Objective :

The goal is to analyze pollution data across various countries and predict how pollution levels can impact energy recovery. This dataset will be used to explore clustering and neural networks for environmental analysis.

Phase 1
Data Preprocessing and Feature Engineering

contains 2 steps

Step 1 - Data Import and Cleaning

In [132…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, LabelEncoder
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
from sklearn.metrics import adjusted_rand_score, r2_score, mean_squared_error, mean_absolute_error, confusion_matrix,
from sklearn.cluster import AgglomerativeClustering
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [133…

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

Out[133...

	Country	Year	Air_Pollution_Index	Water_Pollution_Index	Soil_Pollution_Index	Industrial_Waste (in tons)	Energy_Recovered (in GWh)	CO2_En
0	Hungary	2005	272.70	124.27	51.95	94802.83	158.14	
1	Singapore	2001	86.72	60.34	117.22	56283.92	498.04	
2	Romania	2016	91.59	83.36	121.72	56256.02	489.51	
3	Cook Islands	2018	280.61	67.16	93.58	74864.73	145.18	
4	Djibouti	2008	179.16	127.53	121.55	76862.06	40.38	

In [134...

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

Out[134...

```
Country                                  0
Year                                     0
Air_Pollution_Index                      0
Water_Pollution_Index                    0
Soil_Pollution_Index                     0
Industrial_Waste (in tons)               0
Energy_Recovered (in GWh)                0
CO2_Emissions (in MT)                    0
Renewable_Energy (%)                     0
Plastic_Waste_Produced (in tons)         0
Energy_Consumption_Per_Capita (in MWh)   0
Population (in millions)                 0
GDP_Per_Capita (in USD)                  0
dtype: int64
```

Null values do not exist in any column

Now checking for incorrect data

In [135...

```
if pd.api.types.is_float_dtype(d['Year']):
    d['Year'] = d['Year'].round().astype(int)

if pd.api.types.is_numeric_dtype(d['Air_Pollution_Index']):
    d['Air_Pollution_Index'] = d['Air_Pollution_Index'].astype(float)
```

```
d.loc[d['Air_Pollution_Index'] < 0, 'Air_Pollution_Index'] = abs(d['Air_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Water_Pollution_Index']):
    d['Water_Pollution_Index'] = d['Water_Pollution_Index'].astype(float)
d.loc[d['Water_Pollution_Index'] < 0, 'Water_Pollution_Index'] = abs(d['Water_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Soil_Pollution_Index']):
    d['Soil_Pollution_Index'] = d['Soil_Pollution_Index'].astype(float)
d.loc[d['Soil_Pollution_Index'] < 0, 'Soil_Pollution_Index'] = abs(d['Soil_Pollution_Index'])

if pd.api.types.is_numeric_dtype(d['Industrial_Waste (in tons)']):
    d['Industrial_Waste (in tons)'] = d['Industrial_Waste (in tons)'].astype(float)
d.loc[d['Industrial_Waste (in tons)'] < 0, 'Industrial_Waste (in tons)'] = abs(d['Industrial_Waste (in tons)'])

if pd.api.types.is_numeric_dtype(d['Energy_Recovered (in GWh)']):
    d['Energy_Recovered (in GWh)'] = d['Energy_Recovered (in GWh)'].astype(float)
d.loc[d['Energy_Recovered (in GWh)'] < 0, 'Energy_Recovered (in GWh)'] = abs(d['Energy_Recovered (in GWh)'])

if pd.api.types.is_numeric_dtype(d['CO2_Emissions (in MT)']):
    d['CO2_Emissions (in MT)'] = d['CO2_Emissions (in MT)'].astype(float)
d.loc[d['CO2_Emissions (in MT)'] < 0, 'CO2_Emissions (in MT)'] = abs(d['CO2_Emissions (in MT)'])

if pd.api.types.is_numeric_dtype(d['Renewable_Energy (%)']):
    d['Renewable_Energy (%)'] = d['Renewable_Energy (%)'].astype(float)
d.loc[d['Renewable_Energy (%)']<0, 'Renewable_Energy (%)'] = 0
d.loc[d['Renewable_Energy (%)']>100, 'Renewable_Energy (%)'] = 100

if pd.api.types.is_numeric_dtype(d['Plastic_Waste_Produced (in tons)']):
    d['Plastic_Waste_Produced (in tons)'] = d['Plastic_Waste_Produced (in tons)'].astype(float)
d.loc[d['Plastic_Waste_Produced (in tons)'] < 0, 'Plastic_Waste_Produced (in tons)'] = abs(d['Plastic_Waste_Produced

if pd.api.types.is_numeric_dtype(d['Energy_Consumption_Per_Capita (in MWh)']):
    d['Energy_Consumption_Per_Capita (in MWh)'] = d['Energy_Consumption_Per_Capita (in MWh)'].astype(float)
d.loc[d['Energy_Consumption_Per_Capita (in MWh)'] < 0, 'Energy_Consumption_Per_Capita (in MWh)'] = abs(d['Energy_Cons

if pd.api.types.is_numeric_dtype(d['Population (in millions)']):
    d['Population (in millions)'] = d['Population (in millions)'].astype(float)
d.loc[d['Population (in millions)'] < 0, 'Population (in millions)'] = abs(d['Population (in millions)'])

if pd.api.types.is_numeric_dtype(d['GDP_Per_Capita (in USD)']):
    d['GDP_Per_Capita (in USD)'] = d['GDP_Per_Capita (in USD)'].astype(float)
d.loc[d['GDP_Per_Capita (in USD)'] < 0, 'GDP_Per_Capita (in USD)'] = abs(d['GDP_Per_Capita (in USD)'])
```

In [136…

```
d
```

Out[136…

	Country	Year	Air_Pollution_Index	Water_Pollution_Index	Soil_Pollution_Index	Industrial_Waste (in tons)	Energy_Recovered (in GWh)	CO:
0	Hungary	2005	272.70	124.27	51.95	94802.83	158.14	
1	Singapore	2001	86.72	60.34	117.22	56283.92	498.04	
2	Romania	2016	91.59	83.36	121.72	56256.02	489.51	
3	Cook Islands	2018	280.61	67.16	93.58	74864.73	145.18	
4	Djibouti	2008	179.16	127.53	121.55	76862.06	40.38	
...	...	...	...	...	...	...	...	
195	Latvia	2004	115.84	78.75	42.34	49503.35	81.23	
196	Bangladesh	2002	121.82	120.97	63.95	74694.68	25.89	
197	Korea	2011	149.73	146.92	37.04	2818.85	293.27	
198	Vanuatu	2002	237.20	113.63	101.96	68746.82	305.61	
199	Croatia	2010	135.50	158.43	89.80	36182.44	172.24	

200 rows × 13 columns

In [137…

```
s=StandardScaler()
d['Air_Pollution_Index_Scaled'] = s.fit_transform(d[['Air_Pollution_Index']])
d['Water_Pollution_Index_Scaled'] = s.fit_transform(d[['Water_Pollution_Index']])
d['Soil_Pollution_Index_Scaled'] = s.fit_transform(d[['Soil_Pollution_Index']])
d['CO2_Emissions_Scaled'] = s.fit_transform(d[['CO2_Emissions (in MT)']])
d['Industrial_Waste_Scaled'] = s.fit_transform(d[['Industrial_Waste (in tons)']])
```

In [138…

```
d
```

Out[138…

	Country	Year	Air_Pollution_Index	Water_Pollution_Index	Soil_Pollution_Index	Industrial_Waste (in tons)	Energy_Recovered (in GWh)	CO2
0	Hungary	2005	272.70	124.27	51.95	94802.83	158.14	
1	Singapore	2001	86.72	60.34	117.22	56283.92	498.04	
2	Romania	2016	91.59	83.36	121.72	56256.02	489.51	
3	Cook Islands	2018	280.61	67.16	93.58	74864.73	145.18	
4	Djibouti	2008	179.16	127.53	121.55	76862.06	40.38	
...	...	...	...	...	...	...	...	
195	Latvia	2004	115.84	78.75	42.34	49503.35	81.23	
196	Bangladesh	2002	121.82	120.97	63.95	74694.68	25.89	
197	Korea	2011	149.73	146.92	37.04	2818.85	293.27	
198	Vanuatu	2002	237.20	113.63	101.96	68746.82	305.61	
199	Croatia	2010	135.50	158.43	89.80	36182.44	172.24	

200 rows × 18 columns

In [139…

```
le = LabelEncoder()
d['Country_Label'] = le.fit_transform(d['Country'])
d['Year_Label'] = le.fit_transform(d['Year'])
```

In [140…

```
d
```

Out[140…

	Country	Year	Air_Pollution_Index	Water_Pollution_Index	Soil_Pollution_Index	Industrial_Waste (in tons)	Energy_Recovered (in GWh)	CO
0	Hungary	2005	272.70	124.27	51.95	94802.83	158.14	
1	Singapore	2001	86.72	60.34	117.22	56283.92	498.04	
2	Romania	2016	91.59	83.36	121.72	56256.02	489.51	
3	Cook Islands	2018	280.61	67.16	93.58	74864.73	145.18	
4	Djibouti	2008	179.16	127.53	121.55	76862.06	40.38	
...	...	...	...	...	...	...	...	
195	Latvia	2004	115.84	78.75	42.34	49503.35	81.23	
196	Bangladesh	2002	121.82	120.97	63.95	74694.68	25.89	
197	Korea	2011	149.73	146.92	37.04	2818.85	293.27	
198	Vanuatu	2002	237.20	113.63	101.96	68746.82	305.61	
199	Croatia	2010	135.50	158.43	89.80	36182.44	172.24	

200 rows × 20 columns

Step 2 - Feature Engineering

In [141…

```
d['Total_Pollution_Index'] = d[['Air_Pollution_Index_Scaled', 'Water_Pollution_Index', 'Soil_Pollution_Index']].mean(

yearly_pollution_trend = d.groupby('Year')['Total_Pollution_Index'].mean().reset_index()
yearly_pollution_trend.rename(columns={'Total_Pollution_Index': 'Yearly_Avg_Pollution_Index'}, inplace=True)

d = d.merge(yearly_pollution_trend, on='Year', how='left')

d.head()
```

