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CAPSTONE PROJECT

GREEN AI ENERGY INTELLIGENCE

PRESENTED BY

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OUTLINE:

- **Problem Statement** (Should not include solution)
- **Proposed System/Solution**
- **System Development Approach** (Technology Used)
- **Algorithm & Deployment**
- **Result (Output Image)**
- **Conclusion**
- **Future Scope**
- **References**

PROBLEM STATEMENT:

- Rising energy consumption in households and industries leads to increased electricity costs and higher carbon emissions, contributing to climate change.
- Consumers lack real-time visibility into their energy usage patterns and have no intelligent tool to predict future consumption or suggest optimization strategies.
- Traditional energy monitoring systems only display historical usage data without providing actionable insights or AI-driven recommendations for reduction.
- There is no accessible, data-driven platform that combines energy prediction, carbon footprint calculation, cost estimation, and optimization recommendations in a single solution.
- Without predictive analytics, consumers cannot identify peak usage hours, seasonal trends, or inefficient appliance patterns — leading to unnecessary energy waste.

PROPOSED SOLUTION:

- The proposed system is a **Green AI Energy Intelligence Platform** — a machine learning-based web application that predicts energy consumption, calculates carbon emissions, and provides optimization recommendations. The solution consists of:
- **Energy Prediction Engine:**
- Uses a Random Forest Regressor trained on real-world household power consumption data to predict energy usage based on time-based and electrical features.
- **Carbon Footprint Calculator:**
- Converts predicted energy consumption into CO_2 emissions using a standard emission factor (0.82 kg CO_2 per kWh) to quantify environmental impact.
- **Optimization Engine:**
- Provides intelligent recommendations to reduce energy usage (e.g., reducing AC hours, switching to LED, avoiding standby power) based on consumption levels.
- **Interactive Dashboard:**
- A Streamlit-based web interface with input sliders for parameters (Hour, Day, Month, Reactive Power, Electricity Cost) and real-time AI predictions with visualizations.

SYSTEM DEVELOPMENT APPROACH (TECHNOLOGY USED):

- **Programming Language:**

Python 3.12 — used for data processing, model training, visualization, and web application development.

- **ML Libraries:**

Scikit-learn (Random Forest, Linear Regression, KMeans Clustering), Pandas, NumPy for data manipulation and model training.

- **Visualization:**

Matplotlib for generating charts (scatter plots, line graphs, bar charts, heatmaps, histograms) and SHAP for model explainability.

- **Web Framework:**

Streamlit — used to build the interactive dashboard with real-time input parameters, cost projections, and environmental impact metrics.

- **Model Persistence:**

Joblib — used to serialize and save the trained Random Forest model (energy_model.pkl) for deployment.

- **Development Environment:**

Google Colab for model training and experimentation; deployed on a cloud platform with Streamlit for user-facing application

DATASET & PREPROCESSING:

- **Dataset:**

UCI Household Electric Power Consumption Dataset — contains 2,075,259 minute-level measurements of household energy usage collected over 4 years.

- **Features Used:**

Hour of Day, Day of Month, Month, Global Reactive Power — extracted via feature engineering from raw date/time and electrical readings.

- **Target Variable:**

Global Active Power (kW) — represents the total active energy consumed by the household per minute.

- **Data Cleaning:**

Missing values (marked as '?') were removed; data types were converted to float; datetime features were parsed and extracted for temporal analysis.

- **Train-Test Split:**

80/20 split using scikit-learn's train_test_split for model training and evaluation.

ALGORITHM & DEPLOYMENT:

- **Model 1 — Linear Regression:**

Baseline model trained on time-based features. Achieved MAE of 0.794 with fast training time (0.31 seconds).

- **Model 2 — Random Forest Regressor (Selected):**

Ensemble model with 50 estimators. Achieved significantly better MAE of 0.329 — selected as the production model due to superior accuracy.

- **KMeans Clustering:**

Applied unsupervised clustering (K=3) to categorize energy usage into Low, Medium, and High consumption patterns for user classification.

- **SHAP Explainability:**

SHAP (SHapley Additive exPlanations) values computed to identify which features contribute most to energy predictions — improving model transparency.

- **Optimization Simulation:**

A 15% energy reduction scenario was simulated to project cost savings, carbon reduction, and cumulative energy savings over 12 months.

