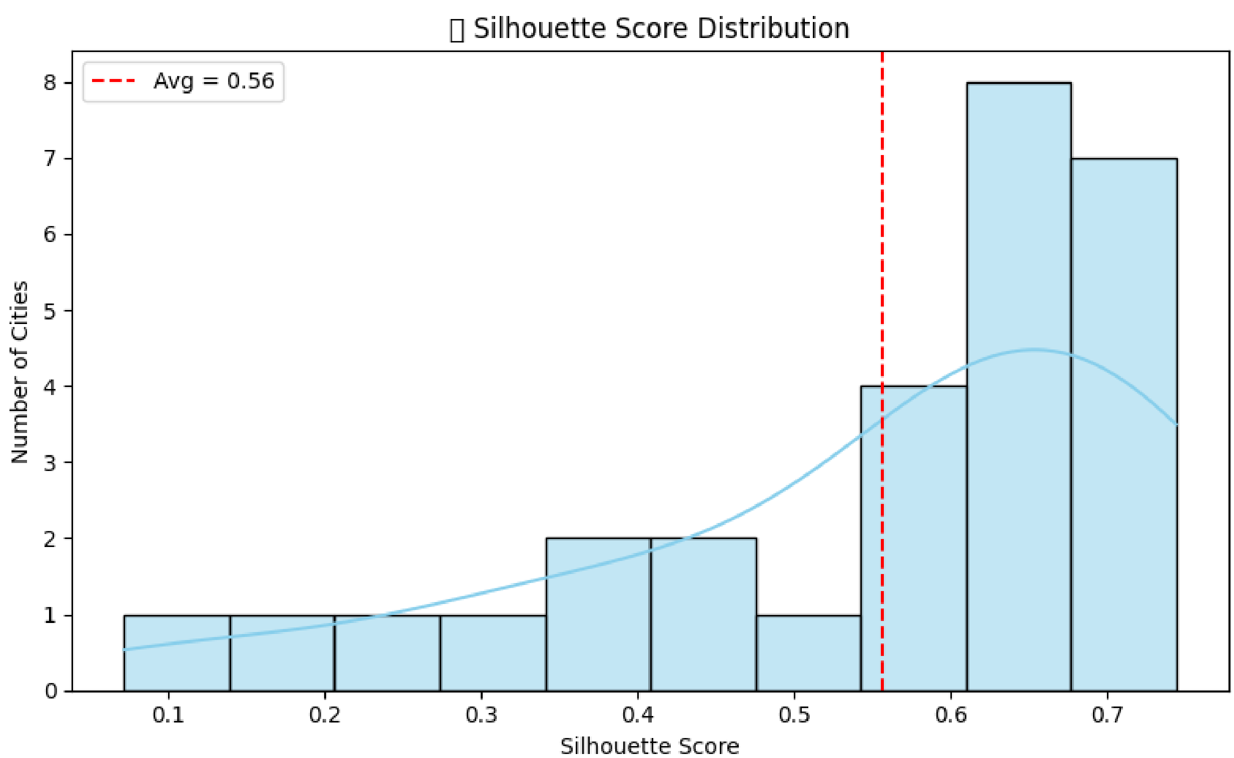
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 75ms/step
□ Silhouette Score (Overall Clustering Quality): 0.56

/tmp/ipython-input-19-1480003489.py:93: UserWarning:

Glyph 128260 (\N{ANTICLOCKWISE DOWNWARDS AND UPWARDS OPEN CIRCLE
ARROWS}) missing from font(s) DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128260 (\N{ANTICLOCKWISE DOWNWARDS AND UPWARDS OPEN CIRCLE
ARROWS}) missing from font(s) DejaVu Sans.
```




```
# === 8. Silhouette Distribution Plot ===
plt.figure(figsize=(8, 5))
sns.histplot(encoded_df['Silhouette'], bins=10, kde=True,
color='skyblue')
plt.axvline(silhouette_avg, color='red', linestyle='--', label=f"Avg =
{silhouette_avg:.2f}")
plt.title("□ Silhouette Score Distribution")
plt.xlabel("Silhouette Score")
plt.ylabel("Number of Cities")
plt.legend()
plt.tight_layout()
plt.show()

# === 9. Cluster-wise City Summary ===
cluster_summary = encoded_df.groupby('Cluster')['City'].apply(list)
for c, cities in cluster_summary.items():
    print(f"\n□ Cluster {c} ({len(cities)} cities):")
    print(", ".join(cities))
```