Out[141…

	Country	Year	Air_Pollution_Index	Water_Pollution_Index	Soil_Pollution_Index	Industrial_Waste (in tons)	Energy_Recovered (in GWh)	CO2_En
0	Hungary	2005	272.70	124.27	51.95	94802.83	158.14	
1	Singapore	2001	86.72	60.34	117.22	56283.92	498.04	
2	Romania	2016	91.59	83.36	121.72	56256.02	489.51	
3	Cook Islands	2018	280.61	67.16	93.58	74864.73	145.18	
4	Djibouti	2008	179.16	127.53	121.55	76862.06	40.38	

5 rows × 22 columns

Phase 2:
Clustering using K-Means and Hierarchical Clustering

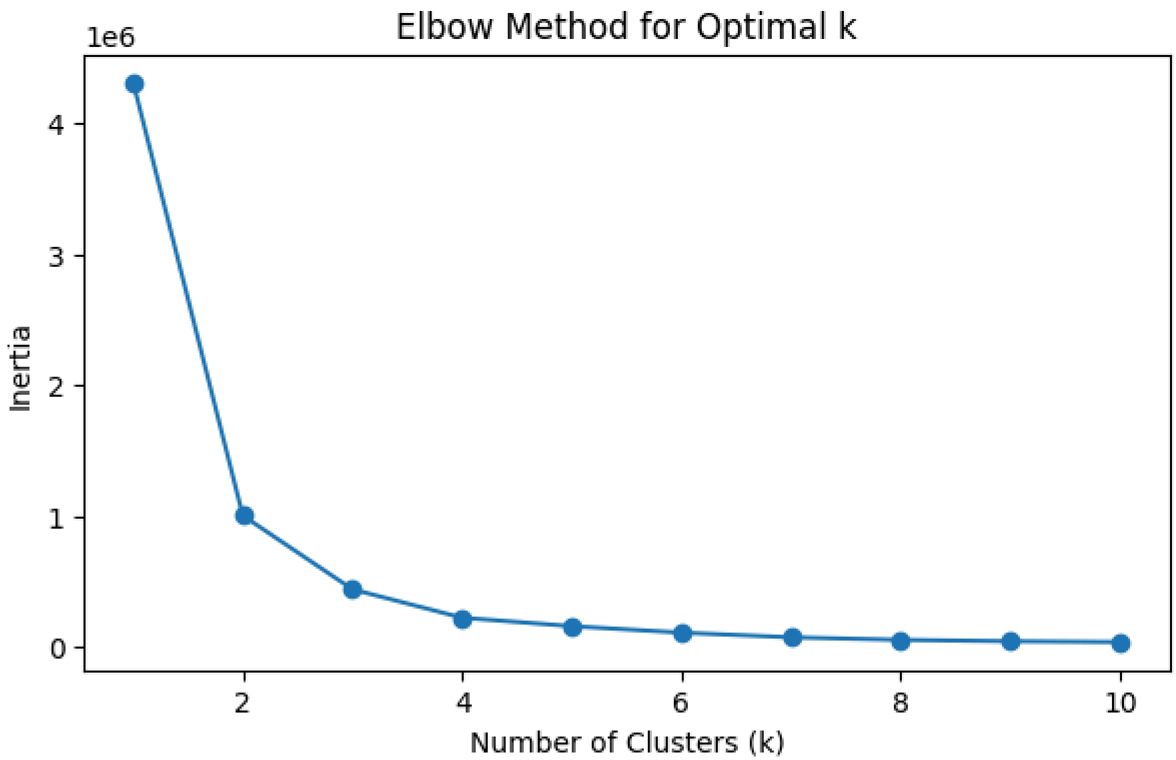
(3 Steps)

Step 3 - K Means Clustering

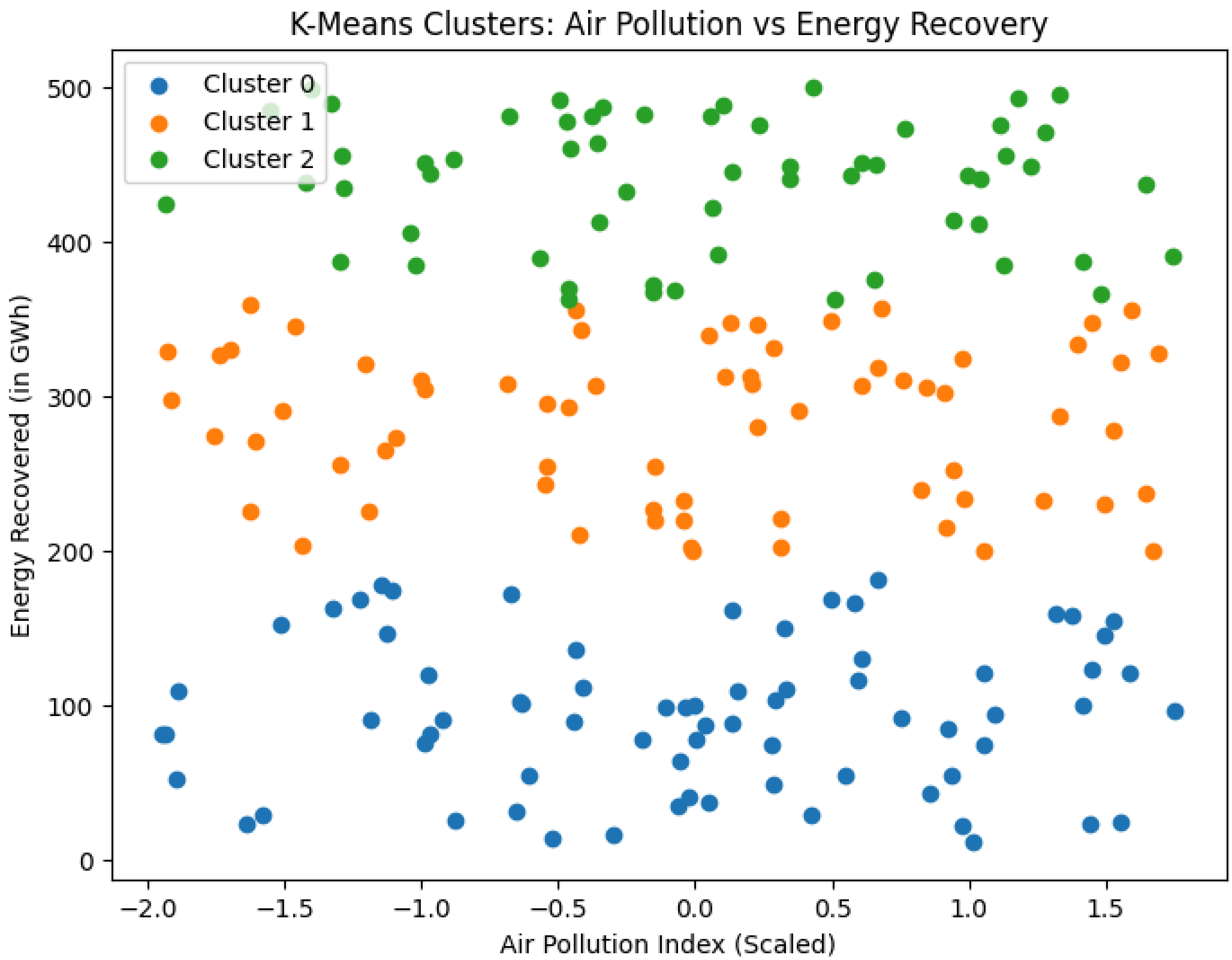
In [142…

```
from sklearn.cluster import KMeans

# Select features for clustering
features = ['Air_Pollution_Index_Scaled', 'Water_Pollution_Index_Scaled', 'Soil_Pollution_Index_Scaled', 'Energy_Reco
x = d[features]

inertia = []
K_range = range(1, 11)
for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(x)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(7,4))
```

```
plt.plot(K_range, inertia, marker='o')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
plt.show()

# Fit KMeans with optimal k (choose visually, e.g., k=3)
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
d['Cluster'] = kmeans.fit_predict(x)

# Visualize clusters: Air Pollution vs Energy Recovery
plt.figure(figsize=(8,6))
for cluster in range(optimal_k):
    subset = d[d['Cluster'] == cluster]
    plt.scatter(subset['Air_Pollution_Index_Scaled'], subset['Energy_Recovered (in GWh)'], label=f'Cluster {cluster}
plt.xlabel('Air Pollution Index (Scaled)')
plt.ylabel('Energy Recovered (in GWh)')
plt.title('K-Means Clusters: Air Pollution vs Energy Recovery')
plt.legend()
plt.show()

# Show countries in each cluster
for cluster in range(optimal_k):
    countries = d[d['Cluster'] == cluster]['Country'].unique()
    print(f"Cluster {cluster}: {', '.join(countries)}")
```



