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# Machine Learning Insights into Nordic CO2 Emission Trends

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## Abstract

Rapid industrial development has substantially increased carbon emissions, leading to heightened concentrations of greenhouse gases and resultant climate change. This phenomenon poses diverse threats, including risks to food security, water availability, extreme weather events, disease proliferation, economic downturns, and population migration. Recognizing climate change as the greatest threat to global health, the World Health Organization (WHO) emphasizes its significance. Since 1970, CO<sub>2</sub> emissions have surged by 90%, comprising 78% of total greenhouse gas emissions. Predicting these emissions is challenging due to dynamic scenarios influenced by climate impacts, carbon factors, and socio-economic attributes, rendering accurate prediction crucial yet complex. To address this complexity, artificial intelligence and machine learning techniques are increasingly utilized to study environmental phenomena characterized by high variability. This paper conducts a thorough analysis of CO<sub>2</sub> emission predictions for Nordic countries (Denmark, Norway, Sweden, Finland, and Iceland) spanning from 2018 to 2029. Employing data exploration, visualization, and machine learning techniques, the study leverages the International Greenhouse Gas Emissions dataset, spanning from 1990 to 2017. The research seeks to unravel historical emission trends and forecast future CO<sub>2</sub> levels. Methodologically, it encompasses data preprocessing, exploratory analysis, and the application of machine learning models, including multiple linear regression, ridge regression, lasso regression, and polynomial regression. The findings reveal varying predictive capabilities, with polynomial regression emerging as the standout performer. In the context of model performance, the polynomial regression model exhibits noteworthy results, with a mean absolute error (MAE) of 18667.84, a root mean squared error (RMSE) of 53277.75, an R-squared value of 0.995, and an explained variance of 0.995. This superior performance positions polynomial regression as a robust choice for predicting CO<sub>2</sub> emissions, particularly in capturing nonlinear relationships in environmental phenomena. The analysis extends further, encompassing a detailed examination of country-specific observations, yearly changes, and recommendations for effective emission reduction strategies.

**Keywords:** Nordic Countries, CO<sub>2</sub> Emissions, Machine Learning, Polynomial Regression

## 1. Introduction

Climate change poses a significant threat to all living organisms worldwide, impacting various aspects such as food security (Wiebe, Robinson, & Cattaneo, 2019), escalating water scarcity (Ismail and Go, 2021), disturbing environmental equilibrium, increasing the frequency of extreme weather events

(Phelan, 2011), and fostering the emergence of new diseases (El-Sayed and Kamel, 2020). These challenges contribute to stress on public health systems, socio-economic issues, unemployment, and migration (Hernández-Delgado, 2015). Recognizing the severity of the situation, the World Health Organization (WHO) has declared climate change as the most substantial threat to global health in the 21st century (Goklany, 2009).

Climate change, often attributed to anthropogenic activities, refers to alterations in Earth's climates on various scales—local, regional, and global—since the pre-industrial period, dating back to 1850 (Kumar, 2023). The primary contributors to this phenomenon are the burning of fossil fuels and deforestation, leading to a rapid surge in carbon dioxide concentration in the Earth's atmosphere (Baes, Goeller, Olson, & Rotty, 1977). Notably, since 1970, CO<sub>2</sub> emissions have surged by approximately 90%, resulting in a 78% increase in total greenhouse gas (GHG) emissions (McKinnon, 2012).

Research reports emphasize the global energy system as a major human-induced source of carbon dioxide emissions, crucial for the economic development of nations reliant on energy for production and services. Mitigating climate change involves exploring scenarios to transform global energy systems and reduce greenhouse gas emissions (Lin and Li, 2011).

In recent years, the Nordic countries—Denmark, Finland, Iceland, Norway, and Sweden—have emerged as prominent leaders in the green transition, symbolizing a shift away from fossil fuel-based economies toward sustainable, renewable energy sources. According to the World Bank, all five nations rank among the top 20 globally in renewable energy production per capita, reflecting their commitment to fostering a sustainable and green economy. This dedication is emphasized by ambitious targets aimed at lowering carbon emissions and increasing the utilization of renewable energy sources (Aslani, Antila, & Wong, 2012).

