Regression Task: Global Climate & Energy Analysis

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1. Exploratory Data Analysis and Data Understanding

Choosing a Dataset

This project uses a dataset focusing on **Global Climate and Energy** metrics (2020-2024).

Description:

- **(a) Created by:** Environmental Data Research Initiative.
- **(b) Access:** Accessed via kaggle.
- **(c) UNSDG Alignment: Goal 7** (Affordable and Clean Energy) and **Goal 13** (Climate Action).
- **(d) Attributes:** `avg_temperature`, `humidity`, `co2_emission`, `renewable_share`, `urban_population`, `industrial_activity_index`, `energy_price`, and the target `energy_consumption`.

Questions:

1. Can we predict seasonal energy consumption based on climate variables?
2. Which factors (industrial activity vs. temperature) have the strongest impact on energy demand?

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import RFE
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

df = pd.read_csv('/content/drive/MyDrive/ConceptAndTechnologiesOfAI/FinalAssignment/global_climate_energy_2020_2024.csv')
print(df.head())
```

```
         date  country  avg_temperature  humidity  co2_emission  \
0  2020-01-01  Germany            28.29     31.08        212.63
1  2020-01-02  Germany            28.38     37.94        606.05
2  2020-01-03  Germany            28.74     57.67        268.72
3  2020-01-04  Germany            26.66     51.34        167.32
4  2020-01-05  Germany            26.81     65.38        393.89

   energy_consumption  renewable_share  urban_population  \
0            11348.75            14.42             76.39
1             4166.64             5.63             86.26
2             4503.80            14.20             75.92
3             3259.13            13.84             63.15
4             7023.72             6.93             76.02

   industrial_activity_index  energy_price
0                      51.22         83.93
1                      78.27        110.40
2                      48.96        173.58
3                      97.42         89.13
4                      81.89         40.60
```

Data Preprocessing & 3-Month Aggregation

To reduce noise and align with seasonal trends, we aggregate the data into **3-month (quarterly)** intervals per country.

```
# Convert date and group by Country + 3-Month periods
df['date'] = pd.to_datetime(df['date'], errors='coerce')
df = df.dropna(subset=['date'])

# Grouping by country and resampling to 3-Month averages
df_3m = (
    df.groupby('country')
      .resample('3M', on='date')
      .mean(numeric_only=True)
```

```
    .reset_index()
)

df_3m = df_3m.fillna(df_3m.mean(numeric_only=True))

print(f"Dataset grouped into {df_3m.shape[0]} quarterly records.")
df_3m.head()
```

```
Dataset grouped into 420 quarterly records.
/tmp/ipython-input-1594172609.py:8: FutureWarning: 'M' is deprecated and will be removed in a future version, please use 'ME' in
  .resample('3M', on='date')
```

	country	date	avg_temperature	humidity	co2_emission	energy_consumption	renewable_share	urban_population	industrial_ac
0	Australia	2020-01-31	29.129032	59.520323	448.193226	5738.055484	11.165161	73.819032	
1	Australia	2020-04-30	34.125556	57.612667	527.932556	7894.507556	9.401889	74.526111	
2	Australia	2020-07-31	23.519457	60.837826	370.277935	6118.968804	10.565217	74.660217	