```
merged_df.to_csv("your_merged_ce_data.csv", index=False)
print("□ Saved: your_merged_ce_data.csv")

# === 10. Save cluster results ===
encoded_df.to_csv("city_clusters_autoencoder.csv", index=False)
```

```
/tmp/ipython-input-20-1075552831.py:9: UserWarning:

Glyph 128207 (\N{STRAIGHT RULER}) missing from font(s) DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128207 (\N{STRAIGHT RULER}) missing from font(s) DejaVu Sans.
```




```
□ Cluster 0 (6 cities):
Kolkata, Kanpur, Nagpur, Vadodara, Nashik, Jabalpur

□ Cluster 1 (8 cities):
Indore, Coimbatore, Ranchi, Amritsar, Varanasi, Meerut, Madurai,
Allahabad

□ Cluster 2 (14 cities):
```

```
Delhi, Chennai, Hyderabad, Pune, Ahmedabad, Jaipur, Lucknow, Surat,
Patna, Bhopal, Guwahati, Ludhiana, Agra, Rajkot
□ Saved: your_merged_ce_data.csv
```

```python
# Load cluster labels from saved CSV (from Phase 4)
cluster_df = pd.read_csv("city_clusters_autoencoder.csv")

# Confirm the column names in cluster_df
print(cluster_df.columns)
```

```
Index(['Dim1', 'Dim2', 'Cluster', 'City', 'Silhouette'],
dtype='object')
```

```python
import pandas as pd

# Load your original merged CE dataset (adjust file path)
merged_df = pd.read_csv("your_merged_ce_data.csv")

# Load clustering results from autoencoder step (adjust file path)
cluster_df = pd.read_csv("city_clusters_autoencoder.csv")  # Has
'City', 'Cluster', etc.

# Merge cluster info with original CE dataset on city names
merged = pd.merge(
    merged_df,
    cluster_df[['City', 'Cluster']],
    left_on='City_Name',
    right_on='City',
    how='inner'
)

# If after merge you see duplicate cluster columns (Cluster_x,
Cluster_y),
# keep 'Cluster_y' as final 'Cluster' and drop the rest
if 'Cluster_y' in merged.columns and 'Cluster_x' in merged.columns:
    merged['Cluster'] = merged['Cluster_y']
    merged.drop(columns=['Cluster_x', 'Cluster_y'], inplace=True)