In 2020, the Nordic region witnessed a substantial reduction of over ten percent in greenhouse gas emissions, attributed to the global impact of the COVID-19 pandemic (Guevara et al., 2022). This notable decline, surpassing expectations despite a prolonged downward trend, was particularly evident in the energy sector, responsible for 68 percent of total emissions over the past decade. Notably, this sector experienced a remarkable 59 percent reduction in 2020 (Monitor, 2020). The international aviation sector, with comparatively smaller emissions, also saw a significant 67 percent decline due to travel restrictions. Figure 1 illustrates data from the Nordic Statistics Database, specifically EMIS11, focusing on Greenhouse Gas Emissions. The information pertains to national emissions measured in 1000 tonnes of CO<sub>2</sub> equivalents, organized by reporting country, sector, and a time span ranging from 1990 to 2020. Variations in emissions among Nordic countries—Denmark, Finland, Norway, and Sweden—stemmed from distinct fossil fuel and industrial usage patterns.

While the Nordic region possesses a relatively decarbonized electricity supply, per capita greenhouse gas emissions slightly surpass those of other industrialized regions due to a cold climate and the prevalence of energy-intensive industries. Recognizing the unique emission compositions of each country, Nordic nations have set ambitious emission reduction targets for 2050, highlighting the necessity for tailored strategies (Egeli, 2023). Iceland, exhibiting the highest per capita emissions, contrasts with

Norway's elevated energy consumption offset by a renewable electricity supply, while Sweden achieved lower per capita emissions through nuclear power and a transition to biofuels (Lind et al., 2023).

The importance of predicting carbon dioxide emissions is particularly accentuated for northern countries with unique geographical and climatic conditions, rendering them more susceptible to the impacts of climate change. Accurate predictions empower policymakers, researchers, and industries to formulate targeted strategies, addressing the specific challenges and opportunities inherent in the northern climate.

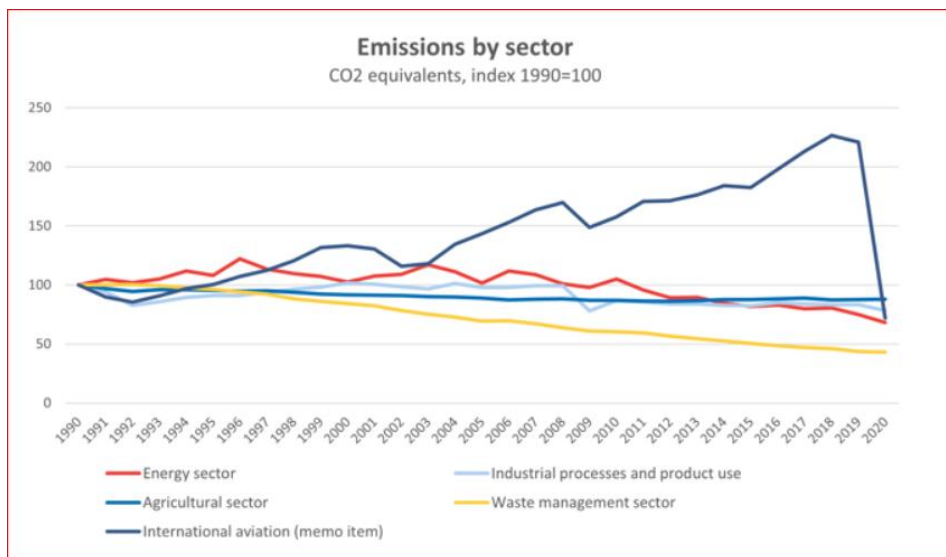


Figure 1: Nordic Greenhouse Gas Emissions (1990-2020) ("EMIS11: Greenhouse gases, national emissions in 1000 tonnes CO2 equivalents by reporting country, sector and time," 2023).