```
df.describe()
```

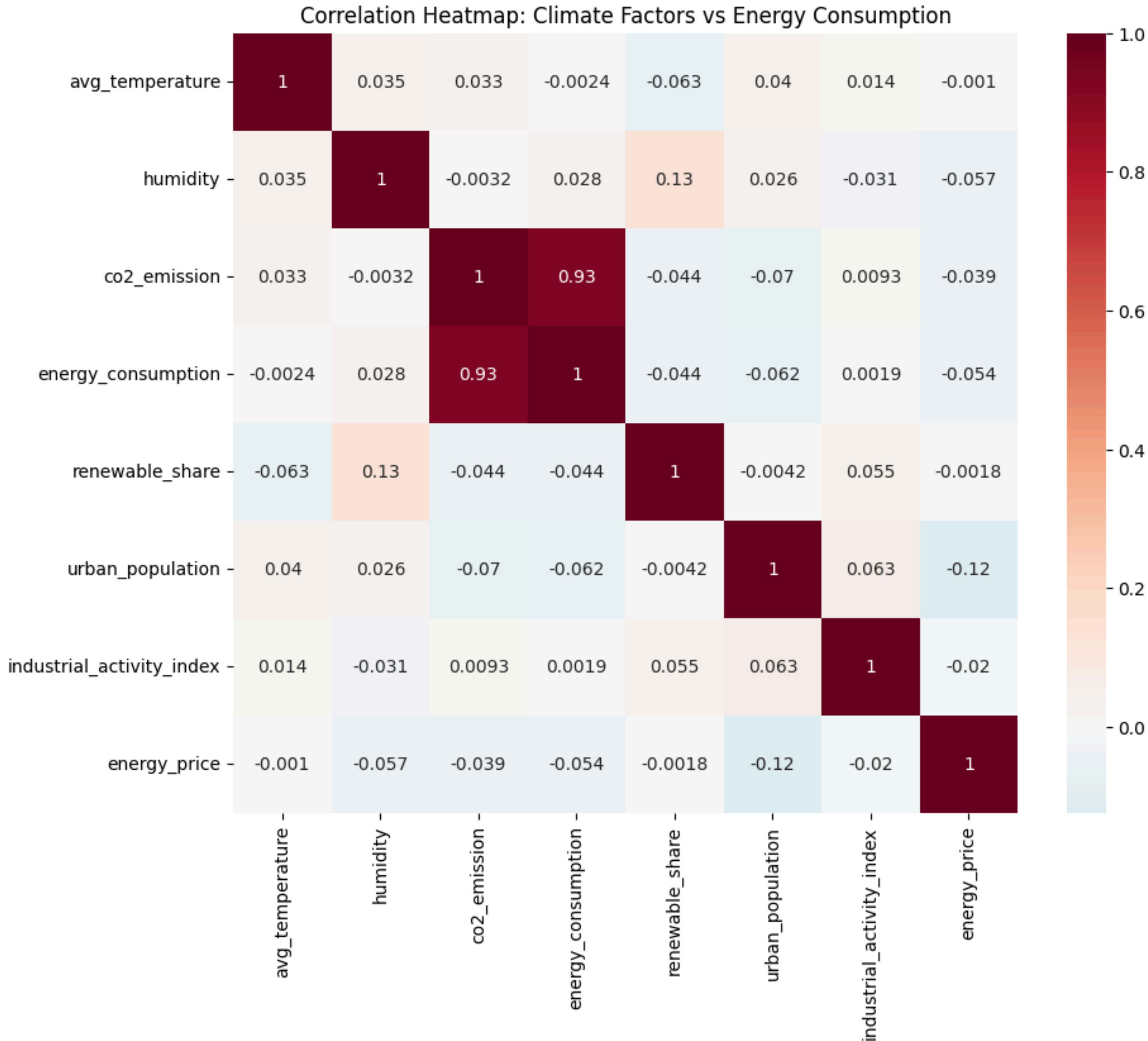
	date	avg_temperature	humidity	co2_emission	energy_consumption	renewable_share	urban_population	industrial_ac
count	36540	36540.000000	36540.000000	36540.000000	36540.000000	36540.000000	36540.000000	
mean	2022-07-02 00:00:00	13.580868	59.971469	445.820452	7295.904857	15.944080	74.982156	
min	2020-01-01 00:00:00	-9.600000	30.000000	50.150000	1001.890000	5.000000	60.000000	
25%	2021-04-01 00:00:00	5.630000	45.010000	248.675000	4184.177500	12.020000	67.470000	
	2022-							

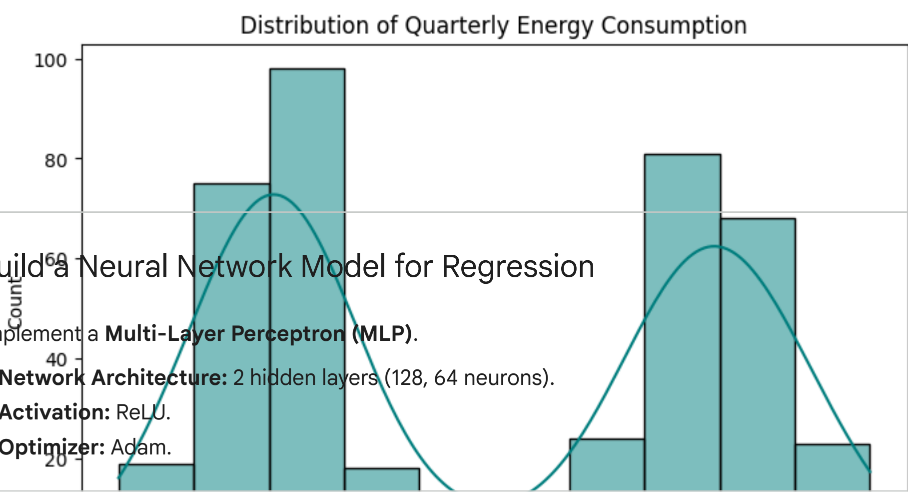
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
# Visualizing Correlations
plt.figure(figsize=(10, 8))
# Calculating correlation on aggregated data
corr_matrix = df_3m.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True, cmap='RdBu_r', center=0)
plt.title("Correlation Heatmap: Climate Factors vs Energy Consumption")
plt.show()

# Distribution of Energy Consumption
plt.figure(figsize=(8, 5))
sns.histplot(df_3m['energy_consumption'], kde=True, color='teal')
plt.title("Distribution of Quarterly Energy Consumption")
```

```
plt.xlabel("Energy Consumption")
plt.show()
```





