CARBON LENS AI

AI CARBON FOOTPRINT REDUCTION

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Abstract

The project uses artificial intelligence techniques to analyze historical data from multiple sources on carbon emissions. We aim to support sustainable decision-makers by providing strategic recommendations based on AI analysis, including improved energy management and resource efficiency.

Manual data analysis is slow, complex, and often inaccurate. AI & ML can process large emission datasets faster and more accurately. Helps predict future emissions and supports smarter environmental.

Introduction

Climate change has become a fundamental global challenge. (1) Rising global carbon dioxide (CO_2) levels, resulting from fossil fuel combustion and industrial activity, are among the most significant drivers of warming. Carbon dioxide emissions from energy sources and energy figures are projected to reach 410 million tons in 2023, bringing the total to approximately 37.4 billion tons of greenhouse gases. (2)(3)(4)

In light of this reality, artificial intelligence (AI) emerges as a powerful tool for analyzing historical data and biodiversity-related emissions. Scientific studies using intelligent learning techniques show that they improve characteristic estimates by only 20% compared to traditional methods, and contribute to reducing polarization by up to 15% through accurate monitoring and smart energy management. (5)(6)

Predictive AI techniques can also help develop long-term plans to reduce emissions, in line with future sustainability requirements and aspirations. In addition, AI caters to a specific area to identify a reliable carbon "infrastructure," especially in Scope 3 (Scope 3) emissions, which are heading towards 90% of the corporate footprint.(7)

Literature Review

1. Statistical & Traditional Time-Series Models

- ARIMA/SARIMAX: Meng & Noman used the ARIMA/SARIMAX model to project emissions across multiple periods (pre, during, and post-COVID-19 pandemic), with seasonal (SARIMAX) models achieving MAPE error values between 0.09 and 0.32 depending on the period. (8)
- A study in China (1980–2019) compared ARIMA, SARIMAX, Holt-Winters, and LSTM, and confirmed that LSTM outperforms with MAPE ~3.1% and RMSE ~60.6%. (9)

2. Space-based emission prospecting systems

- Platforms like Climate TRACE use ML and satellite data to detect emission sources—such as fuel stations and boats. (10)

3. Hybrid & Optimization-Enhanced Models

- Developed an MLP combined with natural algorithms such as TLBO and WOA to predict G8 emissions; TLBO results showed the most accurate prediction (testing MSE ~4.47). (11)

Problem Statement

Artificial Intelligence Applications for Carbon Footprint Reduction

In light of the growing environmental challenges, carbon dioxide (CO_2) emissions have emerged as one of the most pressing global issues. The continuous rise in emissions—driven largely by industrial activity and the consumption of fossil fuels—has significantly contributed to climate change, global warming, and air pollution.

Given the complexity and sheer volume of emission data, traditional manual analysis is no longer practical. It demands considerable time and effort, and often results in high error margins. This highlights the need for leveraging advanced technologies—particularly Artificial Intelligence (AI) and Machine Learning (ML)—to analyze data more efficiently and accurately.

By developing an intelligent model capable of processing and interpreting emission-related data, we can predict future emission levels and support governments, organizations, and environmental bodies in understanding emission patterns and making informed decisions. This approach not only enhances environmental forecasting but also aligns with broader goals of sustainability and ESG (Environmental, Social, and Governance) compliance, offering a scalable solution that can be adapted globally.

1. **Carbon Footprint Assessment:**
   Developing an AI-based system to evaluate and analyze the carbon footprint of

organizations by tracking emissions across operational and supply chain activities.(12)