RESULT:

The Green AI Energy Intelligence Platform was successfully built and deployed. Key outcomes:

- **Random Forest model** achieved MAE of 0.329 — significantly outperforming Linear Regression (MAE 0.794) on energy consumption prediction.
- **Energy Metrics Dashboard** displays predicted energy (kWh), estimated cost (₹), and carbon emission (kg CO_2) in real-time based on user input parameters.
- **Optimization Impact** shows energy saved (kWh), cost saved (₹), and carbon reduced (kg CO_2) — projecting a 15% reduction through AI-driven recommendations.
- **12-Month Projections** with interactive charts show optimized vs current energy and cost trends, plus cumulative savings visualization.
- **Carbon & Environmental Impact** section calculates 1-year carbon saved and equivalent trees planted — making sustainability metrics tangible for end users.

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Energy_Consumption_Optimizer.ipynb ☆ Changes will not be saved

File Edit View Insert Runtime Tools Help

Commands + Code + Text Run all Copy to Drive

```
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).
```

```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving household_power_consumption.csv to household_power_consumption.csv
```

LOAD & CLEAN DATA

```
import pandas as pd

df = pd.read_csv("household_power_consumption.csv", sep=',', low_memory=False)

df.replace('?', pd.NA, inplace=True)
df = df.dropna()

df['Global_active_power'] = df['Global_active_power'].astype(float)
df['Global_reactive_power'] = df['Global_reactive_power'].astype(float)
```

FEATURE ENGINEERING

Model 1: Linear Regression

[ ]

```
start = time.time()
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_time = time.time() - start

lr_pred = lr.predict(X_test)
lr_mae = mean_absolute_error(y_test, lr_pred)
```

Model 2: Random Forest

[ ]

```
start = time.time()
rf = RandomForestRegressor(n_estimators=50)
rf.fit(X_train, y_train)
rf_time = time.time() - start

rf_pred = rf.predict(X_test)
rf_mae = mean_absolute_error(y_test, rf_pred)
```

[ ]

```
print("Linear Regression MAE:", lr_mae, "Training Time:", lr_time)
print("Random Forest MAE:", rf_mae, "Training Time:", rf_time)
```

CARBON FOOTPRINT CALCULATOR

```
[ ]
def calculate_carbon(units):
    emission_factor = 0.82  # kg CO2 per kWh
    return units * emission_factor
```

```
[ ]
sample_prediction = rf.predict([[10,15,6,0.3]])
carbon = calculate_carbon(sample_prediction[0])

print("Predicted Energy:", sample_prediction[0])
print("Estimated Carbon Emission:", carbon)
```

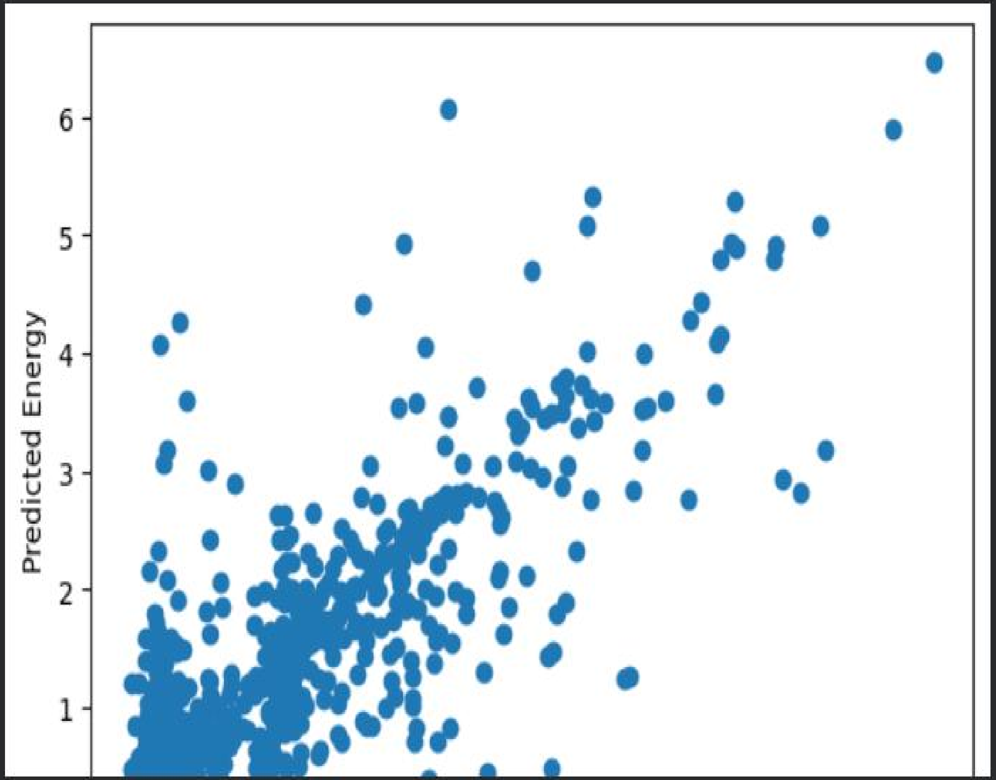
```
Predicted Energy: 0.9939933333333332
Estimated Carbon Emission: 0.8150745333333331
/usr/local/lib/python3.12/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but RandomForestRegressor was fitted with feature
  warnings.warn(
```