# Define CE action mapping based on cluster label
action_map = {
    0: 'Rethink',
    1: 'Redesign',
    2: 'Reuse'
}

# Map cluster to CE Action
merged['CE_Action'] = merged['Cluster'].map(action_map)

# Show sample output
print(merged[['City_Name', 'Cluster', 'CE_Action']].head(10))
```

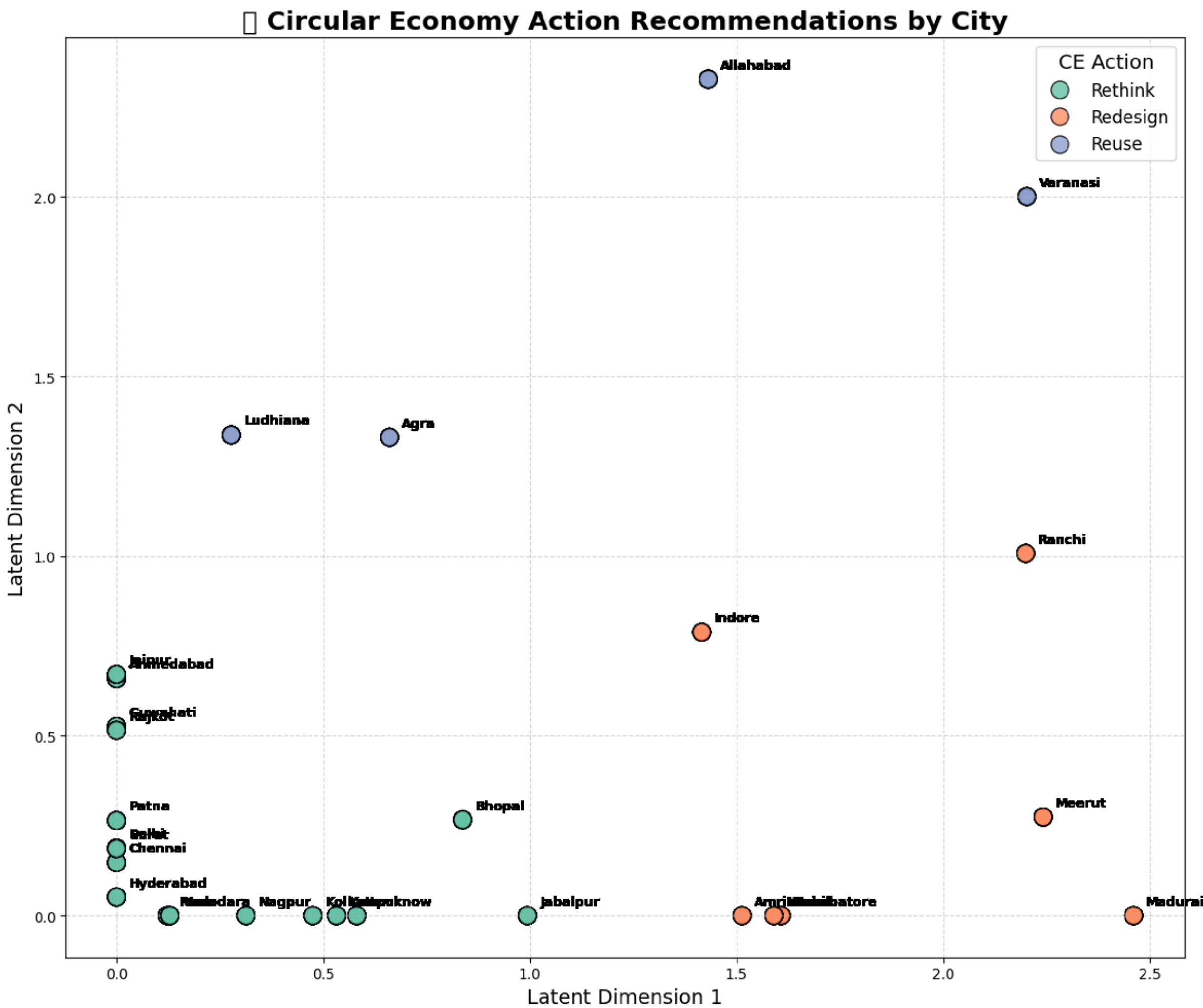
```python
# Save final dataframe with CE action recommendations
merged.to_csv("ce_action_recommendations.csv", index=False)
print("✅ Saved: ce_action_recommendations.csv")
```

```
  City_Name  Cluster CE_Action
0     Delhi        0   Rethink
1     Delhi        0   Rethink
2     Delhi        0   Rethink
3     Delhi        0   Rethink
4     Delhi        0   Rethink
5     Delhi        0   Rethink
6     Delhi        0   Rethink
7     Delhi        0   Rethink
8     Delhi        0   Rethink
9     Delhi        0   Rethink
✅ Saved: ce_action_recommendations.csv
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

# If 'Dim1' and 'Dim2' are missing, merge from cluster_df
if 'Dim1' not in merged.columns or 'Dim2' not in merged.columns:
    merged = merged.merge(
        cluster_df[['City', 'Dim1', 'Dim2']],
        left_on='City_Name',
        right_on='City',
        how='left'
    )

plt.figure(figsize=(12, 10))

# Use a distinct color palette for the CE_Action categories
palette = sns.color_palette("Set2", n_colors=3)

sns.scatterplot(
    data=merged,
    x='Dim1',
    y='Dim2',
    hue='CE_Action',
    palette=palette,
    s=150,
    edgecolor='black',
    alpha=0.8
)

# Annotate city names slightly offset
for i, row in merged.iterrows():
    plt.text(row['Dim1'] + 0.03, row['Dim2'] + 0.03, row['City_Name'],
fontsize=9, weight='bold')
```

```
plt.title("🔄 Circular Economy Action Recommendations by City",
fontsize=18, weight='bold')
plt.xlabel("Latent Dimension 1", fontsize=14)
plt.ylabel("Latent Dimension 2", fontsize=14)
plt.legend(title='CE Action', fontsize=12, title_fontsize=14)
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-49-1996795105.py:38: UserWarning:

Glyph 128260 (\N{ANTICLOCKWISE DOWNWARDS AND UPWARDS OPEN CIRCLE
ARROWS}) missing from font(s) DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128260 (\N{ANTICLOCKWISE DOWNWARDS AND UPWARDS OPEN CIRCLE
ARROWS}) missing from font(s) DejaVu Sans.
```