2. **Energy Efficiency Optimization:**
   Utilizing AI technologies to analyze energy consumption patterns and provide recommendations to enhance operational efficiency and reduce waste. (13)
3. **Implementation of Continuous Improvement Methodology (PDCA):**
   Integrating the PDCA model (Plan–Do–Check–Act) into environmental management systems using AI tools. This administrative model is widely used for process improvement and quality management. Based on verified results, appropriate actions are taken—if outcomes are positive, changes can be expanded; if problems arise, the plan or processes are adjusted accordingly. (13)
4. **Development of Smart Solutions:**
   Designing AI-powered solutions to modernize HVAC (heating, ventilation, and air conditioning) systems for better performance and lower energy usage. (13)
5. **Gap Analysis:**
   Employing AI to analyze gaps between current environmental performance and accepted environmental standards or benchmarks. (14)
6. **Enhancing Corporate Reputation:**
   Creating AI-driven marketing strategies that highlight environmental responsibility and strengthen the organization's brand image. (14)
7. **Market Expansion:**
   Using AI to identify and target new markets that demand higher environmental standards, helping businesses align with global sustainability trends. (14)
8. **Regulatory Compliance Monitoring:**
   Developing intelligent systems to monitor and ensure continuous compliance with environmental regulations and standards. (15)
9. **Renewable Energy Integration:**
   Exploring how AI can facilitate the integration of renewable energy sources into industrial operations to support decarbonization. (16)
10. **Accurate Environmental Reporting:**
    Building AI tools capable of generating precise and comprehensive reports on environmental performance and sustainability metrics. (17)

Importance

1. **Real-time Data Collection & Automation**
   AI systems can automatically ingest emissions data from IoT sensors, smart meters, ERP systems, and external sources, streamlining data handling and reducing errors. Research shows AI can cut manual data processing by up to 80%, offering continuous, accurate visibility into Scope 1/2/3 emissions across an organization. (18)
2. **Predictive Analytics & Proactive Intervention**
   By analyzing historical and live data, AI forecasts emissions trends and signals potential spikes before they occur—shifting management from reactive to proactive. Noted in studies of supply chains and green finance, predictive AI identifies high-emission events, creating opportunities for early mitigation. (19)
3. **Enhanced Visibility of Scope 3 Emissions**
   Scope 3 emissions often contribute over 70% of a company's total carbon footprint. AI enhances this visibility by extracting data from supplier reports and using lifecycle assessments. Reported improvements in estimation accuracy of up to 65% compared to traditional spreadsheet methods. (20)
4. **Energy & Operational Efficiency**
   AI algorithms detect inefficiencies in equipment, HVAC, and industrial processes—even emulating successes like Google's 40% reduction in data-center cooling energy. Reinforcement-learning models dynamically adjust operational parameters, lowering both emissions and costs. (21)
5. **Actionable Optimization Strategies**
   Beyond identification, Carbon-Lens AI generates recommendations—such as shifting energy use to cleaner grid hours, changing suppliers, or revising logistics routes. Renewable scheduling and circular economy tactics are cited as key methods for tangible emission reductions. (22)
6. **Automated Reporting & Compliance**
   AI platforms provide structured, auditable emissions reporting aligned with frameworks like the GHG Protocol, CDP, Science-Based Targets, and regulatory regimes (EU CSRD, CBAM). This simplifies compliance efforts and reduces risk exposure. (23)
7. **Strengthened ESG & Stakeholder Confidence**
   Demonstrable carbon tracking and reduction via AI enhances corporate transparency, boosting ESG ratings and building trust with investors,

customers, and partners. Predicted to be crucial for long-term brand value and competitive positioning. (24)

8. **Cost Savings & ROI**
   Operational optimization, energy scheduling, and predictive maintenance cumulatively drive energy cost reductions—building a strong business case for Carbon-Lens AI implementation. (25)
9. **Reducing AI's Own Carbon Impact**
   Research in "Green Algorithms" and tools like eco2AI and Clover highlight how to minimize the carbon footprint of AI systems themselves—through efficient model design, carbon-aware scheduling, and optimized hardware usage. Tools such as eco2AI and CodeCarbon assist developers in tracking and reducing AI-related emissions. (26)

Methodology

To analyze the problem of global carbon dioxide (CO_2) emissions, we collected a comprehensive dataset from Kaggle, specifically the file GCB2022v27_MtCO2_flat.csv, which contains global CO_2 emissions data from 1750 to 2022. The dataset includes annual emission values for over 200 countries, disaggregated by source: coal, oil, gas, cement, flaring, and other industrial activities. To explore and understand the dataset, we first used Julius.AI, a no-code AI tool for visual data analysis. The tool helped us interpret the structure of the dataset, explore emission patterns, and generate key visualizations that summarize the data. This phase provided initial insights into the global emission landscape and highlighted the need for further processing before modeling.