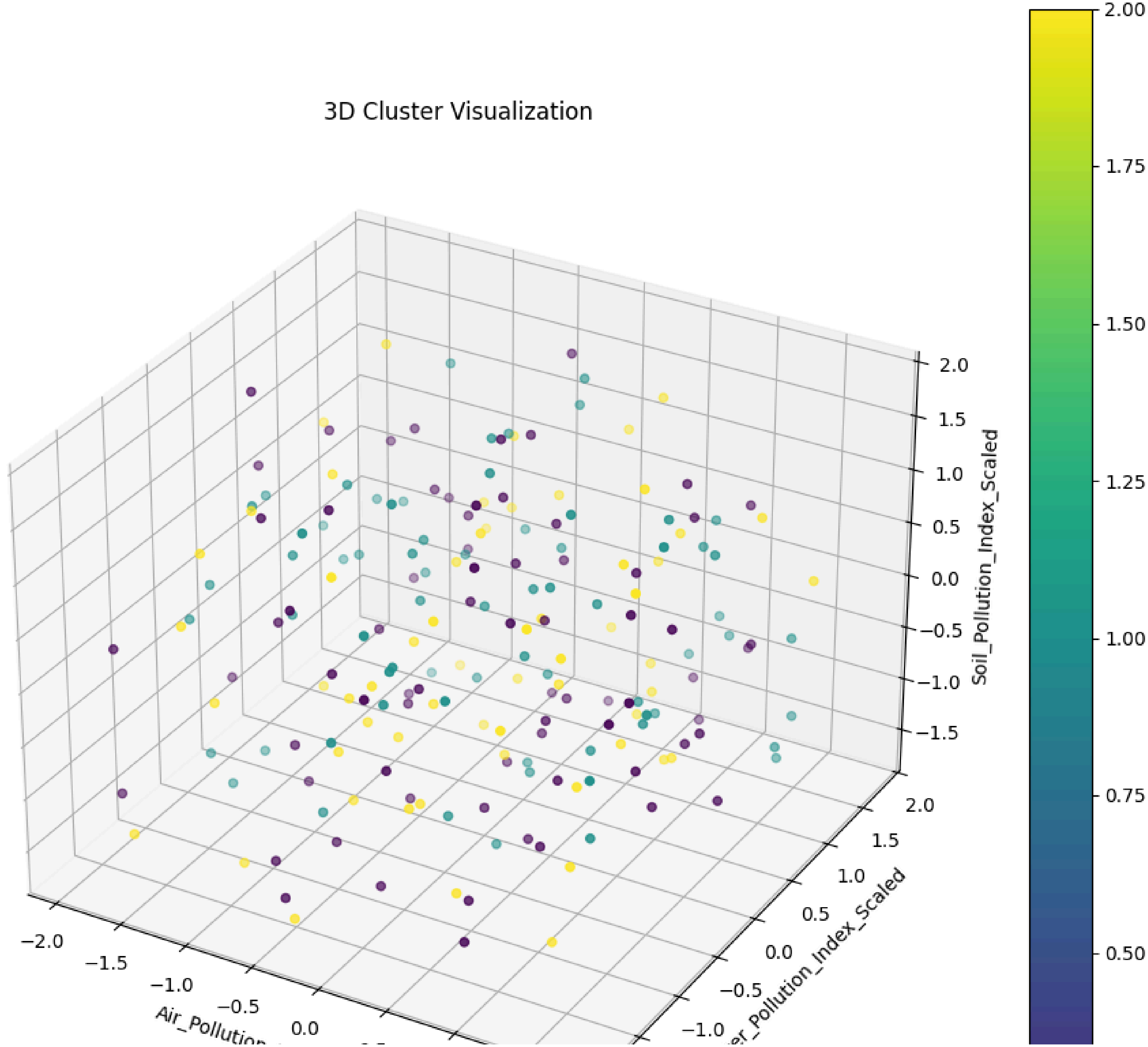
Elbow Method for Optimal k
1e6
4
3
2
1
0
Inertia
2
4
6
8
10
Number of Clusters (k)


K-Means Clusters: Air Pollution vs Energy Recovery
Cluster 0
Cluster 1
Cluster 2
Energy Recovered (in GWh)
Air Pollution Index (Scaled)
0
100
200
300
400
500
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

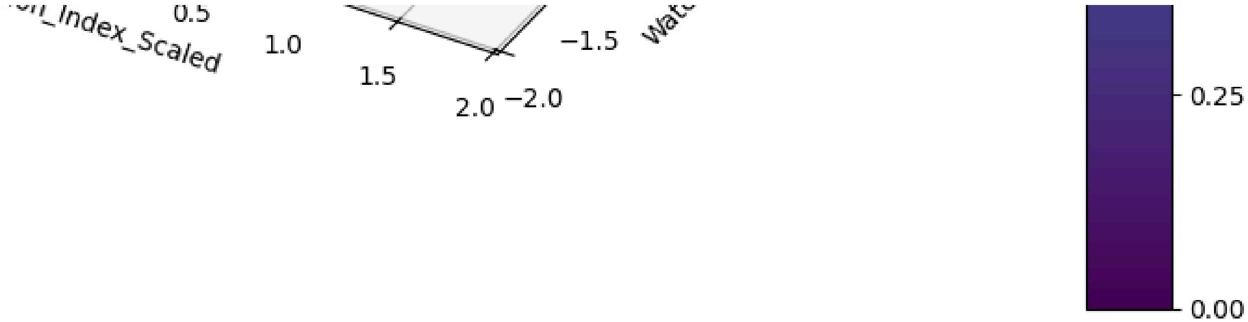
```
Cluster 0: Hungary, Cook Islands, Djibouti, Croatia, Ukraine, Northern Mariana Islands, Thailand, Bulgaria, Senegal,
Costa Rica, Mozambique, Netherlands, Tokelau, Kyrgyz Republic, Nigeria, Colombia, British Indian Ocean Territory (Cha
gos Archipelago), Libyan Arab Jamahiriya, Gambia, Bahamas, Tajikistan, Zimbabwe, Cambodia, Pitcairn Islands, Israel,
Falkland Islands (Malvinas), Mali, Guernsey, Saint Lucia, Tunisia, Benin, Italy, Equatorial Guinea, Malta, Suriname,
Gibraltar, Pakistan, Moldova, Afghanistan, United Kingdom, Vietnam, Martinique, Sudan, Dominica, Christmas Island, Bh
utan, Cote d'Ivoire, Guyana, Spain, Denmark, Palestinian Territory, Latvia, Bolivia, Sweden, Holy See (Vatican City S
tate), Dominican Republic, Honduras, Luxembourg, Puerto Rico, Indonesia, Mauritania, Cuba, Saint Kitts and Nevis, Sai
nt Helena, Solomon Islands, Bangladesh
Cluster 1: Congo, Madagascar, South Africa, Slovenia, Oman, Solomon Islands, Malaysia, Heard Island and McDonald Isla
nds, Angola, Togo, Portugal, Western Sahara, Bouvet Island (Bouvetoya), Brunei Darussalam, Liberia, Bosnia and Herzeg
ovina, Paraguay, Cyprus, Guinea-Bissau, Zambia, French Guiana, Grenada, Australia, Saint Pierre and Miquelon, Aruba,
India, Panama, Albania, Japan, France, Botswana, Andorra, Jordan, Lao People's Democratic Republic, Bahrain, United A
rab Emirates, Ecuador, Switzerland, Morocco, Montenegro, Armenia, Malawi, Chad, Kenya, United States Minor Outlying I
slands, Bermuda, Faroe Islands, Fiji, Belgium, Palestinian Territory, China, French Southern Territories, Peru, Chil
e, Lebanon, Nicaragua, Rwanda, Nepal, Norfolk Island, Spain, Papua New Guinea, Philippines, Moldova, Pitcairn Island
s, Korea, Vanuatu
Cluster 2: Singapore, Romania, Central African Republic, Swaziland, Sri Lanka, Macedonia, Greece, Maldives, Georgia,
Argentina, Mexico, Hong Kong, Germany, Belize, Kazakhstan, United States Virgin Islands, Micronesia, Niger, Lithuani
a, Estonia, Iran, Netherlands Antilles, Cape Verde, British Virgin Islands, Indonesia, San Marino, Antarctica (the te
rritory South of 60 deg S), Sierra Leone, Saint Barthelemy, Ghana, Saint Vincent and the Grenadines, Egypt, Eritrea,
Kuwait, Haiti, Mayotte, Sweden, Austria, Bangladesh, Finland, Norway, Burundi, Taiwan, New Caledonia, Antigua and Bar
buda, South Georgia and the South Sandwich Islands, Mauritania, Macao, Latvia, Cuba, El Salvador, Kenya, Kiribati, Cz
ech Republic, Barbados
```

In [143…

```python
fig = plt.figure(figsize=(12,12))
ax = fig.add_subplot(111, projection='3d')

sc = ax.scatter(
    x['Air_Pollution_Index_Scaled'],
    x['Water_Pollution_Index_Scaled'],
    x['Soil_Pollution_Index_Scaled'],
    c=d['Cluster'],
    cmap='viridis'
)

ax.set_xlabel('Air_Pollution_Index_Scaled')
ax.set_ylabel('Water_Pollution_Index_Scaled')
ax.set_zlabel('Soil_Pollution_Index_Scaled')
plt.title('3D Cluster Visualization')
plt.colorbar(sc, label='Cluster')
plt.show()
```



3D Cluster Visualization
Air_Pollution
Soil_Pollution_Index_Scaled
Cluster
2.00
1.75
1.50
1.25
1.00
0.75
0.50



In [144…

```
cluster_analysis = pd.DataFrame({'Cluster': d['Cluster'], 'Country': d['Country']})
print(cluster_analysis.groupby('Cluster')['Country'].value_counts(normalize=True))
```