```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Select features and target
features = [
    'Recycling Rate (%)',
    'Population Density',
    'Municipal Efficiency Score (1-10)',
    'Cost of Waste Management (₹/Ton)',
    'Awareness Campaigns Count',
    'Landfill Capacity (Tons)',
    'Waste_TPD',
    'Waste_per_capita',
    'Total_Population',
    'SDG 12',
    'Composite Score',
    'Recycling_Efficiency',
```

```
    'Circular_Score'
]

X = merged[features].copy()
y = merged['CE_Action']

# Encode target
le = LabelEncoder()
y_encoded = le.fit_transform(y)  # Rethink:0, Redesign:1, Reuse:2

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded,
test_size=0.2, random_state=42, stratify=y_encoded)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from sklearn.metrics import classification_report, accuracy_score

models = []
names = ['MLP_1layer', 'MLP_2layer', 'Dropout_MLP', 'BatchNorm_MLP',
'WideDeep_MLP']
histories = []
scores = []

for name in names:
    model = Sequential()
    model.add(Dense(64, input_shape=(X_train_scaled.shape[1],),
activation='relu'))

    if name == 'MLP_2layer':
        model.add(Dense(32, activation='relu'))

    elif name == 'Dropout_MLP':
        model.add(Dropout(0.3))
        model.add(Dense(32, activation='relu'))

    elif name == 'BatchNorm_MLP':
        model.add(BatchNormalization())
        model.add(Dense(32, activation='relu'))

    elif name == 'WideDeep_MLP':
        model.add(Dense(128, activation='relu'))
        model.add(Dense(64, activation='relu'))

    model.add(Dense(3, activation='softmax'))
```

```
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])

    history = model.fit(X_train_scaled, y_train, epochs=100,
batch_size=8, verbose=0, validation_split=0.2)

    y_pred = model.predict(X_test_scaled)
    y_pred_labels = y_pred.argmax(axis=1)

    acc = accuracy_score(y_test, y_pred_labels)
    scores.append(acc)
    models.append(model)
    histories.append(history)

    print(f"\n□ Model: {name}")
    print(f"Accuracy: {acc:.4f}")
    print(classification_report(y_test, y_pred_labels,
target_names=le.classes_))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.


5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step

□ Model: MLP_1layer
Accuracy: 0.9143
              precision    recall  f1-score   support

    Redesign       0.80      0.91      0.85        35
     Rethink       0.95      0.91      0.93        85
       Reuse       1.00      0.95      0.97        20

    accuracy                           0.91       140
   macro avg       0.92      0.92      0.92       140
weighted avg       0.92      0.91      0.92       140


/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step

□ Model: MLP_2layer
Accuracy: 0.9143
              precision    recall  f1-score   support

    Redesign       0.85      0.94      0.89        35
     Rethink       0.96      0.89      0.93        85
       Reuse       0.86      0.95      0.90        20

    accuracy                           0.91       140
   macro avg       0.89      0.93      0.91       140
weighted avg       0.92      0.91      0.91       140


/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.


5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step

□ Model: Dropout_MLP
Accuracy: 0.9786
              precision    recall  f1-score   support

    Redesign       0.95      1.00      0.97        35
     Rethink       0.99      0.98      0.98        85
       Reuse       1.00      0.95      0.97        20

    accuracy                           0.98       140
   macro avg       0.98      0.98      0.98       140
weighted avg       0.98      0.98      0.98       140


/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.


5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step

□ Model: BatchNorm_MLP
Accuracy: 0.8714
              precision    recall  f1-score   support
```

```
    Redesign       0.82      0.91      0.86        35
     Rethink       0.94      0.85      0.89        85
       Reuse       0.75      0.90      0.82        20

    accuracy                           0.87       140
   macro avg       0.84      0.89      0.86       140
weighted avg       0.88      0.87      0.87       140


/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
dense.py:87: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the
first layer in the model instead.