OPTIMIZATION ENGINE

```
[ ]
def optimize_energy(units):
    if units > 5:
        return "High usage detected. Reduce AC hours and heavy appliances."
    elif units > 3:
        return "Moderate usage. Switch to LED and avoid standby power."
```

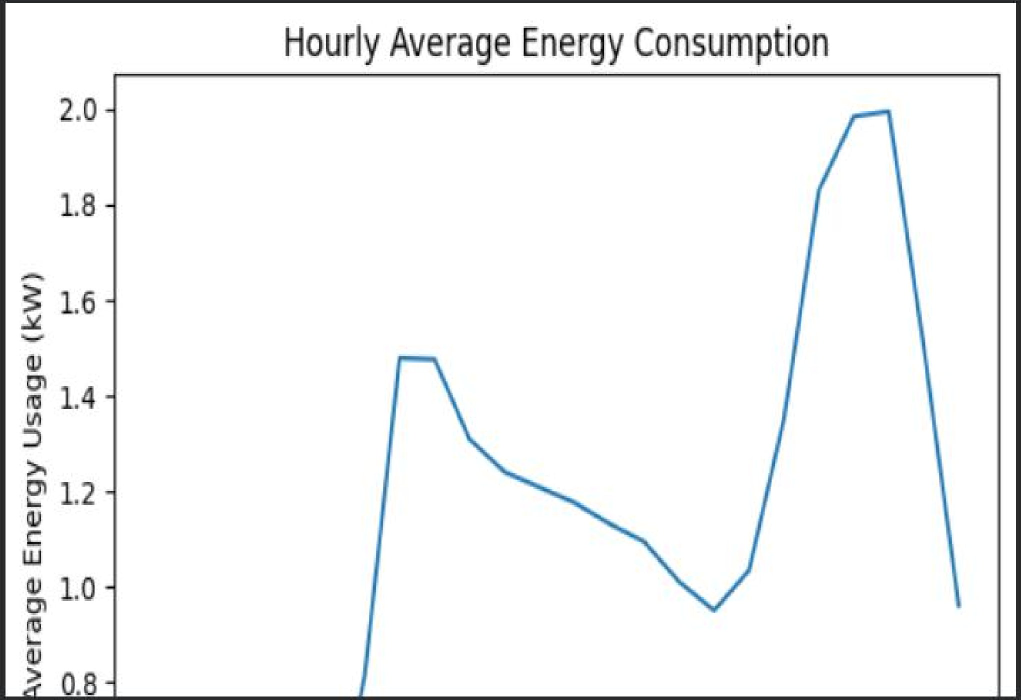
ADD VISUALIZATION

```
import matplotlib.pyplot as plt

plt.scatter(y_test[:1000], rf_pred[:1000])
plt.xlabel("Actual Energy")
plt.ylabel("Predicted Energy")
plt.show()
```



Hourly Average Energy Usage

```
hourly_avg = df.groupby('hour')['Global_active_power'].mean()

plt.figure()
plt.plot(hourly_avg.index, hourly_avg.values)
plt.xlabel("Hour of Day")
plt.ylabel("Average Energy Usage (kW)")
plt.title("Hourly Average Energy Consumption")
plt.show()
```