After the exploratory phase, we performed the following data preprocessing steps using Python: Cleaned column names from hidden characters and whitespaces.

Filtered data to include only the period from 1950 to 2022, where data coverage is more complete.

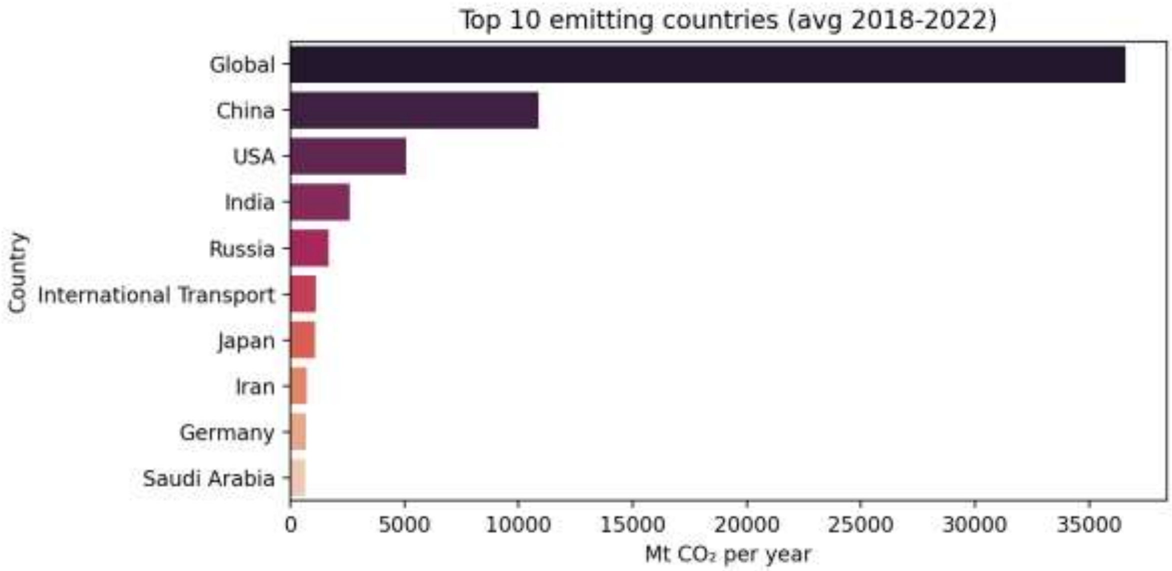
Converted non-numeric values (especially in the Year column) to numeric using errors='coerce'.

Dropped rows with missing values to ensure model reliability.

Encoded country names into numerical codes to fit ML input formats.

We then trained a Random Forest Regressor, a supervised ML algorithm suitable for regression problems with nonlinear patterns. This model was selected due to its robustness, high accuracy, and ability to estimate feature importance. It was trained on 80% of the cleaned data and evaluated on the remaining 20%.