5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step

 Model: WideDeep_MLP
Accuracy: 0.9357
              precision    recall  f1-score   support

    Redesign       0.87      0.97      0.92        35
     Rethink       0.97      0.92      0.95        85
       Reuse       0.90      0.95      0.93        20

    accuracy                           0.94       140
   macro avg       0.92      0.95      0.93       140
weighted avg       0.94      0.94      0.94       140
```

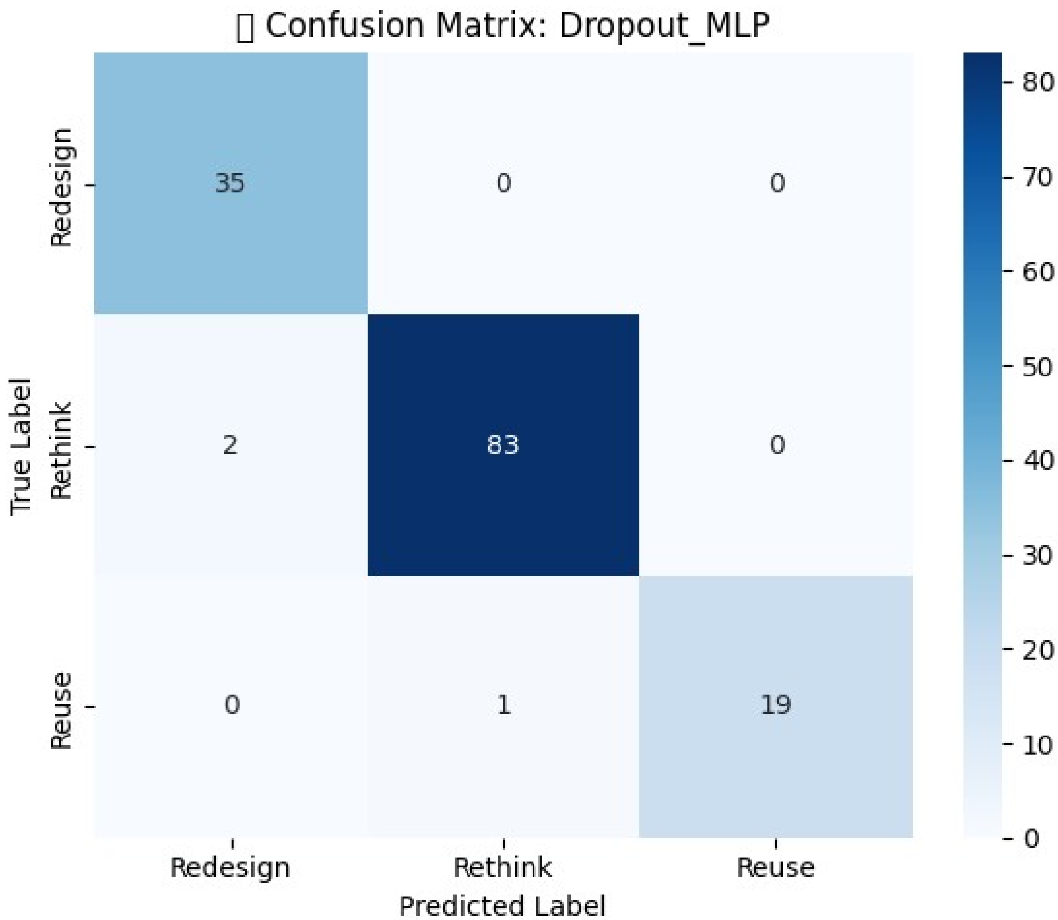
```python
best_idx = scores.index(max(scores))
best_model = models[best_idx]
print(f"\n Best Model: {names[best_idx]} with Accuracy:
{scores[best_idx]:.4f}")
```

```
 Best Model: Dropout_MLP with Accuracy: 0.9786
```

```python
from sklearn.metrics import f1_score, confusion_matrix, roc_auc_score
from sklearn.preprocessing import label_binarize
import seaborn as sns
import matplotlib.pyplot as plt

# Get the trained Dropout_MLP model (assuming it's at index 2)
dropout_model = models[names.index('Dropout_MLP')]

# Predict
y_pred_probs = dropout_model.predict(X_test_scaled)
```

```
y_pred_labels = y_pred_probs.argmax(axis=1)

# === F1 Score ===
f1_macro = f1_score(y_test, y_pred_labels, average='macro')
print(f"□ F1 Score (macro): {f1_macro:.4f}")

# === Confusion Matrix ===
cm = confusion_matrix(y_test, y_pred_labels)

plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=le.classes_, yticklabels=le.classes_)
plt.title("□ Confusion Matrix: Dropout_MLP")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()