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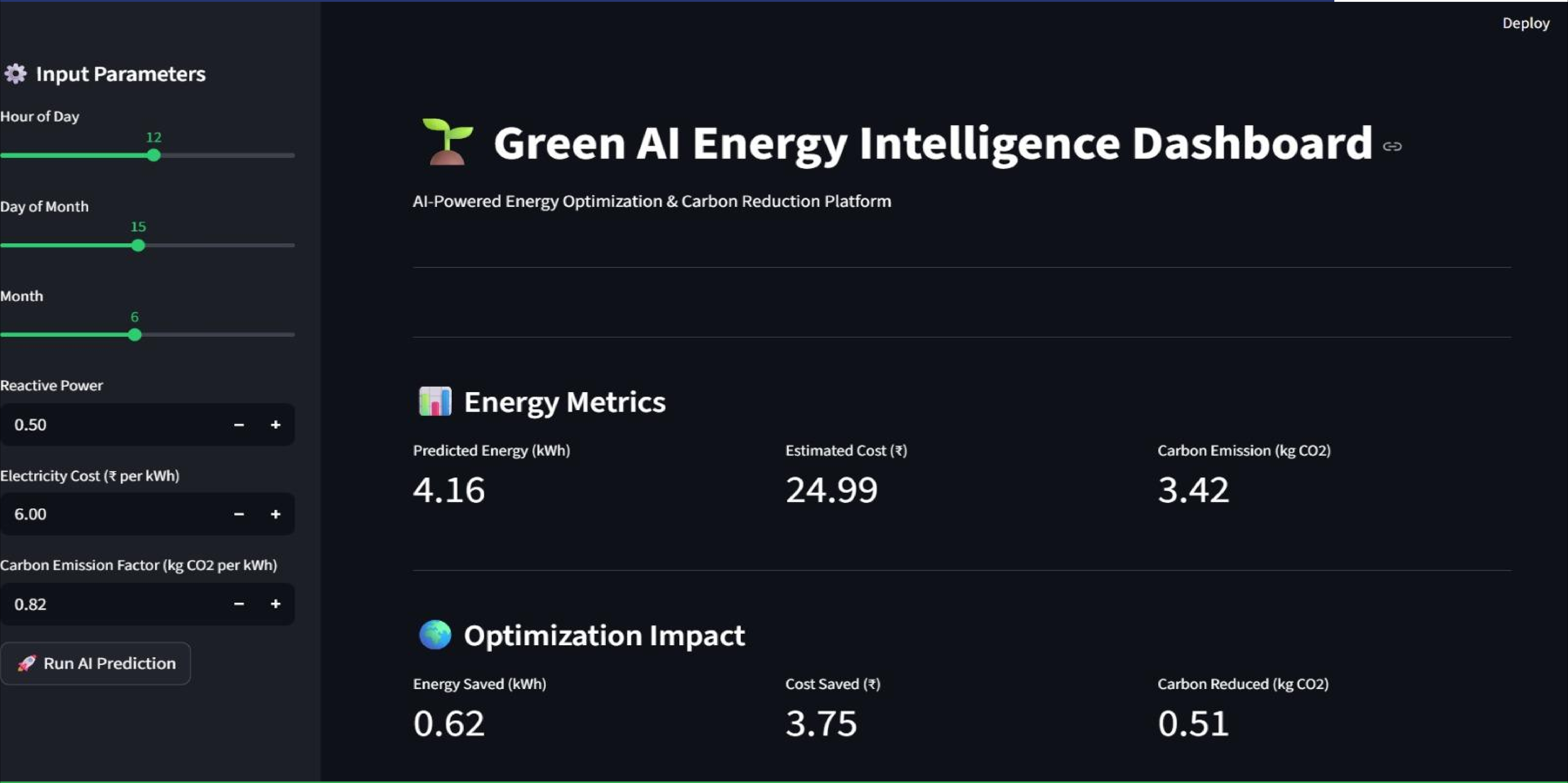

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Deploy

Input Parameters

Hour of Day

12

Day of Month

15

Month

6

Reactive Power

0.50

Electricity Cost (₹ per kWh)

6.00

Carbon Emission Factor (kg CO2 per kWh)