Results & Discussion

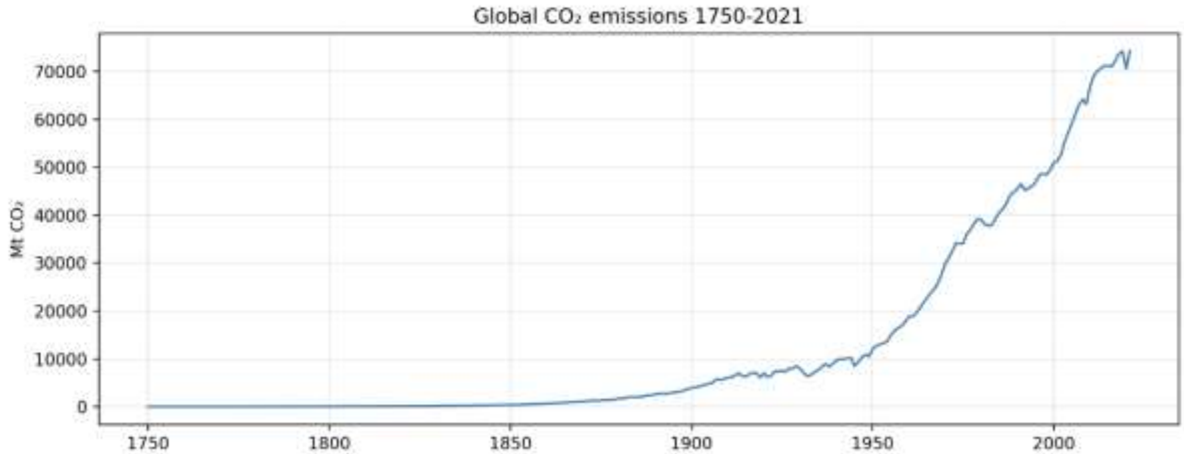


Top 10 Emitting Countries (2018–2022 Average)

The bar chart generated shows the average annual emissions (in $MtCO_2$) from the top 10 countries.

The leading emitters include Global, China, the United States, and India, which together account for the majority of global emissions during this period.

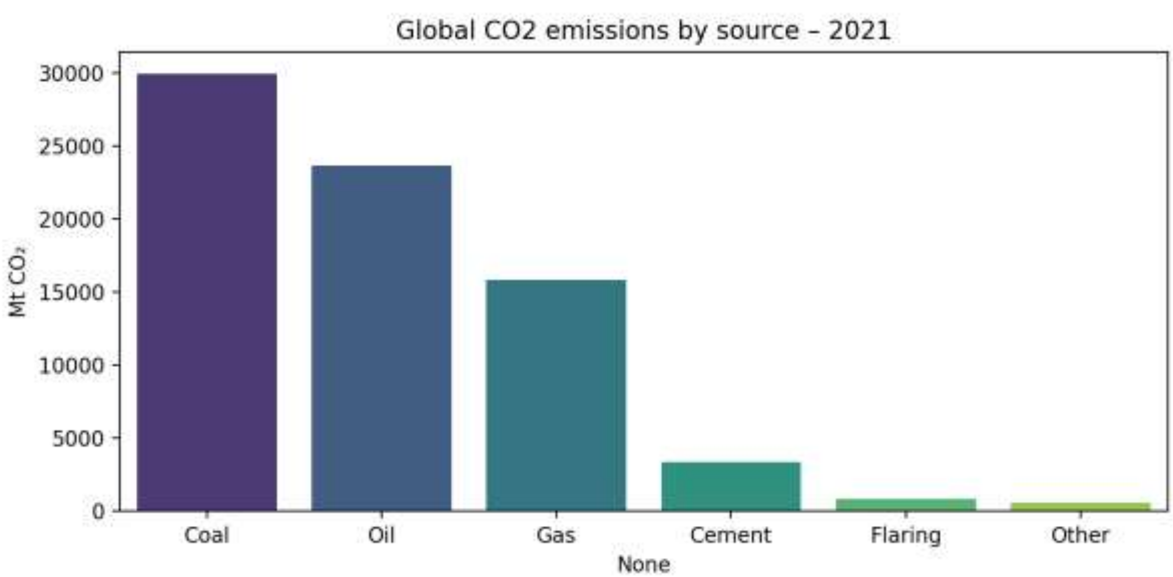
Global CO_2 Emissions Over Time (1750–2022)



The line plot illustrates historical emissions.

CO_2 emissions remained low until the Industrial Revolution, increased slowly through the 19th century, and accelerated dramatically after 1950. The global emissions surpassed 70Gt CO_2 annually in recent years, reflecting modern industrial intensity.

Global Emissions by Source (Latest Year: 2021)



This bar chart shows contributions from each emission source. Coal was the leading source, followed by oil and gas. Minor contributors included cement production and flaring. This data helps policymakers focus reduction efforts on the most impactful sectors.