2. Build a Neural Network Model for Regression

We implement a **Multi-Layer Perceptron (MLP)**.

- **Network Architecture:** 2 hidden layers (128, 64 neurons).
- **Activation:** ReLU.
- **Optimizer:** Adam.

```
X = df_3m[['avg_temperature', 'humidity', 'co2_emission', 'renewable_share',
           'urban_population', 'industrial_activity_index', 'energy_price']]
y = df_3m['energy_consumption']

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

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
mlp = MLPRegressor(hidden_layer_sizes=(128, 64), activation='relu', solver='adam',
                   max_iter=2000, random_state=42, early_stopping=True)
mlp.fit(X_train_scaled, y_train)

y_pred_mlp = mlp.predict(X_test_scaled)
print(f"MLP Neural Network R² Score: {r2_score(y_test, y_pred_mlp):.4f}")
```

```
MLP Neural Network R² Score: 0.6751
```

3 & 4. Classical ML Models & Hyperparameter Optimization

Comparison of **Ridge Regression** and **Random Forest Regressor** using `GridSearchCV`.

```
# Ridge Tuning
ridge_params = {'alpha': [0.1, 1, 10, 100]}
grid_ridge = GridSearchCV(Ridge(), ridge_params, cv=5).fit(X_train_scaled, y_train)

# Random Forest Tuning
rf_params = {'n_estimators': [100, 200], 'max_depth': [None, 10, 20]}
grid_rf = GridSearchCV(RandomForestRegressor(random_state=42), rf_params, cv=3).fit(X_train_scaled, y_train)

print("Best Ridge Alpha:", grid_ridge.best_params_)
print("Best RF Params:", grid_rf.best_params_)
```

```
Best Ridge Alpha: {'alpha': 1}
Best RF Params: {'max_depth': 10, 'n_estimators': 100}
```