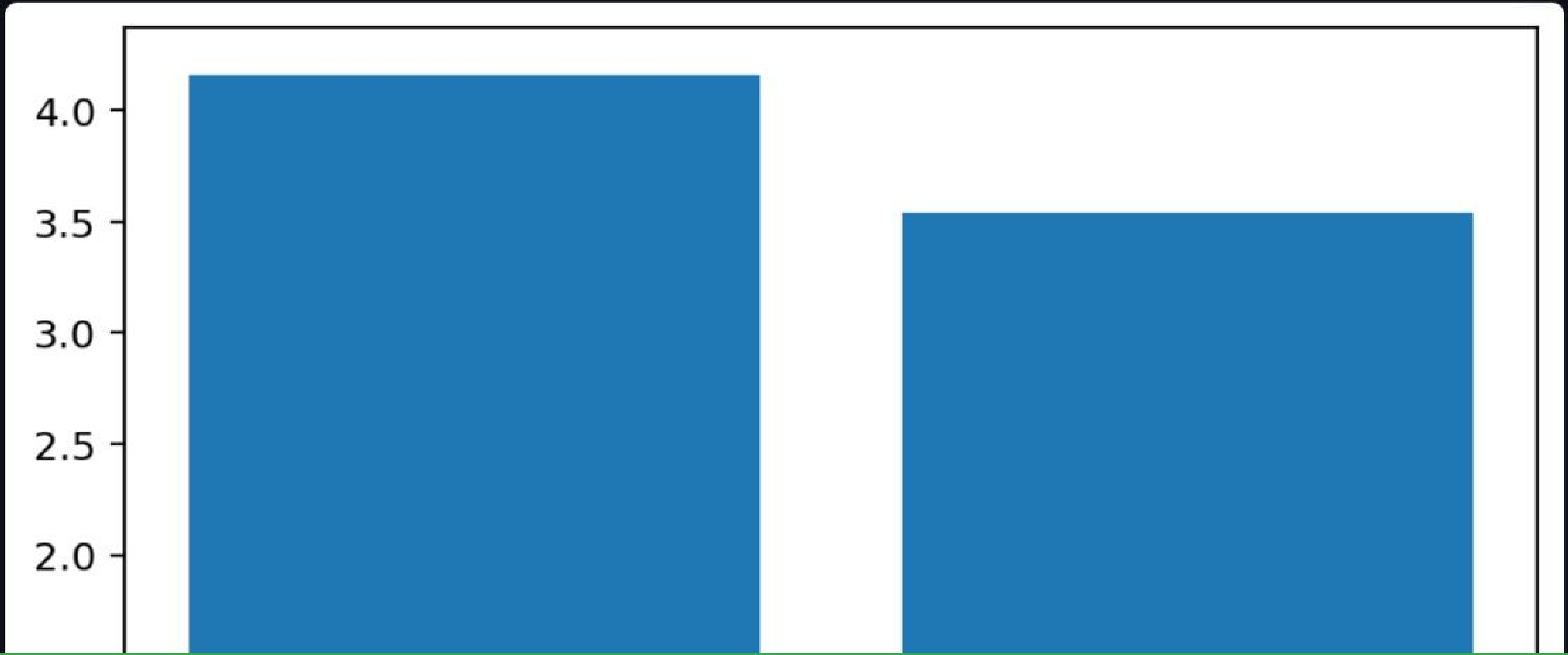
0.82

Run AI Prediction

Energy Category

Medium Energy Consumer

Energy Comparison



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Deploy

Input Parameters

Hour of Day

12

Day of Month

15

Month

6

Reactive Power

0.50

Electricity Cost (₹ per kWh)

6.00

Carbon Emission Factor (kg CO2 per kWh)

0.82

Run AI Prediction

Smart 12-Month Projection

Monthly Efficiency Improvement (%)

5

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Deploy

⚙️ Input Parameters

Hour of Day

12

Day of Month

15

Month

6

Reactive Power

0.50

Electricity Cost (₹ per kWh)