Achieving effective emissions reduction necessitates a multifaceted approach, integrating precise modeling and prediction of greenhouse gas concentrations and identifying contributing factors at individual, community, and national levels. This endeavor involves leveraging data science and methods based on artificial intelligence to comprehend emission trends and gain insights, with the aim of formulating effective reduction strategies (Dwivedi et al., 2022).

Machine Learning (ML) is a branch of artificial intelligence that involves the development of algorithms and statistical models enabling computer systems to learn and improve task performance without explicit programming. ML has found widespread applications across various domains. It has been employed in temperature prediction (Y. Wang et al., 2023), heating and cooling load prediction (Guo et al., 2023), stock price prediction and data analysis (M. AL-ASADI, 2022; Mukherjee, Sadhukhan, Sarkar, Roy, & De, 2023). Additionally, ML has been instrumental in cancer prediction and healthcare (M. Al-Asadi and Altun, 2022; Mustafa A Al-Asadi and Tasdemir, 2022; Belmili, Chelabi, & Kermi, 2023), sports analytics (Mustafa A Al-Asadi and Tasdemir, 2022; Mustafa A Al-Asadi and Tasdemir, 2021; Mustafa AADEL AL-ASADI, TAŞDEMİR, & TEZCAN, 2018; TAŞDEMİR and AL-ASADI, 2018), computational journalism (Mustafa A Al-Asadi and Tasdemir, 2022), traffic accident prediction, smart city technologies (Chhabra, Aiden, Sabharwal, & Al-Asadi, 2023; Yadav, Mitra, Kumar, Bhushan, & Al-Asadi, 2023), and cyber security (Aiden, Sabharwal, Chhabra, & Al-Asadi, 2023). The versatility of ML underscores its significance in advancing predictive modeling and analysis across diverse fields.

The studies on CO2 emission prediction cover a variety of techniques and methodologies. Sachin Kumar (2023) introduces a hybrid machine learning model, merging PCA and Linear Elastic Regression, outperforming traditional model (Kumar, 2023). Ankit Prakash and Sunil Kumar Singh (2023) focus on predicting CO2 emissions from coal sources, emphasizing the importance of tailoring methodologies (Prakash and Singh, 2023). Run Liu et al. (2023) propose a novel model for estimating emissions from LDGVs in China, enhancing prediction accuracy (Liu et al., 2023). B. Durga Bhavani et al. (2023) address CO2 emissions through machine learning models and EDA, providing valuable insights for policymakers (Bhavani, Sreeja, Prasanna, Tapasya, & Priyanka, 2023). Khalid Almutairi et al. (2022) predict CO2 emissions for 2040 in Saudi Arabia, highlighting the importance of optimal system configurations (Almutairi, Almutairi, Harb, & Marey, 2022). Weijun Wang and Jixian Wang (2021) examine CO2 emissions in China's transport sector, crucial for carbon peak commitments (W. Wang and Wang, 2021). Mamdouh el haj and Assad Mamdouh (2021) predict CO2 emissions for Middle Eastern countries with high accuracy using MLP ANN (Assad, Mahariq, Al Barakeh, Khasawneh, & Amooie, 2021). Mohammad Ghalandari et al. (2021) forecast carbon dioxide emissions in European countries, with MLP preferred for its effectiveness (Ghalandari, Forootan Fard, Komeili Birjandi, & Mahariq, 2021). Shisheng Chen et al. (2018) focus on indoor air quality audits, emphasizing challenges in predicting HCHO (Chen, Mihara, & Wen, 2018). Weibo Zhao and Dongxiao Niu (2017) predict CO2 emissions in China's power generation industry, suggesting advancements in prediction models (Chen, et al., 2018). Tan Chun Ho et al. (2015) present an efficient regression model for predicting CO2 emissions from the manufacturing industry and construction sector in Malaysia (Ho, Mat, & San, 2015). Finally, Yang Yanli et al. (2013) contribute a composite regression method to estimate CO2 emissions reduction from biogas utilization in China, offering trustworthy simulation results (Yang, Li, & Zhang, 2013).