Tabular Summary

We also extracted and presented two key tables: Emissions by Source in 2021 ($MtCO_2$)

Source	Mt_CO2_2021
Coal	29959.19616
Oil	23674.21485
Gas	15843.65894
Cement	3345.184746
Flaring	833.051123
Other	592.291496

Top 10 Countries by Average Emissions (2018–2022)

Country	Avg_Mt_CO2_2018_22
Global	36574.25041
China	10880.8639
USA	5089.707017
India	2595.400376
Russia	1693.146269
International Transport	1120.126733
Japan	1089.762461
Iran	720.6880858
Germany	693.9232398
Saudi Arabia	654.061352

Local Analysis: Jordan

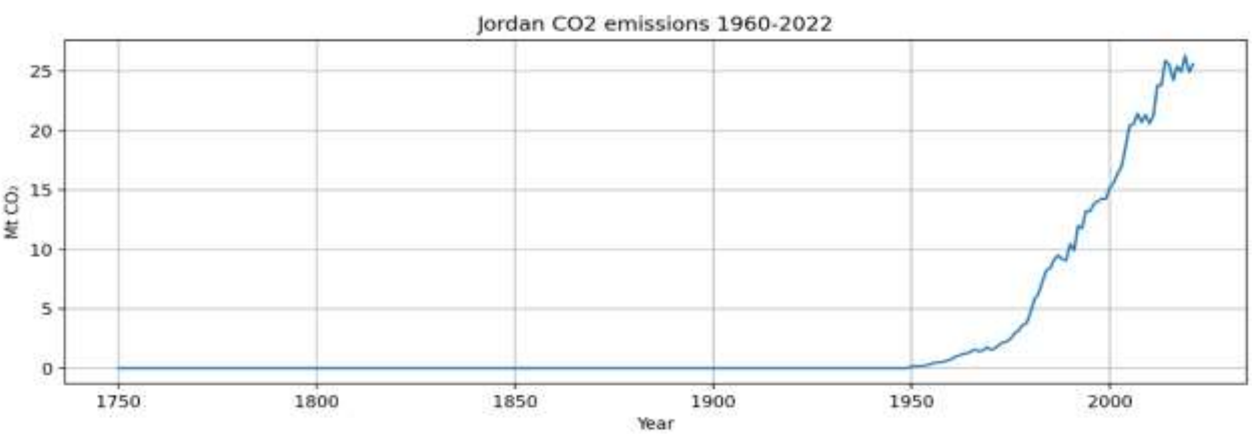


Figure 1: CO_2 Emissions in Jordan (1960–2022)

This line chart illustrates the historical trend of carbon dioxide (CO_2) emissions in Jordan from 1960 to 2022. Emissions were nearly negligible until the early 1970s, after which they began to rise steadily. A noticeable acceleration occurred after 1990 due to industrial expansion and population growth. In recent years, emissions appear to have plateaued at approximately 25–26 Mt CO_2.