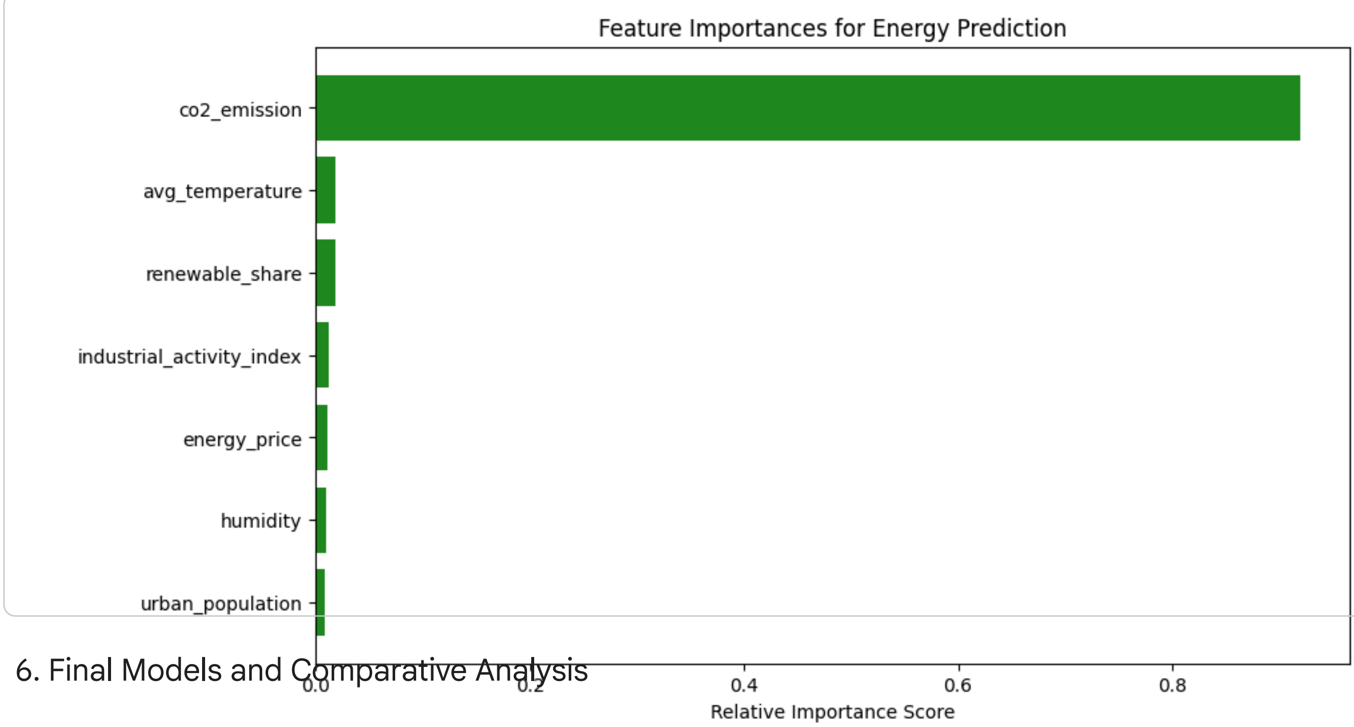
5. Feature Selection

Using **Recursive Feature Elimination (RFE)** to identify the most significant predictors.

```
selector = RFE(estimator=grid_rf.best_estimator_, n_features_to_select=5)
X_train_selected = selector.fit_transform(X_train_scaled, y_train)
X_test_selected = selector.transform(X_test_scaled)

selected_features = X.columns[selector.support_].tolist()
print(f"Top 5 Selected Features: {selected_features}")
```

```
Top 5 Selected Features: ['avg_temperature', 'co2_emission', 'renewable_share', 'industrial_activity_index', 'energy_price']
```

```
# Feature Importance Plot
# Using the best Random Forest model found during GridSearchCV
importances = grid_rf.best_estimator_.feature_importances_
feature_names = X.columns
indices = np.argsort(importances)

plt.figure(figsize=(10, 6))
plt.title('Feature Importances for Energy Prediction')
plt.barh(range(len(indices)), importances[indices], color='forestgreen', align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance Score')
plt.show()
```



