Predicting the Future of Clean Energy: How Machine Learning Can Accelerate SDG 7

# Introduction: The Clean Energy Challenge

In 2015, world leaders committed to ensuring access to affordable, reliable, sustainable, and modern energy for all by 2030 through the United Nations Sustainable Development Goal 7. Yet today, billions still lack access to clean energy, and the transition from fossil fuels remains one of humanity's greatest challenges.

The question isn't just "Can we transition to renewable energy?" but rather "How quickly can we do it, and what factors will make the difference?"

This is where Artificial Intelligence enters the conversation.

# The Problem: Why Countries Struggle with Renewable Energy Adoption

## The Current Landscape

As of 2020, renewable energy accounts for approximately 29% of global electricity generation. While this represents progress, the pace of adoption varies dramatically between countries. Some nations like Norway and Iceland generate over 90% of their electricity from renewables, while others remain heavily dependent on fossil fuels.

## Key Challenges

1. **Unpredictable Transitions:** Countries struggle to forecast their renewable energy adoption rates, making it difficult to plan infrastructure and investments.
2. **Resource Allocation:** Without predictive insights, governments can't effectively allocate budgets for solar panels, wind farms, or hydroelectric dams.
3. **Unrealistic Targets:** Many countries set ambitious renewable energy goals without understanding the factors that influence adoption success.
4. **Lack of Data-Driven Insights:** Policymakers often lack tools to understand which interventions will have the greatest impact.

# The Solution: Machine Learning for Energy Forecasting

## Our Approach

I developed a **Renewable Energy Adoption Predictor** using supervised machine learning to forecast renewable energy adoption rates based on historical data from 176 countries over 20 years (2000-2020).

## How It Works

The system analyses multiple factors that influence renewable energy adoption:

### Economic Indicators:

 GDP per capita

 GDP growth rate

 Energy intensity of the economy

### Energy Infrastructure:

 Current electricity from renewables  Fossil fuel electricity generation

 Nuclear energy capacity

### Social Factors:

 Population with access to electricity  Access to clean cooking fuels

 Population density

### Geographic Features:

 Country location (latitude/longitude)  Land area

 Natural resource availability

### Environmental Metrics:

 CO2 emissions per capita

 Low-carbon electricity percentage

## The Machine Learning Pipeline

### Step 1: Data Preprocessing

 Cleaned 3,649 data points across 21 features

 Handled missing values using median imputation  Applied standard scaling for numerical features

 Split data into 80% training and 20% testing sets

**Step 2: Model Training** We compared three supervised learning algorithms:

1. **Linear Regression:** A baseline model providing interpretability
2. **Random Forest Regressor:** An ensemble method that handles non-linear relationships
3. **Gradient Boosting Regressor:** Advanced boosting algorithm for maximum accuracy

**Step 3: Model Evaluation** Each model was evaluated using:

Mean Absolute Error (MAE)

Root Mean Squared Error (RMSE)

R² Score (percentage of variance explained) 5-fold Cross-Validation

# The Results: What We Discovered

## Model Performance

After rigorous testing, the **Random Forest Regressor** emerged as the best-performing model, achieving:

 High R² score indicating strong predictive power  Low prediction errors on unseen country data

 Robust cross-validation results

## Key Insights

### Most Influential Factors for Renewable Energy Adoption:

1. **Current Renewable Infrastructure:** Countries with existing renewable energy capacity are more likely to expand it further.
2. **Economic Development (GDP per capita):** Wealthier nations have more resources to invest in clean energy infrastructure.
3. **Access to Clean Cooking Fuels:** This indicator reflects overall energy access and infrastructure development.
4. **Energy Intensity:** Countries with higher energy efficiency tend to adopt renewables faster.
5. **Geographic Location:** Solar and wind potential vary significantly by latitude and climate.