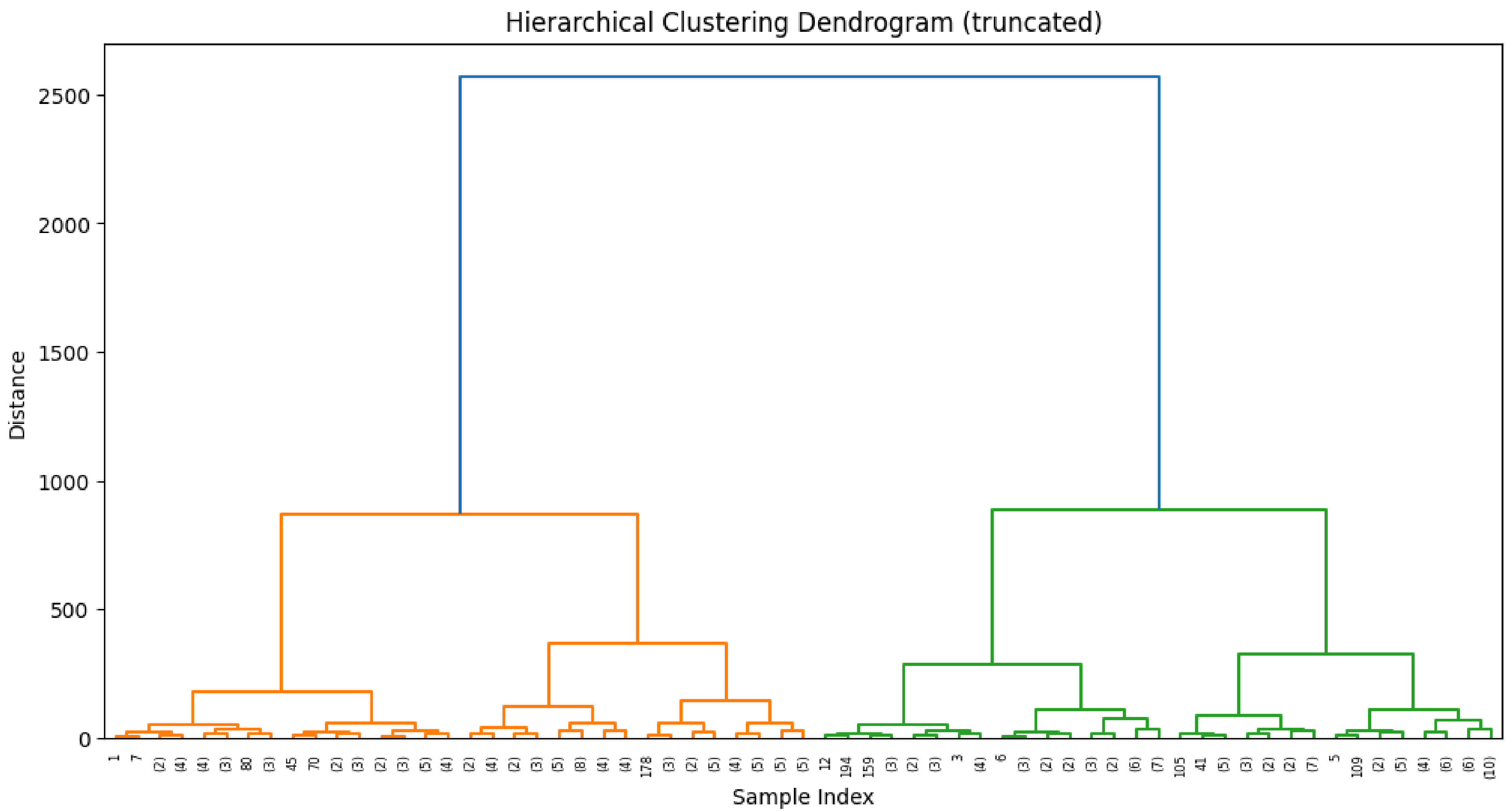
```
Cluster  Country
0        Afghanistan                     0.027778
         Croatia                         0.027778
         Guyana                          0.027778
         Latvia                          0.027778
         Mali                            0.027778
                                           ...
2        Sri Lanka                       0.016949
         Swaziland                       0.016949
         Sweden                          0.016949
         Taiwan                          0.016949
         United States Virgin Islands    0.016949
Name: proportion, Length: 187, dtype: float64
```

Step 4 - Hierarchial Clustering

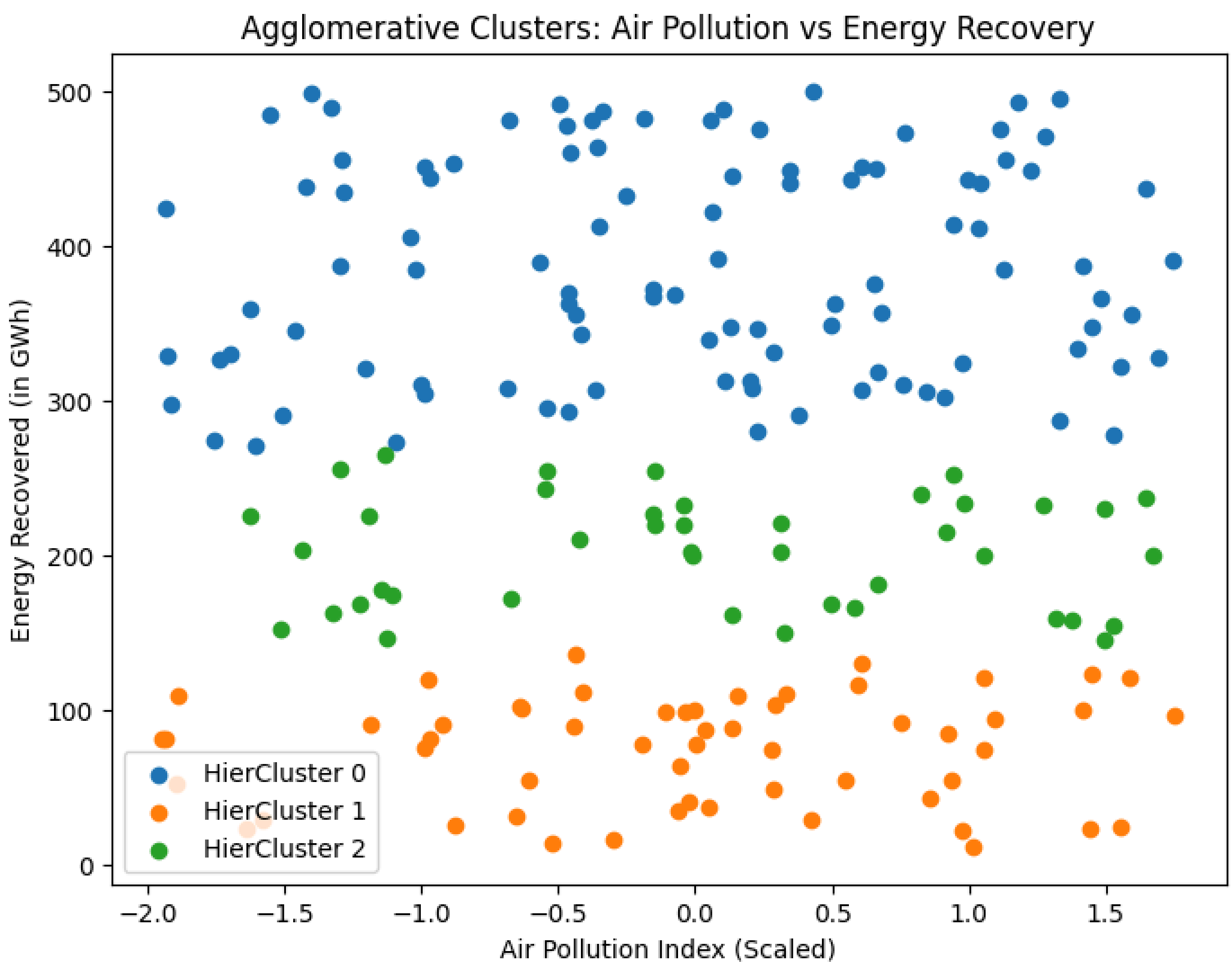
In [145…

```
# Select features for hierarchical clustering (reuse x)
X_hier = x.copy()

# Compute linkage matrix for dendrogram
linked = linkage(X_hier, method='ward')

plt.figure(figsize=(12, 6))
dendrogram(linked, truncate_mode='level', p=5)
plt.title('Hierarchical Clustering Dendrogram (truncated)')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
```

```
plt.show()

# Choose number of clusters (e.g., 3 for comparison with KMeans)
n_clusters = optimal_k
agglo = AgglomerativeClustering(n_clusters=n_clusters, metric='euclidean', linkage='ward')
d['HierCluster'] = agglo.fit_predict(X_hier)

# Compare with KMeans clusters
ari = adjusted_rand_score(d['Cluster'], d['HierCluster'])
print(f"Adjusted Rand Index (KMeans vs Hierarchical): {ari:.3f}")

# Visualize clusters (2D example: Air Pollution vs Energy Recovery)
plt.figure(figsize=(8,6))
for cluster in range(n_clusters):
    subset = d[d['HierCluster'] == cluster]
    plt.scatter(subset['Air_Pollution_Index_Scaled'], subset['Energy_Recovered (in GWh)'], label=f'HierCluster {clust
plt.xlabel('Air Pollution Index (Scaled)')
plt.ylabel('Energy Recovered (in GWh)')
plt.title('Agglomerative Clusters: Air Pollution vs Energy Recovery')
plt.legend()
plt.show()
```



Adjusted Rand Index (KMeans vs Hierarchical): 0.457



In [146…

```
cluster_analysis = pd.DataFrame({'Hier_Cluster': d['HierCluster'], 'Country': d['Country']})
print(cluster_analysis.groupby('Hier_Cluster')['Country'].value_counts(normalize=True))
```

```
Hier_Cluster  Country
0             Germany                                 0.019608
              Kenya                                   0.019608
              Kuwait                                  0.019608
              Mexico                                  0.019608
              Romania                                 0.019608
                                                         ...
2             South Africa                            0.023810
              Sweden                                  0.023810
              Togo                                    0.023810
              United States Minor Outlying Islands    0.023810
              Vietnam                                 0.023810
Name: proportion, Length: 187, dtype: float64
```

Comparison

In [147…

```python
# comparing and printing comparison that is cluster analysis
cluster_analysis = pd.DataFrame({'KMeans_Cluster': d['Cluster'], 'Hierarchical_Cluster': d['HierCluster'], 'Country'
print(cluster_analysis.groupby(['KMeans_Cluster', 'Hierarchical_Cluster'])['Country'].value_counts(normalize=True))
```

```
KMeans_Cluster  Hierarchical_Cluster  Country
0               1                     Guyana                          0.035714
                                      Latvia                          0.035714
                                      Mali                            0.035714
                                      Moldova                         0.035714
                                      Bahamas                         0.017857
                                                                         ...
2               0                     Sri Lanka                       0.016949
                                      Swaziland                       0.016949
                                      Sweden                          0.016949
                                      Taiwan                          0.016949
                                      United States Virgin Islands    0.016949
Name: proportion, Length: 189, dtype: float64
```

In [148…

```python
cluster_analysis = pd.DataFrame({
    'KMeans_Cluster': d['Cluster'],
    'Hier_Cluster': d['HierCluster'],
    'Country': d['Country']
})

# K-Means
```

```
print(cluster_analysis.groupby('KMeans_Cluster')['Country'].value_counts(normalize=True))

print('\n\n')

# Agglomerative
print(cluster_analysis.groupby('Hier_Cluster')['Country'].value_counts(normalize=True))
```