# === ROC-AUC (One-vs-Rest) ===
# Binarize y_test for multi-class ROC
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])

try:
    auc_ovr = roc_auc_score(y_test_bin, y_pred_probs,
multi_class='ovr')
    print(f"□ ROC-AUC (OvR): {auc_ovr:.4f}")
except ValueError:
    print("⚠ ROC-AUC could not be computed due to class imbalance or
missing classes in y_test.")
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
□ F1 Score (macro): 0.9763

/tmp/ipython-input-41-3134291662.py:26: UserWarning:

Glyph 128269 (\N{LEFT-POINTING MAGNIFYING GLASS}) missing from font(s)
DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128269 (\N{LEFT-POINTING MAGNIFYING GLASS}) missing from font(s)
DejaVu Sans.
```




```
 ROC-AUC (OvR): 0.9994

import shap

# Use SHAP KernelExplainer
explainer = shap.Explainer(best_model.predict, X_test_scaled)
shap_values = explainer(X_test_scaled[:50])  # Use a subset for speed

# SHAP summary plot
shap.summary_plot(shap_values, X_test.iloc[:50],
feature_names=features)

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

```
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
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80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step

 PermutationExplainer explainer:   4%|▍         | 2/50 [00:00<?,
?it/s]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
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81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:   8%|█          | 4/50 [00:29<04:08,
5.40s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  10%|█          | 5/50 [00:33<03:41,
4.92s/it]

78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
 PermutationExplainer explainer:  12%|█         | 6/50 [00:39<03:45,
5.13s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  14%|█         | 7/50 [00:43<03:20,
4.66s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  16%|█         | 8/50 [00:47<03:07,
4.47s/it]
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80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  18%|█▊        | 9/50 [00:52<03:14,
4.74s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  20%|██        | 10/50 [00:56<03:01,
4.53s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  22%|██        | 11/50 [01:00<02:52,
4.43s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  24%|██▍       | 12/50 [01:06<02:58,
4.70s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  26%|██▌       | 13/50 [01:10<02:44,
4.45s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  28%|██▊       | 14/50 [01:13<02:34,
4.28s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

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80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  30%|███       | 15/50 [01:19<02:41,
4.61s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  32%|███       | 16/50 [01:23<02:32,
4.47s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  34%|███       | 17/50 [01:29<02:41,
4.88s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  36%|███       | 18/50 [01:34<02:41,
5.05s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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 PermutationExplainer explainer:  38%|███▊      | 19/50 [01:38<02:27,
4.76s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  40%|████      | 20/50 [01:43<02:26,
4.88s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  42%|████▏     | 21/50 [01:48<02:18,
4.76s/it]
```

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81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  44%|████      | 22/50 [01:52<02:07,
4.56s/it]

83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
83/83 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  46%|████      | 23/50 [01:58<02:11,
4.86s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  48%|████▊     | 24/50 [02:02<02:02,
4.72s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  50%|█████     | 25/50 [02:06<01:51,
4.46s/it]

78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  52%|█████▏    | 26/50 [02:11<01:53,
4.71s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  54%|█████▍    | 27/50 [02:15<01:41,
4.42s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  56%|█████▌    | 28/50 [02:19<01:35,
4.33s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  58%|█████▊    | 29/50 [02:24<01:36,
4.60s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  60%|██████    | 30/50 [02:28<01:29,
4.47s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  62%|██████▏   | 31/50 [02:33<01:23,
4.41s/it]

78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
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 PermutationExplainer explainer:  64%|██████▍   | 32/50 [02:38<01:23,
4.64s/it]

78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  66%|██████▌   | 33/50 [02:42<01:16,
4.51s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  68%|██████▊   | 34/50 [02:46<01:10,
4.39s/it]
```

```
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  70%|███████   | 35/50 [02:52<01:11,
4.75s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  72%|███████▏  | 36/50 [02:56<01:03,
4.57s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  74%|███████▍  | 37/50 [03:00<00:57,
4.43s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  76%|███████▌  | 38/50 [03:05<00:56,
4.72s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

```
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  78%|███████▊  | 39/50 [03:10<00:50,
4.59s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  80%|████████  | 40/50 [03:14<00:44,
4.44s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

```
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  82%|████████▏ | 41/50 [03:19<00:42,
4.72s/it]

78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
78/78 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  84%|████████▍ | 42/50 [03:23<00:35,
4.50s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  86%|████████▌ | 43/50 [03:27<00:31,
4.45s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  88%|████████▊ | 44/50 [03:33<00:28,
4.78s/it]