Table 1 summarizes the most critical recent research directed towards studying in the area of CO2 emission prediction using machine learning and deep learning techniques ; the comparison has been made in terms of classifier, data type, Highlights and assessment.

Table 1: Comparative Summary of Recent Research on CO2

Authors	Classifier	Data Type	Highlights	Assessment
Sachin Kumar, 2023.	Hybrid model (PCA and linear elastic regression)	Time-series (1960-2018), Socio-economic, Energy	Outperforms Linear Regression, Support Vector Regression, and deep learning. MAE: 0.0307, RMSE: 0.0346. Computational efficiency (12.4 ms). Real data from Indian government records. Valuable insights for policymakers.	Comprehensive performance and efficiency demonstrated. Real-world application.
Ankit Prakash & Sunil Kumar Singh, 2023.	Univariate and multivariate time-series models (Autoregression)	Coal supply, CO2 emissions, Peak demand, Peak met (2005-2021)	Comparative study between univariate and multivariate analysis. Performance metrics evaluation. Extends findings to forecast CO2 emissions (2022-2050).	Autoregression ranked 1.85 based on Friedman ranking. Comprehensive evaluation of model performance.
Run Liu, Hong-di He, Zhe Zhang, Cui-lin Wu, Jin-ming Yang, Xing-hang Zhu, Zhong-ren Peng, 2023.	Integrated MOVES model and Machine Learning (Boruta algorithm)	Light-duty gasoline vehicles (LDGVs) emissions	Proposes novel model combining ML and MOVES. Enhances prediction accuracy for NO and CO2	Improved R2 values (average improvement: CO2 0.132, NO 0.261). Valuable insights for LDGV emissions

			emissions. Outperforms MOVES. Valuable insights for refining MOVES.	prediction.
B. Durga Bhavani, K. Sreeja, M. Sai Prasanna, M. Tapasya, M. Priyanka, 2023.	Various Machine Learning Approaches with Exploratory Data Analysis	Not specified	Leverages machine learning models and EDA to predict and forecast CO2 emissions. Emphasizes accurate predictions for effective policies and resource optimization.	Focuses on the critical issue of CO2 emissions. Incorporates EDA for better understanding of data patterns.
Khalid Almutairi, Mubarak Almutairi, Kamal Harb, Omar Marey, 2022.	Machine Learning Methods (MLP and SVR)	Various parameters (GDP, population, oil consumption, natural gas consumption, renewable consumption)	Predicts CO2 emission and electricity consumption for 2040. Determines optimal system configurations. Considers various conditions and factors.	Comprehensive predictions with R2 values of 0.99. Proposed systems achieve economic and environmental sustainability.
Weijun Wang & Jixian Wang, 2021.	Bio-inspired prediction model (MRFO-ELM)	Thirteen influencing factors in China's transport sector	Proposes MRFO-ELM for predicting and understanding determinants of CO2 emissions. Identifies significant factors. Projects peak emissions under different scenarios.	Demonstrates excellent optimization and prediction accuracy. Addresses carbon peak commitments.
Mamdouh El Haj & AssadMamdouh, 2021	MLP ANN (Multilayer Perceptron Artificial Neural Network)	Energy consumption, Share of energy sources, Economic activities	Predicts CO2 emissions for seven Middle Eastern countries. Logsig transfer function yields R-squared value of 0.9998.	High accuracy demonstrated with effective model structure.
Mohammad Ghalandari et al., 2021	ANNs (GMDH and MLP)	Energy resource consumption, GDP	Forecasts CO2 emissions in four European countries. Achieves high R-squared values (0.9999). MLP preferred for lower average relative error.	Strong performance with both GMDH and MLP models. MLP preferred for modeling accuracy.
Shisheng Chen, Kuniaki Mihara, Jianxiu Wen, 2018.	SVM, GP, M5P, BPNN	Time series data in five rooms at SDE, NUS	Focuses on time series prediction of indoor air pollutants. SVM outperforms in accuracy. High predictability for CO2 and TVOC.	Pioneers machine learning in predicting air pollutants. Highlights algorithm impact on accuracy.
Weibo Zhao and Dongxiao Niu, 2017.	Gauss-Optimized Cuckoo Search Algorithm, Wavelet Neural Network, Ridge Regression	STIRPAT model factors (Population, per capita GDP, standard coal consumption, thermal power specific gravity)	Focuses on predicting CO2 emissions in China's power generation industry. Introduces GCS-WNN model. Exhibits higher prediction accuracy.	GCS-WNN model exhibits superior accuracy. Indicates a slowing down of CO2 emission growth.
Tan Chun Ho, Sim Chong Keat Mohd Zubir Mat Jafri and Lim Hwee San, 2015.	Regression Model	GDP, electricity production and consumption, FDI income	Introduces regression model for predicting CO2 emissions. Demonstrates high correlation coefficient and efficiency.	High correlation coefficient (adjusted R2 = 96.75%). Offers valuable insights for early warnings and compliance.
Yang Yanli, Li Guangquan, Zhang Peidong, 2013.	Composite Regression Method	Various factors related to biogas utilization	Presents composite regression method for estimating CO2 emission reductions from biogas utilization. Indicates trustworthy simulation results.	Reflects numerical relations effectively. Provides useful simulation results for CO2 emission reductions.