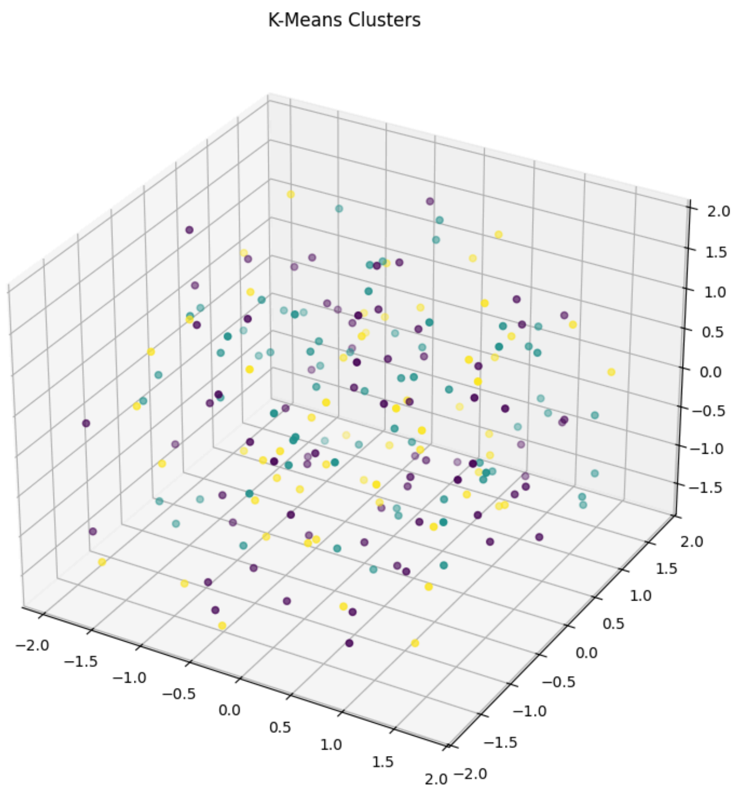
```
KMeans_Cluster  Country
0               Afghanistan                     0.027778
                Croatia                         0.027778
                Guyana                          0.027778
                Latvia                          0.027778
                Mali                            0.027778
                                                  ...
2               Sri Lanka                       0.016949
                Swaziland                       0.016949
                Sweden                          0.016949
                Taiwan                          0.016949
                United States Virgin Islands    0.016949
Name: proportion, Length: 187, dtype: float64
```

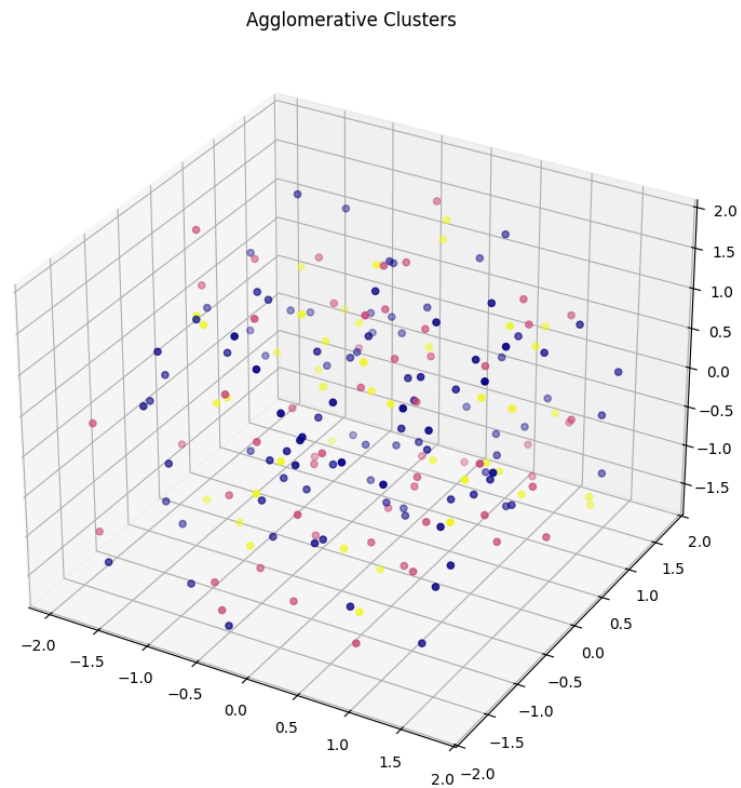
```
Hier_Cluster  Country
0             Germany                                 0.019608
              Kenya                                   0.019608
              Kuwait                                  0.019608
              Mexico                                  0.019608
              Romania                                 0.019608
                                                        ...
2             South Africa                            0.023810
              Sweden                                  0.023810
              Togo                                    0.023810
              United States Minor Outlying Islands    0.023810
              Vietnam                                 0.023810
Name: proportion, Length: 187, dtype: float64
```

```
Hier_Cluster  Country
0             Germany                                 0.019608
              Kenya                                   0.019608
              Kuwait                                  0.019608
              Mexico                                  0.019608
              Romania                                 0.019608
                                                        ...
2             South Africa                            0.023810
              Sweden                                  0.023810
              Togo                                    0.023810
              United States Minor Outlying Islands    0.023810
              Vietnam                                 0.023810
Name: proportion, Length: 187, dtype: float64
```

In [149…

```
fig = plt.figure(figsize=(20,10))

# K-Means
ax1 = fig.add_subplot(121, projection='3d')
sc1 = ax1.scatter(
    x['Air_Pollution_Index_Scaled'], x['Water_Pollution_Index_Scaled'], x['Soil_Pollution_Index_Scaled'],
    c=d['Cluster'], cmap='viridis'
)
ax1.set_title('K-Means Clusters')

# Agglomerative
ax2 = fig.add_subplot(122, projection='3d')
sc2 = ax2.scatter(
    x['Air_Pollution_Index_Scaled'], x['Water_Pollution_Index_Scaled'], x['Soil_Pollution_Index_Scaled'],
    c=d['HierCluster'], cmap='plasma'
)
ax2.set_title('Agglomerative Clusters')

plt.show()
```





Phase 3
Neural Networks for Energy Recovery Prediction

(2 steps)

Step 5 - Introduction to Neural Networks

In [150…

```
nn_features = [
    'Air_Pollution_Index',
    'CO2_Emissions (in MT)',
    'Industrial_Waste (in tons)',
    'Water_Pollution_Index',
    'Soil_Pollution_Index',
    'Renewable_Energy (%)',
```

```
    'Energy_Consumption_Per_Capita (in MWh)'
]
```

In [151…

```
X_nn = d[nn_features]
y_nn = d['Energy_Recovered (in GWh)']
```

In [152…

```
X_train, X_test, y_train, y_test = train_test_split(X_nn, y_nn, test_size=0.2, random_state=42)
```

In [153…

```
model = Sequential([
    Dense(16, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(8, activation='relu'),
    Dense(1)
])

model.compile(optimizer='adam', loss='mse')

history = model.fit(X_train, y_train, epochs=40)
```

```
Epoch 1/40
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\layers\core\dense.py:92: U
serWarning: 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.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 448600256.0000
Epoch 2/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 388234848.0000
Epoch 3/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 332439552.0000
Epoch 4/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 284783296.0000
Epoch 5/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 245661312.0000
Epoch 6/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 212524544.0000
Epoch 7/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 182015712.0000
Epoch 8/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 155760256.0000
Epoch 9/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 133827376.0000
Epoch 10/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 114323056.0000
Epoch 11/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 97315816.0000
Epoch 12/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 83009464.0000
Epoch 13/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 70090296.0000
Epoch 14/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 59297976.0000
Epoch 15/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 49850824.0000
Epoch 16/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 41698920.0000
Epoch 17/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 34888388.0000
Epoch 18/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 28969098.0000
Epoch 19/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 23884196.0000
Epoch 20/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 19535452.0000
Epoch 21/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 16068608.0000
Epoch 22/40
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 12914975.0000
Epoch 23/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 10317933.0000
Epoch 24/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 8214798.5000
Epoch 25/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 6446889.0000
Epoch 26/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5120133.5000
Epoch 27/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 4006151.2500
Epoch 28/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 3026624.0000
Epoch 29/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 2305656.2500
Epoch 30/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 1751162.7500
Epoch 31/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1315912.6250
Epoch 32/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 977470.1875
Epoch 33/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 691555.9375
Epoch 34/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 348997.0938
Epoch 35/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 102589.0703
Epoch 36/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 36780.9609
Epoch 37/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 58592.1133
Epoch 38/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 67560.9688
Epoch 39/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 50459.8555
Epoch 40/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 34813.7500
```

In [154…

```python
y_pred = model.predict(X_test).flatten()
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
```

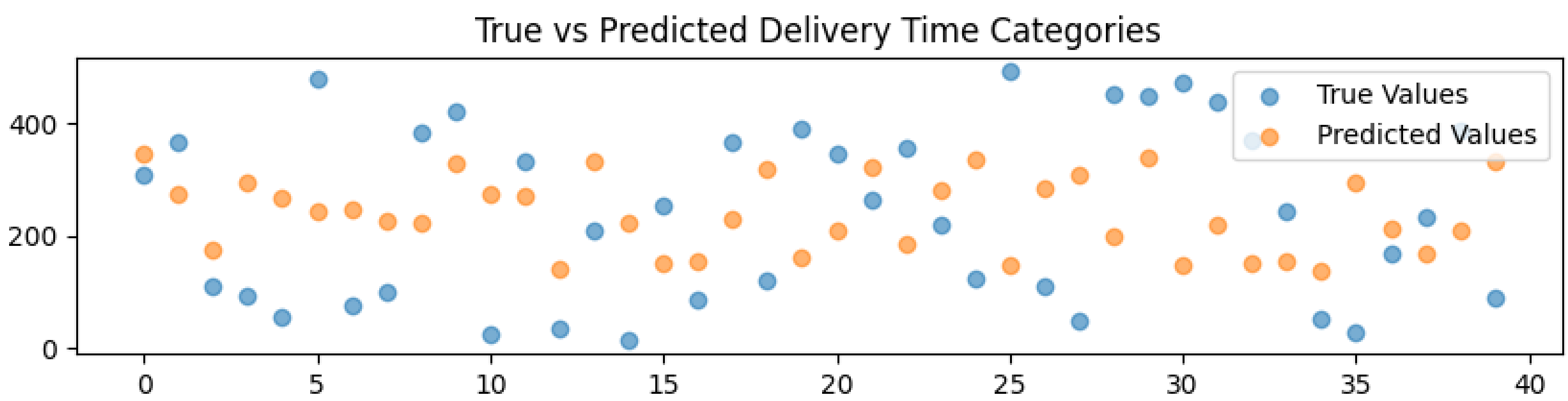
In [155…

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

print(f"R²: {r2:.3f}")
print(f"MSE: {mse:.3f}")
print(f"MAE: {mae:.3f}")
```

```
R²: -0.325
MSE: 32049.143
MAE: 160.471
```

In [156…

```
# y_pred vs y_test graph comparison
plt.figure(figsize=(10,2))
plt.scatter(range(len(y_test)), y_test, label='True Values', alpha=0.6)
plt.scatter(range(len(y_pred)), y_pred, label='Predicted Values', alpha=0.6)
plt.title('True vs Predicted Delivery Time Categories')
plt.legend()
plt.show()
# the orange and blue values are predicted and true so the brown values are predicted correctly values
```



Step 6 - Model Improvement

In [165…