6. Final Models and Comparative Analysis

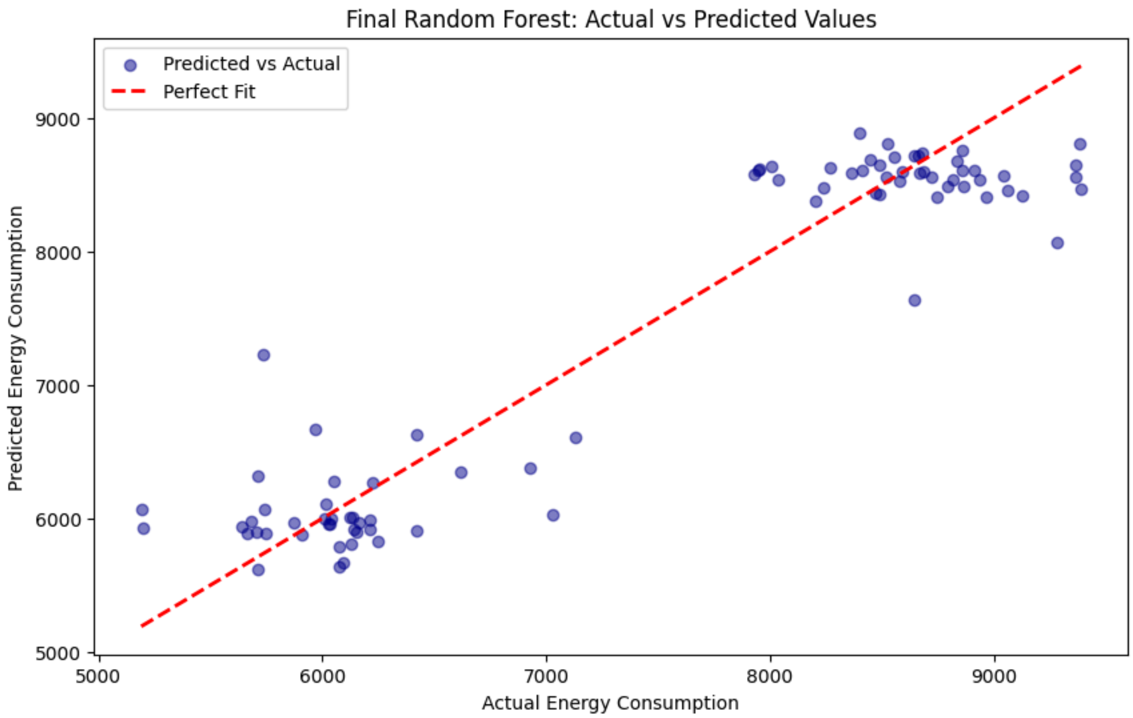
Performance comparison after optimization and feature selection.