80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```

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 PermutationExplainer explainer:  90%|█████████ | 45/50 [03:38<00:23, 4.69s/it]
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
80/80 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
 PermutationExplainer explainer:  92%|█████████▏| 46/50 [03:42<00:18, 4.55s/it]
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
 PermutationExplainer explainer:  94%|█████████▍| 47/50 [03:47<00:14, 4.79s/it]
```
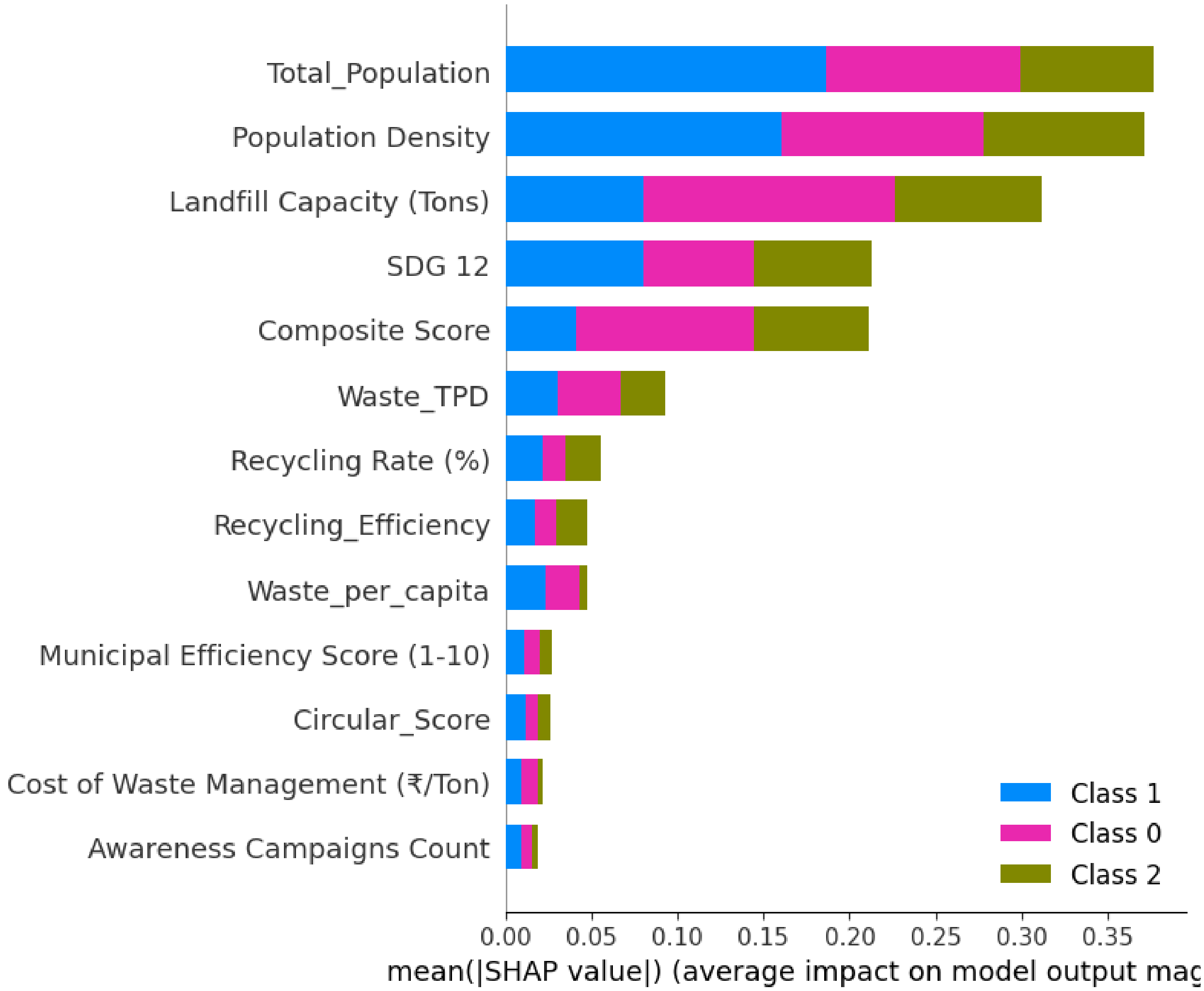

```
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step

 PermutationExplainer explainer:  96%|█████████▌| 48/50 [03:51<00:09,
4.54s/it]