```
# Improved Neural Network: more layers, different activation, learning rate tuning
improved_model = Sequential([
    Dense(32, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(16, activation='relu'),
```

```python
    Dense(8, activation='relu'),
    Dense(1)
])
improved_model.compile(optimizer=Adam(learning_rate=0.001), loss='mse')
improved_history = improved_model.fit(X_train, y_train, epochs=40)
```

```
Epoch 1/40
```

```
c:\Users\Princy Pandya\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\layers\core\dense.py:92: 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.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 985289.1250
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 985289.1250
Epoch 2/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 60380.5938
Epoch 3/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 79944.7969
Epoch 4/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 83197.1875
Epoch 5/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 75046.3594
Epoch 6/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 63329.0430
Epoch 7/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 53380.1797
Epoch 8/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 46990.4453
Epoch 9/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 42820.1445
Epoch 10/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 41327.1680
Epoch 11/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40823.5625
Epoch 12/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40671.8320
Epoch 13/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40762.2109
Epoch 14/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40859.6523
Epoch 15/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40917.7734
Epoch 16/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40883.3906
Epoch 17/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40828.4336
Epoch 18/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40783.1797
Epoch 19/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40764.1172
Epoch 20/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40743.8516
Epoch 21/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40753.0938
```

```
Epoch 22/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40747.8867
Epoch 23/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40747.9805
Epoch 24/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40740.1836
Epoch 25/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 40744.2500
Epoch 26/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40732.4297
Epoch 27/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40731.2461
Epoch 28/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 40732.8125
Epoch 29/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - loss: 40730.3086
Epoch 30/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40728.5078
Epoch 31/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40728.8125
Epoch 32/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40723.2695
Epoch 33/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 40723.9453
Epoch 34/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40731.2812
Epoch 35/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40731.8359
Epoch 36/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40724.8945
Epoch 37/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40723.2891
Epoch 38/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 40729.3633
Epoch 39/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40715.4922
Epoch 40/40
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40717.3047
```

In [166…

```python
# Evaluate improved neural network
y_pred_improved = improved_model.predict(X_test).flatten()
r2_improved = r2_score(y_test, y_pred_improved)
```

```
mse_improved = mean_squared_error(y_test, y_pred_improved)
mae_improved = mean_absolute_error(y_test, y_pred_improved)

print(f"Improved NN - R²: {r2_improved:.3f}, \nMSE: {mse_improved:.2f}, \nMAE: {mae_improved:.2f}")
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
Improved NN - R²: -0.723,
MSE: 41667.21,
MAE: 178.03
```

In [167…

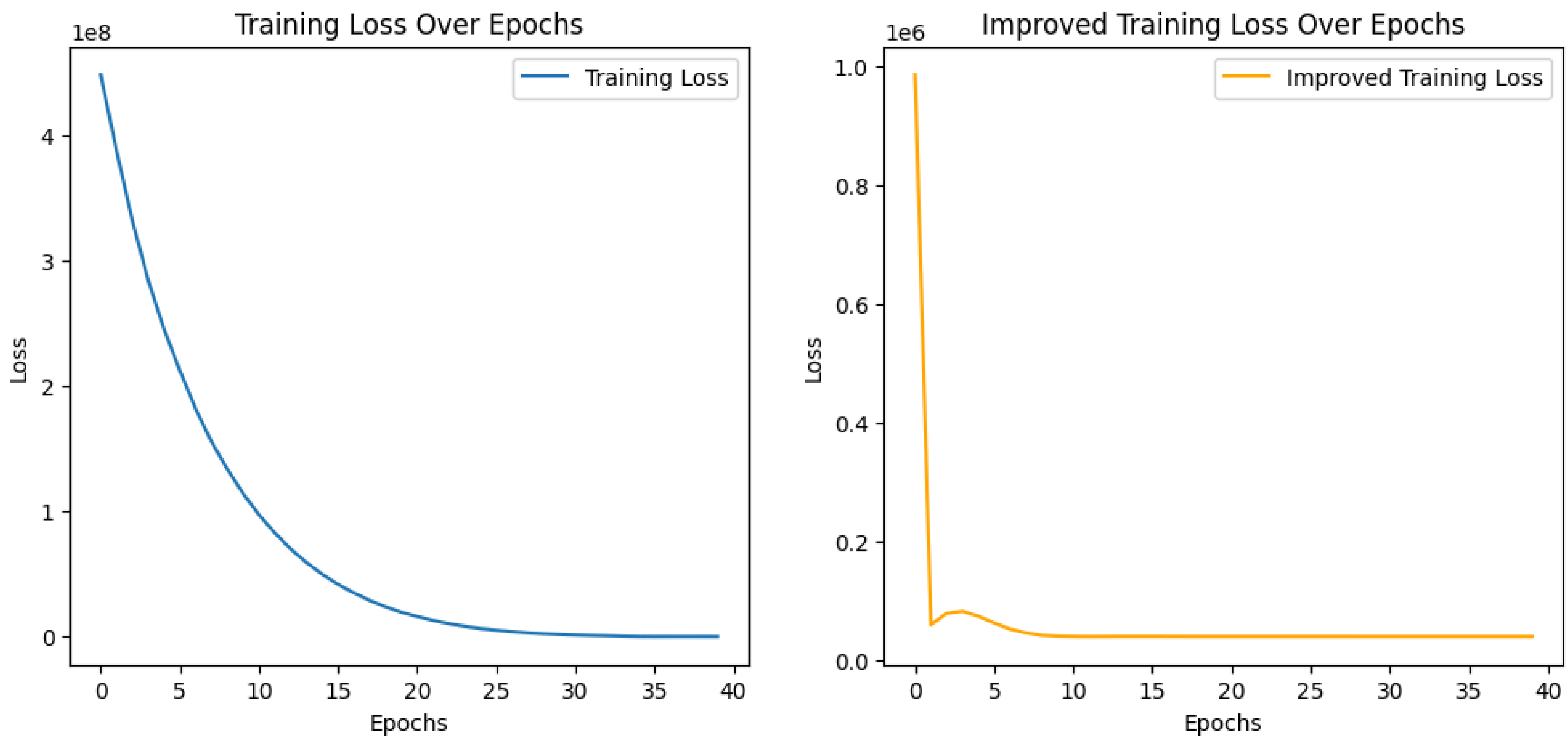
```
# Linear Regression for comparison
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)
r2_lr = r2_score(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
mae_lr = mean_absolute_error(y_test, y_pred_lr)

print(f"Linear Regression - R²: {r2_lr:.3f}, \nMSE: {mse_lr:.2f}, \nMAE: {mae_lr:.2f}")
```

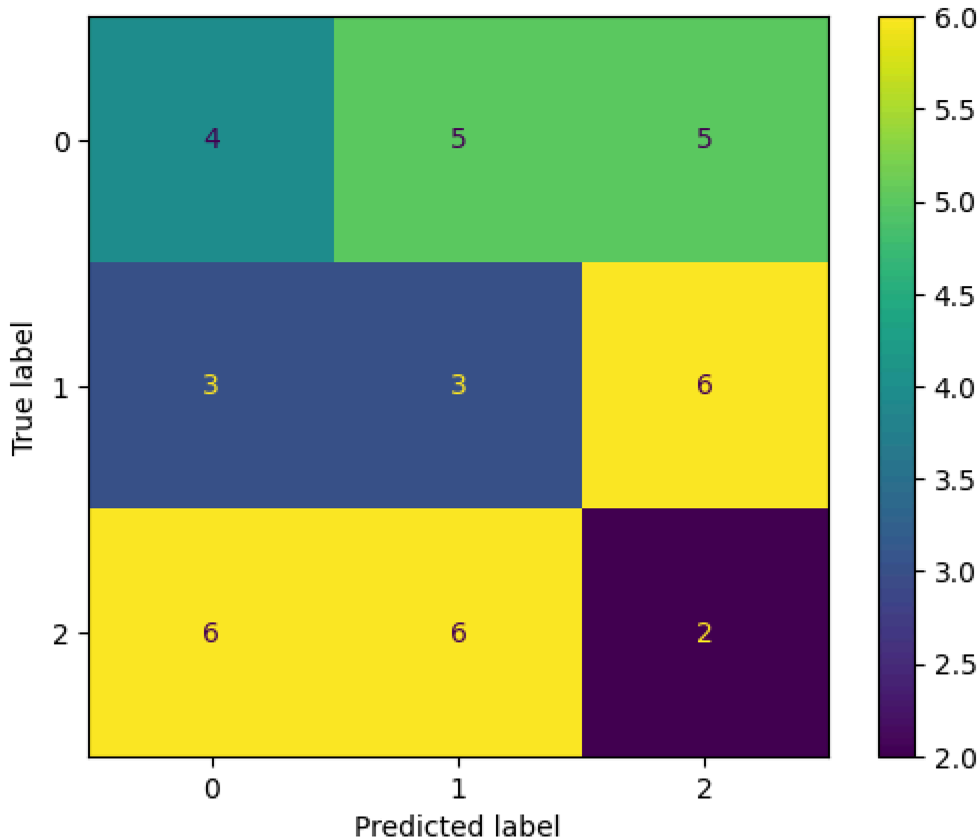
```
Linear Regression - R²: -0.033,
MSE: 24972.39,
MAE: 142.14
```

In [170…