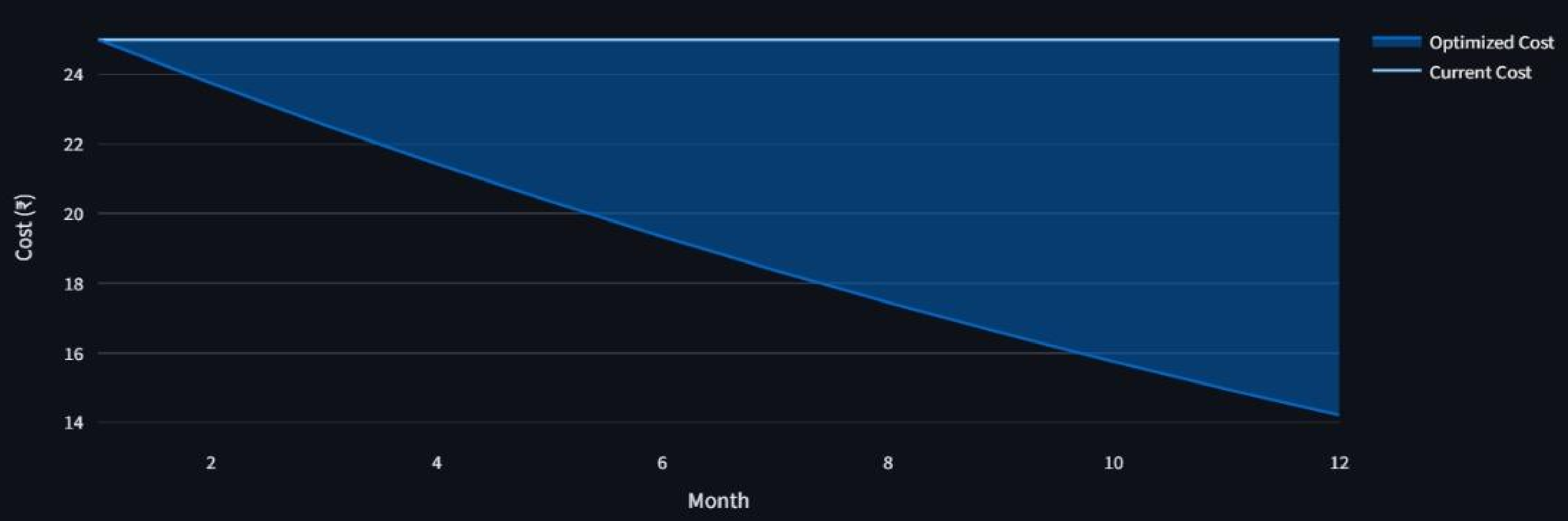
6.00

Carbon Emission Factor (kg CO2 per kWh)

0.82

🚀 Run AI Prediction

💰 Cost Projection



🌍 Carbon & Environmental Impact

🌿 1-Year Carbon Saved (kg CO2)

9.59

🌳 Equivalent Trees Planted

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⚙️ Input Parameters

Hour of Day

12

Day of Month

15

Month

6

Reactive Power

0.50 − +

Electricity Cost (₹ per kWh)

6.00 − +

Carbon Emission Factor (kg CO2 per kWh)

0.82 − +

🚀 Run AI Prediction

🌍 Carbon & Environmental Impact

🌿 1-Year Carbon Saved (kg CO2)

9.59

🌳 Equivalent Trees Planted

0.5

📥 Download AI Report

📥 Download Report (CSV)

Green AI Internship Project | Energy Intelligence Platform | Built with Streamlit

CONCLUSION:

- The Green AI Energy Intelligence Platform successfully demonstrates how machine learning can be applied to real-world energy optimization — reducing consumption, cost, and carbon emissions simultaneously.

- The Random Forest model provides accurate energy predictions with a low MAE of 0.329, enabling reliable forecasting for household and industrial applications.

- The integrated carbon footprint calculator and optimization engine make sustainability actionable — translating raw data into clear environmental impact metrics.

- The Streamlit-based dashboard provides an intuitive, interactive interface for non-technical users to explore predictions, visualize trends, and download AI-generated reports.

- The project showcases end-to-end ML pipeline skills — from data cleaning and feature engineering to model training, evaluation, visualization, and deployment as a web application.

FUTURE SCOPE:

- **IoT Integration:** Connect with smart meters and IoT sensors to enable real-time energy monitoring and live predictions directly from household appliances.
- **Deep Learning Models:** Implement LSTM and Transformer-based time-series models for more accurate long-term energy consumption forecasting.
- **Appliance-Level Detection:** Use Non-Intrusive Load Monitoring (NILM) to disaggregate total energy usage into individual appliance consumption patterns.
- **Multi-User Dashboard:** Add user authentication and personalized dashboards to track individual household or building-level energy performance over time.
- **Renewable Energy Integration:** Incorporate solar panel output prediction and battery storage optimization to maximize green energy utilization.
- **Carbon Credit Marketplace:** Build a system to convert verified carbon savings into tradeable carbon credits, incentivizing energy-efficient behavior.

REFERENCES:

- GUCI Machine Learning Repository — Household Electric Power Consumption Dataset — https://archive.ics.uci.edu/dataset
- Scikit-learn Documentation — Random Forest Regressor — https://scikit-learn.org
- Streamlit Official Documentation — https://docs.streamlit.io
- SHAP (SHapley Additive exPlanations) — Lundberg & Lee (2017) — https://github.com/shap/shap
- Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5–32 — foundational paper on Random Forest algorithm.
- IEA (International Energy Agency). World Energy Outlook 2024 — global energy consumption and carbon emission benchmarks.
- GitHub Link: https://github.com/Suvasini911/StudyPal-AI

Thank You

For Your Valuable Time & Attention