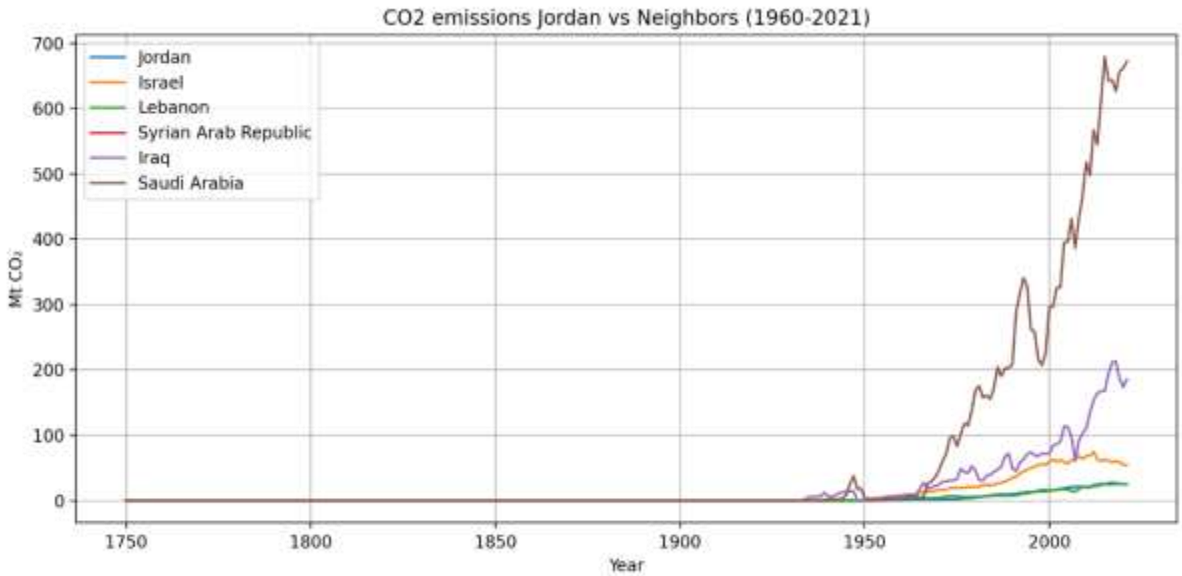


Figure 2: Jordan's CO_2 Emissions Compared to Regional Neighbors (2021)

This bar chart compares Jordan's total CO_2 emissions in 2021 to selected neighboring countries. Jordan emitted approximately 25.6 Mt CO_2, which is:

An order of magnitude lower than Saudi Arabia (~672 Mt)
Roughly one-seventh of Iraq (~186 Mt)
About half of Israel (~55 Mt)
Nearly equal to Lebanon (~25 Mt)

Insight: Jordan's total contribution to regional emissions is relatively small in absolute terms.

How Exploratory Data Analysis Informed Our Model Design

Before building the machine learning model, we conducted an exploratory data analysis (EDA) using both visualizations and AI-supported tools like Julius.AI. This step played a crucial role in shaping the design of our predictive model, ensuring we selected the right inputs, timeframe, and algorithm.

1. **Identifying Key Emission Sources**
   Through visual analysis (e.g., CO_2 emissions by source), we observed that coal, oil, and "Other" sources had the strongest correlation with total CO_2

emissions. This helped us focus on the most relevant features and exclude unnecessary ones from the model.

2. **Selecting a Suitable Timeframe**
   The dataset spans from 1750 to 2022, but our analysis showed that data before 1950 was incomplete or inconsistent. Therefore, we filtered the dataset to include only the 1950–2022 period, improving the accuracy and consistency of the model.
3. **Defining the Problem Type**
   From the structure of the data and the nature of the target variable (Total), it was clear that the task was a regression problem, not a classification problem. This directly informed our choice of using a Random Forest Regressor.
4. **Handling Missing or Corrupted Data**
   During the analysis, we discovered missing or invalid entries, especially in columns like Year and Total. Based on that, we implemented data cleaning techniques such as:
   Converting non-numeric values to NaN using errors='coerce'
   Dropping rows with missing critical values

Model Building and Evaluation

Following the data preparation phase, we developed a predictive model using the Random Forest Regressor algorithm to estimate the total carbon dioxide (CO_2) emissions based on a set of temporal and environmental variables.

1. Data Preprocessing

We began by loading the cleaned dataset and converting the categorical variable Country into a numeric format using label encoding to allow compatibility with the machine learning model. The features (X) included:
Year, Country_Code, Coal, Oil, Gas, Cement, Flaring, and Other
The target variable (y) was:
Total CO_2 emissions per country-year

The data was then split into training and testing subsets using an 80/20 ratio

Preprocessing Code:

```
import pandas as pd


try:
    df = pd.read_csv('GCB2022v27_MtCO2_flat.csv', encoding='utf-8', sep=';')
except UnicodeDecodeError:
    df = pd.read_csv('GCB2022v27_MtCO2_flat.csv', encoding='latin1', sep=';')


df.columns = df.columns.astype(str).str.strip().str.replace('\ufeff', '')


required_columns = ['Year', 'Country', 'Total', 'Coal', 'Oil', 'Gas', 'Cement', 'Flaring', 'Other']
missing_columns = [col for col in required_columns if col not in df.columns]


if not missing_columns:
    df['Year'] = pd.to_numeric(df['Year'], errors='coerce')
    df_filtered = df[df['Year'] >= 1950].dropna(subset=['Year']).copy()
    ml_df = df_filtered[required_columns].copy()
    ml_df['Year'] = ml_df['Year'].astype(int)
    ml_df.dropna(inplace=True)
    ml_df.to_csv('CO2_cleaned_1950_onwards.csv', index=False)
    print(ml_df.head())
    ml_df.info()
else:
    print(f"Missing columns: {missing_columns}")
    print(df.columns.tolist())
```