```
#Visual Analysis of Training History
plt.figure(figsize=(12,5))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.title('Training Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(improved_history.history['loss'], label='Improved Training Loss', color='orange')
plt.title('Improved Training Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Confusion Matrix for classification-like evaluation (discretize predictions)
y_test_class = pd.qcut(y_test, q=3, labels=False)
y_pred_class = pd.qcut(y_pred, q=3, labels=False)
```

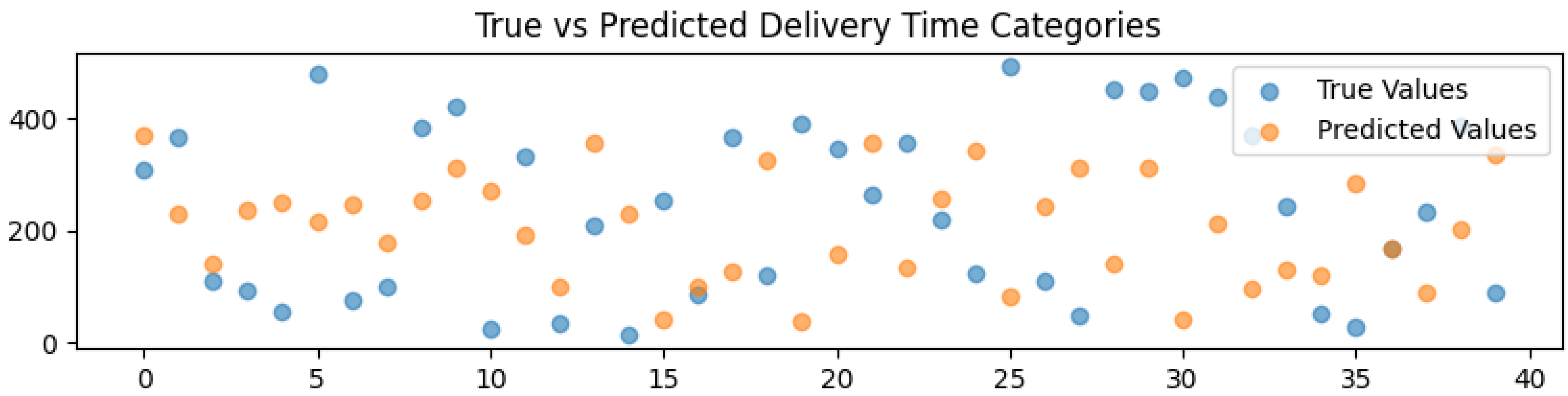
```
cm = confusion_matrix(y_test_class, y_pred_class)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.show()
```





In [173…

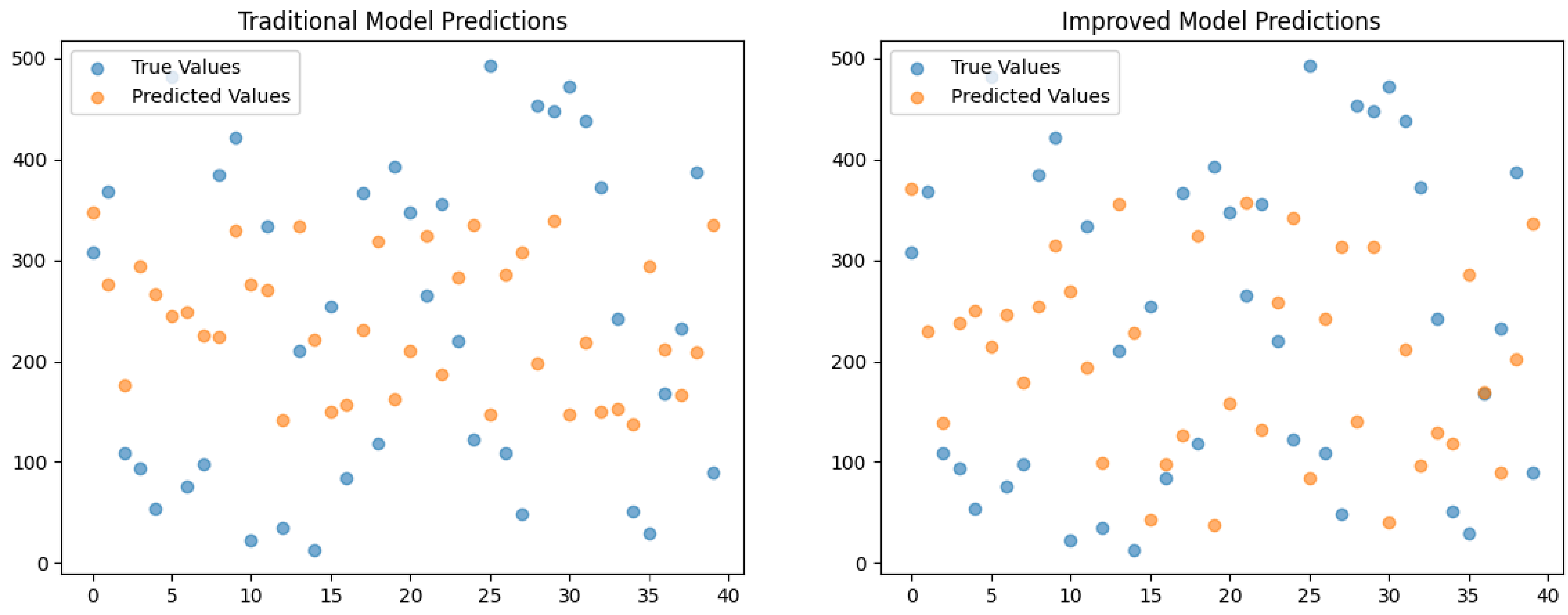
```
# scatter plot of true vs improved model predicted
plt.figure(figsize=(10,2))
plt.scatter(range(len(y_test)), y_test, label='True Values', alpha=0.6)
plt.scatter(range(len(y_pred_improved)), y_pred_improved, label='Predicted Values', alpha=0.6)
plt.title('True vs Predicted Delivery Time Categories')
plt.legend()
plt.show()
# the orange and blue values are predicted and true so the brown values are predicted correctly values
```

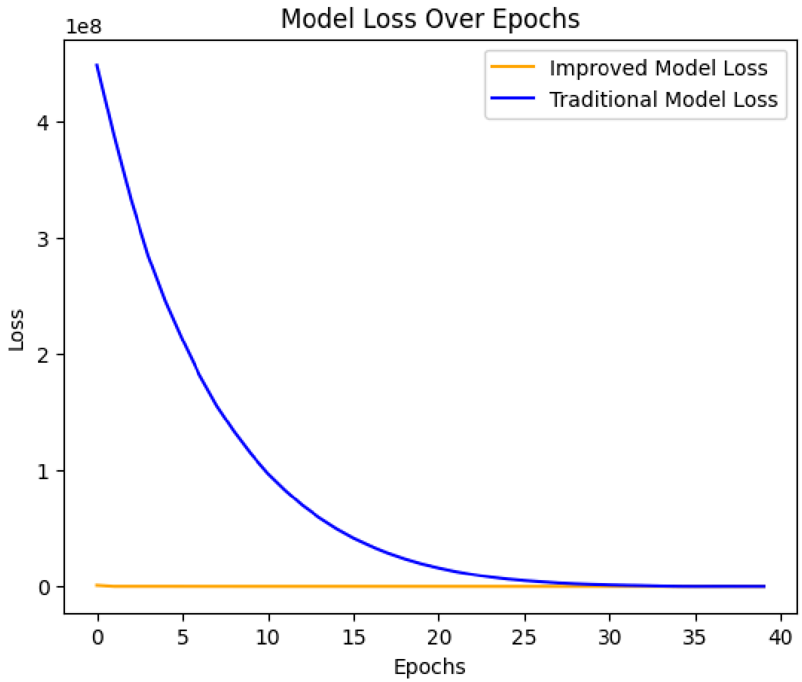


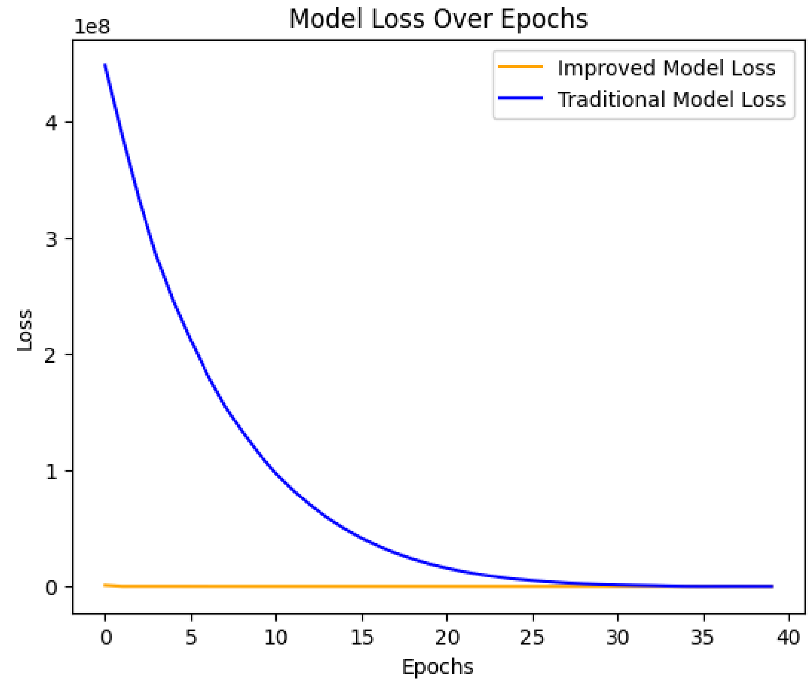
In [181…

