AI-Driven Climate Change Model: Dataset, Feature Selection, Modeling Methods, and Justification

1. Dataset Overview and Source

The data set used in this project is the Climate Change Dataset on Kaggle by Bhadra Mohit. It contains 1000 rows and 10 columns of climate and population data from various countries for certain years. It contains climate columns such as carbon dioxide emissions, sea level rise, rainfall, and temperature and socio-economy columns such as population and consumption of renewable power. One row is the snapshot of one year's climate of the country and hence can be used both for classification (temperature prediction from the risk category) as well as regression (prediction of mean temperature).

It's from reputable sources like NASA, NOAA, and the United Nations, and it's in machine learning-easy-to-consume format too. Its tabular format, tidiness, and having almost no missing values make it a great one to experiment with and test various AI models without necessarily needing to worry about fancy preprocessing.

2. Column-wise Description

The dataset includes the following key columns:

- The data set consists of the following primary columns:
- Year – Year in which data were gathered.
- $.Country – The country involved.
- Avg Temperature (°C) – Average temperature per year, our dependent variable.
- CO2 Emissions (Tons/Capita) refers to the CO_2 per capita emissions, which is one of the most powerful drivers of climate change.
- Sea Level Rise (mm) – Sea level rise due to glaciemelt and thermal expansion.
- Rainfall (mm) – Total annual precipitation, a measure of hydrological cycle variation.
- Population – Total National Population.
- Renewable Energy (%) – Percentage of renewable energy in the country's energy market.

- Severe Meteorological Events – Event frequency of occurrences like heatwaves or storms.
- Forest Area (%) – Forest area percentage, a carbon sink.

3. Why This Dataset Was Selected

This data set has been selected because it has been well balanced between exhaustiveness and utility. Data sets like ClimateSet (CMIP6) and ERA5 Reanalysis are highly exhaustive and need to be interpreted in the domain knowledge context and preprocessed in a way so that they are useful in a meaningful sense. They are typically offered in high-level formats like NetCDF and are meant for scientific simulation, not machine learning.

The Kaggle data is pre-formatted, pre-cleaned, and pre-tagged with informative variables ready for model construction. It is also ready for rapid deployment of artificial intelligence models like Random Forest, LSTM, and Gradient Boosting and explainable artificial intelligence package compliant like SHAP and LIME. It is therefore ready for instant scholarly testing, light forecasting, and scenario planning.

4. Feature Selection and Standardization

Seven features were selected based on exploratory data analysis (EDA) and domain relevance. These are:

1. CO2 Emissions (Tons/Capita)
2. Sea Level Rise (mm)
3. Rainfall (mm)
4. Population
5. Renewable Energy (%)
6. Extreme Weather Events
7. Forest Area (%)

Feature selection was guided by correlation analysis and domain knowledge. For example, **CO_2 emissions and population** are known contributors to temperature change, while **renewable energy usage and forest area** act as mitigating factors. After selection, all features were **standardized using StandardScaler** to bring them to a common scale, improving model training stability and speed.

5. Modeling Methods

Regression Task

The goal was to predict the continuous value of **average temperature** using selected features. Models used:

- **Random Forest Regressor**
- **LSTM (Long Short-Term Memory) Neural Network**
- **Transformer-based Regressor**

Performance was measured using **Root Mean Squared Error (RMSE)**. Among these, **Random Forest** delivered the best balance of accuracy and interpretability.

Classification Task

For classification, the target temperature variable was binned into four categories: **Low**, **Moderate**, **High**, and **Extreme**. Models used:

- **Gradient Boosting Classifier**
- **XGBoost Classifier**
- **MLP Classifier**

The classifiers were trained and evaluated using accuracy and F1-scores. **Gradient Boosting** performed the best and was selected as the final classification model.

6. Model Selection and Justification

Random Forest Regressor

This model was chosen for its **high accuracy, robustness to overfitting, and ease of interpretation**. It performed well on the dataset, achieving the lowest RMSE (~1.12°C). Additionally, it supports **feature importance ranking** and can be explained using **SHAP**, making it ideal for real-world climate applications.

LSTM and Transformer

These deep learning models were evaluated due to their strength in **time-series forecasting**. While LSTM captured sequential trends well (RMSE ~1.37), it required significant computation. The Transformer model achieved RMSE ~1.45 and showed promise but was more resource-intensive and harder to interpret. Hence, these were retained for comparative insights rather than final deployment.

Gradient Boosting for Classification

Gradient Boosting yielded high training accuracy and stable learning curves. It was selected for **future scenario-based climate risk classification**, especially in predictive use cases involving multiple emission scenarios.

7. Literature Survey (5 Papers)

Artificial Intelligence (AI) has emerged as a powerful tool for modeling climate change. Recent literature explores the effectiveness of various models and interpretability frameworks. This section highlights five key studies that inform the methodologies used in this project.

Agrawal (2023) explores generative AI in sustainability, emphasizing interpretable models like **Random Forest** and **XGBoost** for system optimization under constraints. His work supports using these models for both prediction and resource-aware forecasting. Amiri et al. (2024) offer a comprehensive review of AI techniques for climate change mitigation. They highlight **tree-based ensembles** and **LSTM networks** as effective for capturing complex, nonlinear climate patterns—aligning closely with the model choices in this project.

Cavus et al. (2025), although focused on electric vehicles, demonstrate the strength of **LSTM models** in handling time-series data, reinforcing their use in climate forecasting tasks involving temporal dependencies. Chakraborty et al. (2021) advocate for **explainable AI (XAI)** in environmental prediction, using SHAP for model transparency. Their scenario-based modeling approach mirrors this project's use of SHAP and LIME. Chang and Kidman (2023) stress the ethical importance of using interpretable models in climate education. They argue against black-box models, validating the use of transparent techniques like Gradient Boosting in public tools.

Together, these studies support the integration of ensemble and deep learning models, explainability, and scenario planning. However, most fail to combine all elements cohesively—this project addresses that gap by unifying forecasting, classification, and interpretability into one AI pipeline.

8. Final Model Selection and Explainability

Based on comparative results, the final models selected are:

- **Random Forest Regressor** – For continuous temperature prediction.

- **Gradient Boosting Classifier** – For temperature classification and risk scenario generation.

These models deliver high accuracy and allow integration with **SHAP (global interpretability)** and **LIME (local interpretability)** frameworks, ensuring **transparency** and **trust** in predictions.

This project combines a well-curated climate dataset with proven machine learning techniques to develop a predictive system for climate change modeling. The selected features capture a wide array of environmental dynamics, and the use of interpretable models ensures responsible AI deployment. Through model comparison, literature grounding, and scenario simulations, the system provides a meaningful step toward data-driven climate forecasting.

References

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