Model Training:

```
pip install -U scikit-learn

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error, root_mean_squared_error

df = pd.read_csv('CO2_cleaned_1950_onwards.csv')

df['Country_Code'] = df['Country'].astype('category').cat.codes

X = df[['Year', 'Country_Code', 'Coal', 'Oil', 'Gas', 'Cement', 'Flaring', 'Other']]
y = df['Total']

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

model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

r2 = r2_score(y_test, y_pred)
rmse = root_mean_squared_error(y_test, y_pred)

feature_importance = pd.Series(model.feature_importances_,
index=X.columns).sort_values(ascending=False)

print("R² Score:", r2)
print("RMSE:", rmse)
print("\nFeature Importances:")
print(feature_importance)
```

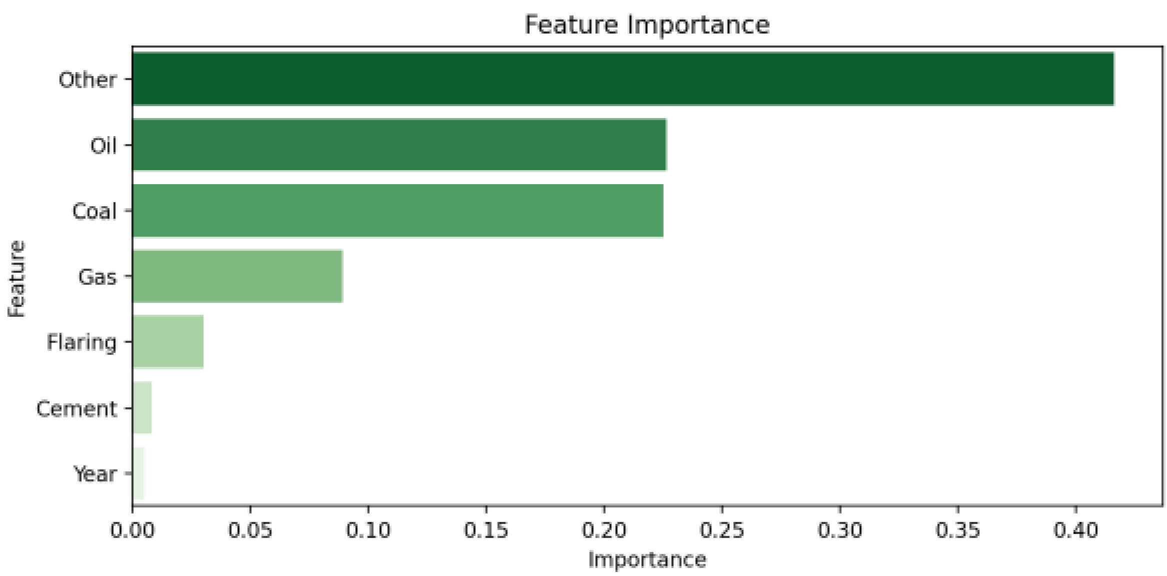
We used a Random Forest Regressor with 300 decision trees (n_estimators=300) and a fixed random seed (random_state=42) for reproducibility. The model was trained on the training set and evaluated on the test set.

The model achieved strong performance on the test data:

R^2 Score = 0.9997 → Explains 99.97% of the variance in the data
RMSE ≈ 75 Mt CO_2 → Low prediction error considering the wide range of national emissions

2. Feature Importance Analysis

A feature importance analysis based on Mean Decrease in Impurity (MDI) showed the following rankings:
Other: Most influential (≈ 41%)
Coal and Oil: Each contributing around 24%& 21%
Gas, Flaring, and Cement: Lesser impact



This confirms that fuel composition is the dominant driver of national CO_2 totals.