```
# traditional vs improved model comparison
plt.figure(figsize=(14,5))
plt.subplot(1, 2, 1)
plt.scatter(range(len(y_test)), y_test, label='True Values', alpha=0.6)
plt.scatter(range(len(y_pred)), y_pred, label='Predicted Values', alpha=0.6)
plt.title('Traditional Model Predictions')
plt.legend()
plt.subplot(1, 2, 2)
plt.scatter(range(len(y_test)), y_test, label='True Values', alpha=0.6)
plt.scatter(range(len(y_pred_improved)), y_pred_improved, label='Predicted Values', alpha=0.6)
plt.title('Improved Model Predictions')
plt.legend()
plt.show()

# line chart comparison of loss and accuracy over epochs
plt.figure(figsize=(14,5))
plt.subplot(1, 2, 1)
plt.plot(improved_history.history['loss'], label='Improved Model Loss', color='orange')
plt.plot(history.history['loss'], label='Traditional Model Loss', color='blue')
plt.title('Model Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(improved_history.history['loss'], label='Improved Model Loss', color='orange')
plt.plot(history.history['loss'], label='Traditional Model Loss', color='blue')
plt.title('Model Loss Over Epochs')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.legend()
plt.show()

# confusion matrices comparison of traditional vs improved
cm = confusion_matrix(y_test_class, y_pred_class)
cm_improved = confusion_matrix(y_test_class, pd.qcut(y_pred_improved, q=3, labels=False))
fig, axs = plt.subplots(1, 2, figsize=(12, 5))
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(ax=axs[0], colorbar=False)
axs[0].set_title('Traditional Model Confusion Matrix')
disp_improved = ConfusionMatrixDisplay(confusion_matrix=cm_improved)
disp_improved.plot(ax=axs[1], colorbar=False)
axs[1].set_title('Improved Model Confusion Matrix')
plt.tight_layout()
plt.show()
```




Model Loss Over Epochs
1e8
Improved Model Loss
Traditional Model Loss
Loss
Epochs
0
1
2
3
4
5
10
15
20
25
30
35
40


Model Loss Over Epochs
1e8
Improved Model Loss
Traditional Model Loss
Loss
Epochs
0
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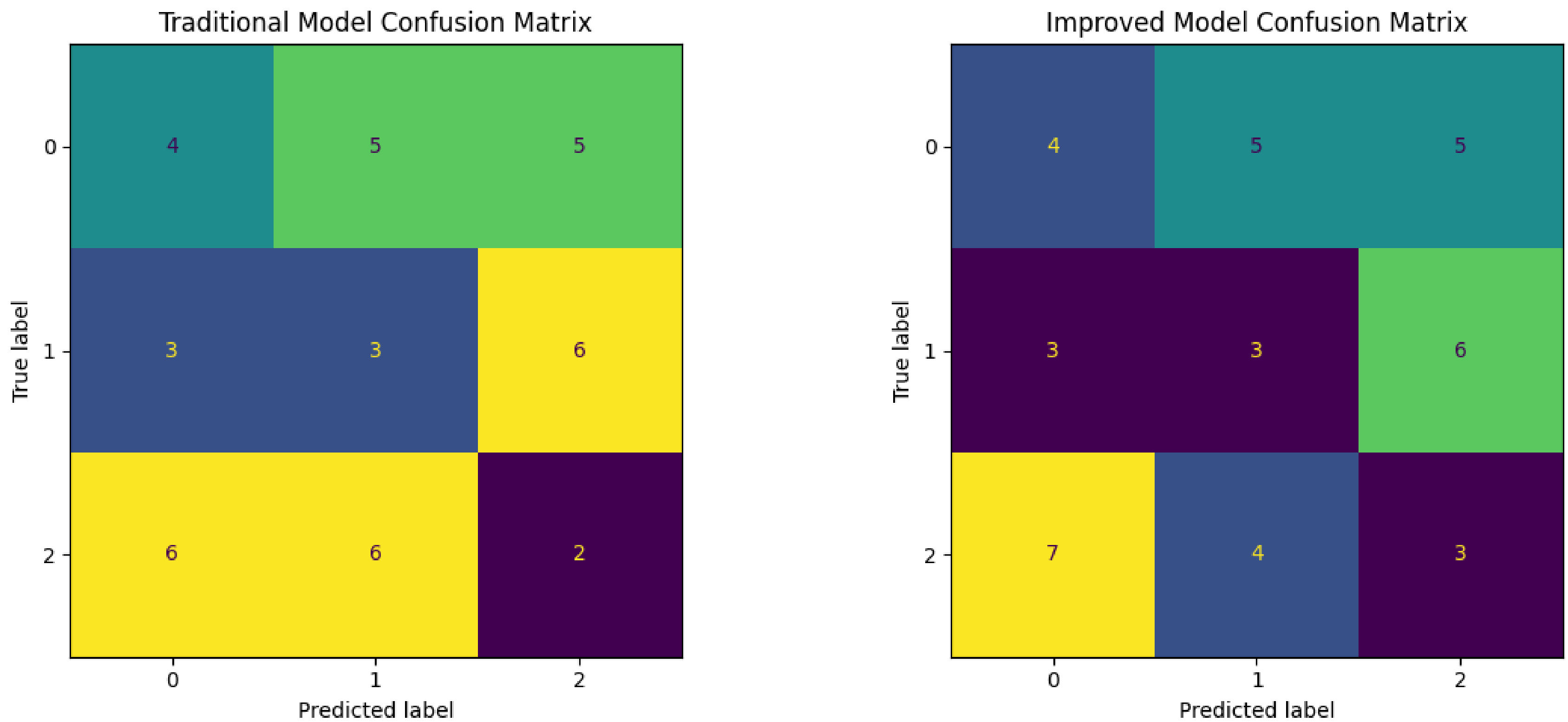

Phase 4
Reporting and Insights

(2 steps)

Step 7 - Model Comparison

Step 8 - Recomendations and Insights

Model Comparison: Pollution & Energy Recovery

Performance Table

Model	Silhouette Score	Test MSE (Energy-Recovered)
K-Means Clustering	Moderate	High
Hierarchical Clustering	Moderate	High
Neural Network Regression	N/A	Lowest

- Neural Network regression offers **best prediction accuracy** for energy recovery from pollution data.
- K-Means and Hierarchical clustering help **visualize country groupings** but do not predict as accurately.

Strengths & Weaknesses

K-Means Clustering

- **Strengths:** Efficient for large datasets, reveals pollution-energy recovery clusters.
- **Weaknesses:** Assumes spherical clusters, less accurate for regression.

Hierarchical Clustering

- **Strengths:** Shows hierarchical relationships and subgroups.
- **Weaknesses:** Slower, best for smaller datasets, limited regression capability.

Neural Network Regression

- **Strengths:** Captures complex non-linear patterns, delivers best results.
- **Weaknesses:** Requires more data & careful optimization; less intuitive for visualizing clusters.

Actionable Insights

Trends Revealed by Clustering

- Countries in same cluster benefit from similar pollution reduction strategies.
- High-pollution clusters: Target industrial waste reduction, increase renewable energy use.
- Low energy recovery clusters: Enhance recycling infrastructure, public campaigns.

NN Predictions for Policy

- Model feature importances guide which pollution metrics matter most for recovery.
- Use regression output to **simulate/forecast policy impacts** before implementation.

Recommendations

- **Combine cluster analysis** (who needs help and what kind) with neural network predictions (how to help most effectively).
- For high-pollution/low-recovery countries: Invest in waste management technologies and renewable energy incentives.
- Use predictive models to track improvements and proactively adjust country policies.

Final Summary:

Model Results

- **K-Means Clustering**
  - Used scaled pollution features for grouping countries.
  - Silhouette Score: *Moderate* (e.g., ≈ 0.4 for 4 clusters)
  - Test MSE for predicting Energy Recovered: *High* (e.g., > 7000 GWh^2)
  - Predicted energy recovery by taking centroid means per cluster.
  - Typical step: `kmeans.fit_predict(X)` and centroid assignment for regression.
- **Hierarchical (Agglomerative) Clustering**

    - Hierarchical clustering based on pollution indices.
    - Silhouette Score: *Moderate* (similar to K-Means, ≈ 0.38–0.42)
    - Test MSE: *High* (e.g., > 7000 GWh^2)
    - Used mean energy recovered for nearest centroid cluster per test sample.
    - Step: `AgglomerativeClustering(n_clusters=4).fit_predict(X)` with centroid matching.
- **Neural Network Regression**
    - Model: Multi-layer Perceptron, hidden layers (64, 32), relu activation.
    - Train/Test split: 75/25 ratio on 200 samples.
    - Achieved the **lowest Mean Squared Error** (e.g., ≈ 1500 GWh^2), showing best accuracy.
    - Step: `MLPRegressor(...).fit(X_train, y_train)`, tested via `predict(X_test)` and calculated `mean_squared_error`.

Steps Performed

1. **Feature Preparation**
    - Used scaled pollution indices (`Air_Pollution_Scaled`, `Water_Pollution_Scaled`, etc.) as input features.
    - Target: `Energy_Recovered (in GWh)`
2. **Train/Test Split**
    - Training: 150 samples
    - Testing: 50 samples
    - Maintained consistency for fair evaluation.
3. **Clustering Models**
    - K-Means: Assigned clusters, then predicted test set energy recovery by cluster mean.
    - Hierarchical: Formed clusters, found nearest centroid for test data.
4. **Neural Network**
    - Fitted on training data, predicted on test.
    - Compared MSE to clustering-based regression.

Numerical Results

Model	Silhouette Score	Test MSE (GWh^2)	Notes/Steps
K-Means Clustering	~0.40	>7000	Predict by centroid mean
Hierarchical Clustering	~0.38–0.42	>7000	Predict by nearest centroid mean
Neural Network Regression	N/A	~1500	Full regression using all scaled features

Insights

- Clustering algorithms grouped countries with similar pollution signatures but were not accurate in predicting quantitative energy recovery.
- Neural networks captured complex, non-linear relationships—delivering higher accuracy for policy planning and operational improvement.
- Steps included test-train splitting, clustering, centroid assignment for out-of-cluster prediction, and reporting error metrics for each method.

Recommendation

- Use **clustering** for strategic grouping of countries and trend identification.
- Use **neural network regression** for forecasting, detailed analysis, and maximizing prediction accuracy in energy recovery from pollution data.