## Real-World Applications

### For Policymakers:

Set evidence-based renewable energy targets

Identify which factors to prioritize for maximum impact Allocate budgets more effectively across clean energy initiatives Track progress against predictions and adjust strategies

### For International Organizations:

 Identify countries that need additional support

 Prioritize resource allocation for development aid  Monitor global progress toward SDG 7 targets

### For Investors:

Assess renewable energy investment opportunities Evaluate country-specific risks and opportunities

Make data-driven decisions about clean energy projects

# The Impact: How This Contributes to SDG 7

## Direct Contributions

1. **Accelerating Energy Transition** By providing accurate predictions, countries can move faster with confidence in their planning.
2. **Ensuring Affordability** Better planning reduces waste and keeps energy costs manageable for populations.
3. **Universal Access** The model helps identify barriers to electricity access and renewable adoption in underserved regions.
4. **Sustainability** Data-driven decisions lead to more sustainable long-term energy policies.

## Measurable Outcomes

 **Better Resource Allocation:** Countries can invest in the most impactful renewable energy projects

 **Reduced Carbon Emissions:** Faster renewable adoption means lower greenhouse gas emissions

 **Energy Security:** Diversifying energy sources reduces dependence on fossil fuel imports

 **Economic Growth:** Clean energy sector creates jobs and stimulates innovation

# Ethical Considerations: Building Responsible AI

## Addressing Bias

**Challenge:** Historical data may favour developed countries with better data collection systems, potentially creating biased predictions that disadvantage developing nations.

### Our Approach:

Included economic, geographic, and social factors to account for different starting points

 Used median imputation rather than dropping data from countries with missing information  Validated model performance across diverse regions

 Made the model transparent and explainable

## Fairness and Equity

**Principle:** AI should not perpetuate existing inequalities in energy access.

### Implementation:

 The model considers each country's unique context

 Features include both economic capacity and infrastructure gaps  Predictions account for different development stages

 Results are meant to guide, not dictate, human decision-making

## Data Privacy and Transparency

 All data used is publicly available and aggregated at country level  No individual or corporate data is involved

 Model methodology is open-source and reproducible

 Results are interpretable and explainable to non-technical stakeholders

## Sustainability of AI Itself

Machine learning models consume energy. We addressed this by:

Using efficient algorithms (tree-based methods over deep learning where appropriate) Training once and deploying for multiple predictions

Providing tools that prevent wasteful energy investments

Net positive impact: Better energy planning saves far more energy than the model consumes

# Technical Implementation: Tools and Technologies

## Technology Stack

**Programming Language:** Python 3.8+

### Core Libraries:

**pandas:** Data manipulation and analysis

**NumPy:** Numerical computing

**scikit-learn:** Machine learning algorithms and evaluation

 **matplotlib & seaborn:** Data visualization

### Machine Learning Techniques:

 Supervised Learning (Regression)

 Ensemble Methods (Random Forest, Gradient Boosting)  Cross-Validation for model robustness

 Feature Importance Analysis

## Development Environment

 **Google Colab / Jupyter Notebook:** For interactive development

 **GitHub:** Version control and collaboration

 **Kaggle:** Dataset source and community

## Why These Choices?

1. **Python:** Industry standard for data science with extensive ML libraries
2. **Scikit-learn:** Robust, well-documented, and production-ready algorithms
3. **Random Forest:** Handles non-linear relationships and provides feature importance
4. **Open Source:** All tools are free and accessible to everyone

# Lessons Learned: Challenges and Solutions

## Challenge 1: Missing Data

**Problem:** Many countries had incomplete data, especially developing nations and conflict zones.

**Solution:** Used median imputation strategically, ensuring we didn't drop entire countries from analysis.

## Challenge 2: Feature Selection

**Problem:** With 21 features, some were redundant or less relevant.

**Solution:** Applied domain knowledge about energy systems and used feature importance analysis to identify key predictors.

## Challenge 3: Model Interpretability

**Problem:** Complex models can be "black boxes" that policymakers don't trust.

**Solution:** Chose Random Forest for its balance of accuracy and interpretability, and provided feature importance visualizations.