Future Integration with Cloud Computing

Although the model has not yet been deployed on cloud platforms (such as AWS or Alibaba Cloud) due to payment requirements, we have prepared an expansion plan that includes:

1. Storing the model in the cloud (e.g., Amazon S3 or Alibaba OSS).
2. Running it through scalable services (e.g., AWS Lambda or EC2).
3. Building an API to enable stakeholders to:
    - Input fuel consumption data.
    - Instantly receive emissions predictions.

Our Vision:
Making the Tool Open and Useful for All

We aim to transform this project into a public platform that allows governments and companies to:

1. Monitor carbon emissions in real time.
2. Evaluate the impact of environmental policies before implementation.
3. Contribute to achieving carbon neutrality through data-driven solutions.
4. Enable organizations and companies to monitor future carbon emissions accurately, as the tool provides a complete estimate of emissions as soon as consumption data is entered.

Future Expansion

We plan to enhance the project to include:

1. Additional data sources (e.g., electricity consumption, heavy industry emissions).
2. Modeling the impact of alternative solutions (e.g., renewable energy, efficiency improvements).

Partnerships with environmental organizations to maximize global impact

Use Cases / Real-world Applications

The predictive model we developed has a wide range of real-world applications that align with global sustainability and environmental governance (ESG) goals. It

can support decision-making, corporate reporting, and climate planning in multiple sectors:

1. **Environmental Policy Support**

   Governments and environmental ministries can use the model to forecast future CO_2 emissions and identify the most significant sources. This allows them to focus regulations and interventions on high-impact sectors.

2. **National ESG Performance Tracking**

   The model can serve as a tool for monitoring a country's progress toward its Net Zero goals. It also supports compliance with international climate agreements, such as the Paris Agreement.

3. **Corporate ESG Reporting**

   Organizations preparing ESG reports can leverage the model to quantify their carbon footprint and analyze the impact of various emission sources. It helps in identifying reduction opportunities and benchmarking progress.

4. **Interactive Dashboards and Cloud Deployment**

   By integrating the model with cloud computing platforms, a real-time dashboard can be developed. This would enable users (governments, companies, NGOs) to input emission data and instantly receive predictions and suggestions for emission reduction.

5. **Educational and Research Tool**

   The model can also be used in universities and research institutions to study global emission trends, explore fuel mix impacts, and support sustainability-related academic projects.

Use Case: Jordan as a Practical Example

Using our model, we analyzed CO_2 emissions in Jordan and found that:

Oil is the dominant source (~59%)

Followed by gas (~32%)

While coal, cement, and flaring contribute minimally These insights enable Jordan to prioritize reducing oil dependency and expanding clean energy alternatives, particularly in the power and transport sectors.

Conclusion

This project demonstrates the potential of machine learning in addressing one of the most pressing global challenges: carbon dioxide emissions. By building a predictive model based on historical CO_2 emission data from 1950 to 2022, we were able to accurately forecast total emissions using key fuel-type indicators such as coal, oil, gas, cement, flaring, and others.

The model, built using the Random Forest Regress or algorithm, achieved excellent performance with an R^2 score of 0.9997 and a root mean squared error (RMSE) of approximately 76 Mt CO_2. Feature importance analysis revealed that “Other” sources (e.g., biomass, unconventional fuels) have become the most influential factors in determining national emissions, followed closely by oil and coal.

Beyond its technical success, the model provides practical value. It can support governments in policy-making, assist companies in ESG reporting, and serve as a foundation for building interactive dashboards or cloud-based tools that offer real-time carbon forecasting and reduction insights.

Looking ahead, this model has the potential to be expanded and integrated with additional economic, demographic, and sector-specific data to further enhance its accuracy and applicability. With further development, it could become a powerful, scalable tool for climate action planning and sustainable development.

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Introduces eco2AI, a tool to measure ML model CO_2 emissions and guide energy-efficient design choices communities.springernature.com+6arxiv.org+6link.springer.com+6.
Also, tools like CodeCarbon and Green Algorithms support measuring and limiting AI's compute emissions is.ijs.si+4link.springer.com+4codecarbon.io+4