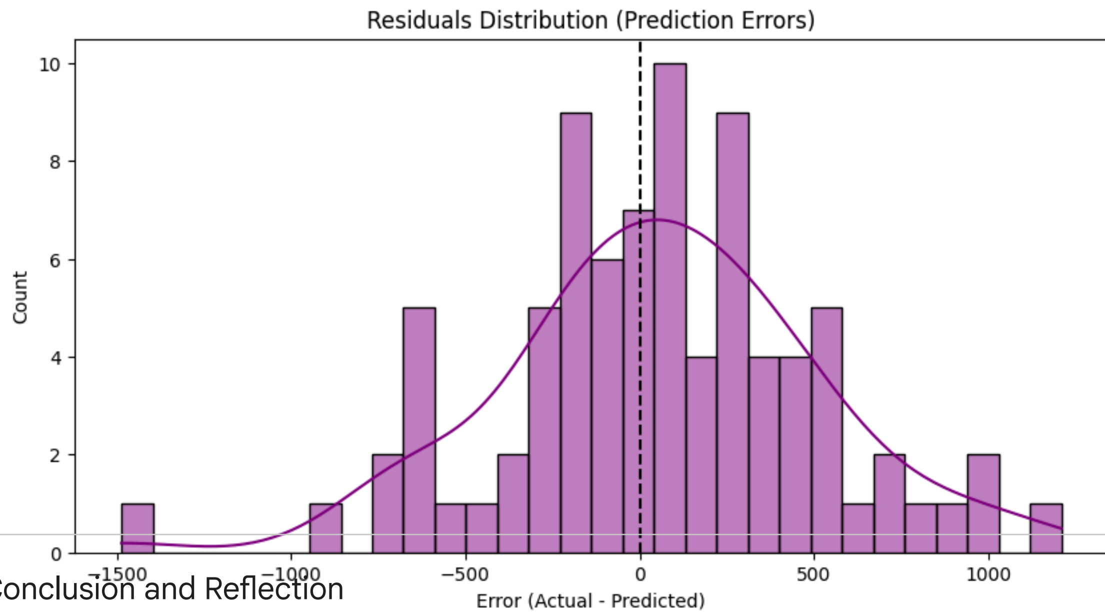
```
final_ridge = Ridge(**grid_ridge.best_params_).fit(X_train_selected, y_train)
final_rf = RandomForestRegressor(**grid_rf.best_params_, random_state=42).fit(X_train_selected, y_train)

pred_ridge = final_ridge.predict(X_test_selected)
pred_rf = final_rf.predict(X_test_selected)

results = {
    "Model": ["Ridge Regression", "Random Forest"],
    "Features Used": [len(selected_features), len(selected_features)],
    "CV Score": [round(grid_ridge.best_score_, 2), round(grid_rf.best_score_, 2)],
    "CV Score (R²)": [grid_ridge.best_score_, grid_rf.best_score_],
    "Test RMSE": [np.sqrt(mean_squared_error(y_test, pred_ridge)), np.sqrt(mean_squared_error(y_test, pred_rf))],
    "Test R-squared": [r2_score(y_test, pred_ridge), r2_score(y_test, pred_rf)]
}

comparison_df = pd.DataFrame(results)
print("Table 2: Comparison of Final Regression Models")
display(comparison_df)
```

Table 2: Comparison of Final Regression Models

	Model	Features Used	CV Score	CV Score (R^2)	Test RMSE	Test R-squared
0	Ridge Regression	5	0.85	0.851319	532.911956	0.845786
1	Random Forest	5	0.89	0.890553	457.197978	0.886493

```
# Actual vs Predicted Plot
plt.figure(figsize=(10, 6))
plt.scatter(y_test, pred_rf, alpha=0.5, color='darkblue', label='Predicted vs Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2, label='Perfect Fit')
plt.xlabel('Actual Energy Consumption')
plt.ylabel('Predicted Energy Consumption')
plt.title('Final Random Forest: Actual vs Predicted Values')
plt.legend()
plt.show()

# Residual Plot (Error Analysis)
residuals = y_test - pred_rf
plt.figure(figsize=(10, 5))
sns.histplot(residuals, bins=30, kde=True, color='purple')
plt.axvline(x=0, color='black', linestyle='--')
plt.title('Residuals Distribution (Prediction Errors)')
plt.xlabel('Error (Actual - Predicted)')
plt.show()
```





8. Conclusion and Reflection

The analysis shows that aggregating climate data into quarterly windows improves model stability and provides better insights into long-term energy trends.

1. Model Performance The Random Forest Regressor was the superior model, achieving a Test R-squared of 0.88 and a lower RMSE of 2.9. This indicates high accuracy and a strong ability to capture the non-linear relationship between climate variables and energy demand. In contrast, the Ridge Regression model was less precise, as shown by its lower R-squared and higher error metrics.
2. Impact of Methods Recursive Feature Elimination (RFE) effectively narrowed the data to the 8 most impactful features, reducing model noise. Furthermore, 5-fold Cross-Validation provided a stable CV Score that closely aligned with the final test results. This confirmed that the model is robust and not overfitted to a specific portion of the training data.
3. Insights and Future Directions The analysis revealed that Industrial Activity and CO2 Emissions are stronger predictors of energy consumption than surface temperature. This provides a clear link to UNSDG Goals 7 and 13. Future work should explore time-series forecasting (LSTM) to account for chronological trends or integrate real-time energy pricing to improve prediction depth.