## Challenge 4: Avoiding Oversimplification

**Problem:** Energy transitions involve complex political, social, and cultural factors beyond data.

**Solution:** Positioned the model as a decision-support tool, not a replacement for human judgment and local expertise.

# Future Enhancements: Taking It Further

## Phase 2: Real-Time Predictions

**Goal:** Integrate live data from World Bank and UN databases for up-to-date predictions.

### Implementation:

 API connections to data sources  Automated retraining pipeline

 Dashboard for real-time monitoring

## Phase 3: Interactive Web Application

**Goal:** Make the tool accessible to policymakers worldwide.

### Features:

 User-friendly interface for non-technical users  Country-specific recommendation engine

 Scenario analysis ("What if we increase clean fuel access by 20%?")  Downloadable reports for policy briefs

**Technology:** Streamlit or Flask for deployment

## Phase 4: Multi-SDG Integration

**Goal:** Expand beyond SDG 7 to show connections with other goals.

### Connections:

SDG 13 (Climate Action): Link renewable energy to carbon reduction SDG 8 (Decent Work): Model job creation in clean energy sector SDG 11 (Sustainable Cities): Urban energy planning

SDG 3 (Health): Reduced air pollution from clean energy

## Phase 5: Deep Learning Enhancement

**Goal:** Explore neural networks for time-series forecasting.

### Approach:

LSTM networks for multi-year predictions

Attention mechanisms to identify critical time periods Ensemble of traditional ML + deep learning

# Call to Action: How You Can Contribute

## For Fellow Developers

1. **Fork the GitHub Repository:** Improve the code, add features, fix bugs
2. **Test with Different Datasets:** Validate the approach with regional data
3. **Build Complementary Tools:** Create visualization dashboards or mobile apps
4. **Contribute to Documentation:** Help make the project more accessible

## For Policymakers and Organizations

1. **Test the Model:** Use it for your country or region's energy planning
2. **Provide Feedback:** Share what works and what needs improvement
3. **Share Data:** Contribute additional datasets to improve accuracy
4. **Adopt the Insights:** Let data guide your renewable energy strategy

## For Researchers and Students

1. **Validate the Approach:** Conduct peer review and academic analysis
2. **Extend the Research:** Explore related problems in sustainability
3. **Teach with It:** Use this project in ML courses and workshops
4. **Publish Findings:** Write papers on AI for sustainable development

# Conclusion: AI as a Force for Good

The transition to clean energy is not just a technical challenge—it's a moral imperative. By 2030, we must ensure that everyone has access to affordable, reliable, and sustainable energy. This isn't just about meeting UN targets; it's about:

**Fighting climate change** and preserving our planet for future generations

**Improving health** by reducing air pollution from fossil fuels

 **Creating economic opportunities** in the growing clean energy sector

 **Ensuring equity** so that everyone benefits from modern energy access

Machine learning offers powerful tools to accelerate this transition. But technology alone isn't enough. We need:

 **Ethical AI development** that prioritizes fairness and transparency

 **Collaboration** between data scientists, policymakers, and communities

 **Human-centred design** that puts people's needs first

 **Continuous learning** as we gather more data and refine our models

This project demonstrates that AI can be more than a business tool—it can be a catalyst for sustainable development and social good. By predicting renewable energy adoption, we're not just making forecasts; we're helping write a better future.

# Key Takeaways

1. **Machine learning can predict renewable energy adoption** with high accuracy using historical data and multiple influencing factors.
2. **Economic development, existing infrastructure, and social factors** are the strongest predictors of renewable energy success.
3. **Ethical AI development is crucial** to ensure predictions don't perpetuate inequalities or disadvantage developing nations.
4. **This approach is scalable and replicable** for other SDGs and sustainability challenges.
5. **Data-driven decision-making** enables faster, more effective progress toward global clean energy goals.

# Resources and Links

**GitHub Repository:** <https://github.com/Phitah02/AI-Machine-Learning-Assignment>

**Live Demo:** [Coming Soon]

**Dataset Source:** [Kaggle Link](https://www.kaggle.com/datasets/anshtanwar/global-data-on-sustainable-energy/data)

**UN SDG 7 Information:** <https://sdgs.un.org/goals/goal7>

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# About the Author

**Peter Kamau Mwaura** is a data scientist and machine learning enthusiast passionate about using AI for social good. This project was developed as part of the PLP Academy AI/ML program, combining technical skills with a commitment to sustainable development.

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### "The future of energy is clean, accessible, and powered by intelligent systems. Together, we can make SDG 7 a reality."

🌍 Let's code for a better world! 🌟

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