81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
81/81 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer:  98%|█████████▊| 49/50 [03:55<00:04,
4.44s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

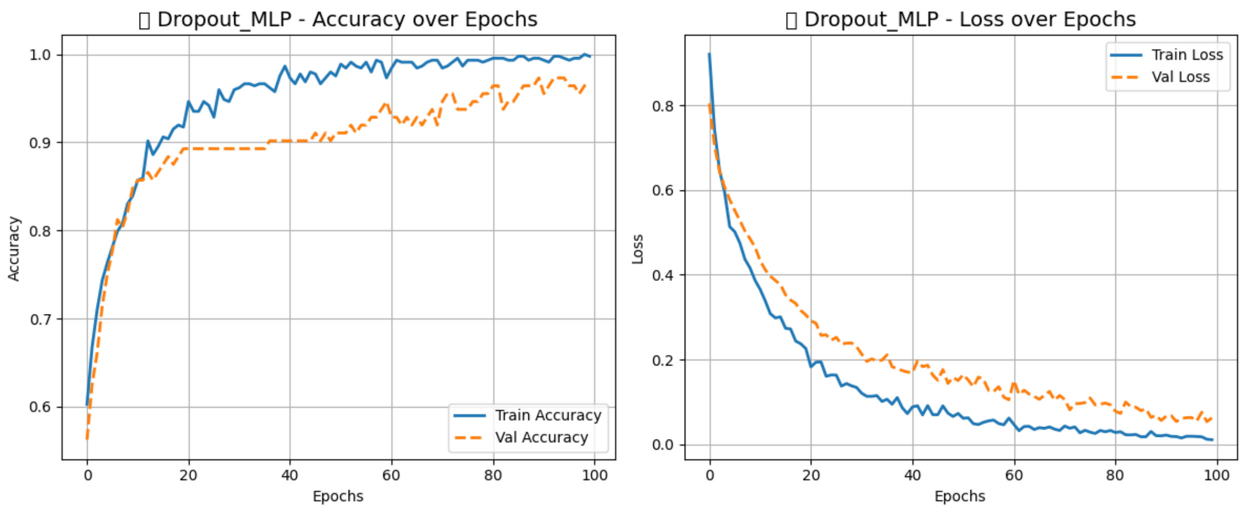
```
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
43/43 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

 PermutationExplainer explainer: 100%|██████████| 50/50 [04:01<00:00,
4.72s/it]

79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
79/79 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
44/44 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step

PermutationExplainer explainer: 51it [04:07,  5.04s/it]
/tmp/ipython-input-43-4008263907.py:8: FutureWarning:

The NumPy global RNG was seeded by calling `np.random.seed`. In a
future version this function will no longer use the global RNG. Pass
`rng` explicitly to opt-in to the new behaviour and silence this
warning.
```




```
import matplotlib.pyplot as plt

# Get the training history for Dropout_MLP (index 2)
history = histories[names.index('Dropout_MLP')]

# Plot training & validation accuracy
plt.figure(figsize=(12, 5))

# --- Accuracy Plot ---
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy',
linewidth=2)
plt.plot(history.history['val_accuracy'], label='Val Accuracy',
linewidth=2, linestyle='--')
plt.title('□ Dropout_MLP - Accuracy over Epochs', fontsize=14)
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```python
plt.grid(True)

# --- Loss Plot ---
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss', linewidth=2)
plt.plot(history.history['val_loss'], label='Val Loss', linewidth=2,
linestyle='--')
plt.title('□ Dropout_MLP - Loss over Epochs', fontsize=14)
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

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

```
/tmp/ipython-input-44-1472516604.py:29: UserWarning:

Glyph 128200 (\N{CHART WITH UPWARDS TREND}) missing from font(s)
DejaVu Sans.

/tmp/ipython-input-44-1472516604.py:29: UserWarning:

Glyph 128201 (\N{CHART WITH DOWNWARDS TREND}) missing from font(s)
DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128200 (\N{CHART WITH UPWARDS TREND}) missing from font(s)
DejaVu Sans.

/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning:

Glyph 128201 (\N{CHART WITH DOWNWARDS TREND}) missing from font(s)
DejaVu Sans.
```


Dropout_MLP - Accuracy over Epochs
Accuracy
Epochs
Train Accuracy
Val Accuracy
Dropout_MLP - Loss over Epochs
Loss
Epochs
Train Loss
Val Loss