Drawing upon existing literature, our research seeks to address significant gaps in the current understanding of CO<sub>2</sub> emission prediction. While previous studies have made substantial progress, there are specific areas that warrant attention to enhance the comprehensiveness and applicability of predictive models.

To begin with, there is a recognized need to advance research efforts towards developing models with global applicability and ensuring comparability across diverse regions. Existing studies indicate an underexplored aspect in this regard. Therefore, our focus is on adapting models for diverse geographical contexts, specifically targeting Nordic countries, in response to the observed US- and China-centric focus in prior research.

Additionally, it is evident that while various models have been employed for predicting carbon dioxide emissions, there is a notable gap in exploring a comprehensive suite of regression techniques that capture both linear and nonlinear relationships. The selected studies exhibit a range of methodologies, yet there is a lack of systematic integration of traditional regression models, such as multiple linear regression, ridge regression, lasso regression, and polynomial regression. Our proposed models strategically combine these techniques, leveraging the strengths of each to provide a nuanced examination of the intricate relationships governing carbon dioxide emissions.

Furthermore, the dataset chosen for our study, the International Greenhouse Gas Emissions database, offers a notable advantage over many other datasets used in the literature. It provides a comprehensive and up-to-date global perspective on greenhouse gas emissions, covering the period from 1990 to the latest available year. Notably, this dataset is aligned with scientific guidance from the Intergovernmental Panel on Climate Change (IPCC), adhering to established protocols and ensuring the reliability and accuracy of the data.

Moreover, our research aims to fill a gap in comprehensive studies that intersect economic, environmental, and technological factors within the context of predicting CO<sub>2</sub> emissions. Focusing on Nordic countries, we seek to contribute to the advancement of knowledge in sustainable energy systems by considering the intricate interplay between economic, environmental, and technological factors.

In conclusion, the identified gaps in the surveyed literature guide our research towards a more nuanced and region-specific exploration of CO<sub>2</sub> emission prediction, contributing to the broader field of environmental science and sustainability.

**The main contributions of the research paper are as follows.**

- Bridged gaps in CO<sub>2</sub> emission prediction studies using a robust global dataset, specifically the International Greenhouse Gas Emissions dataset spanning from 1990 to 2017. To our knowledge, this dataset has not been previously utilized in any research or academic investigation.
- Provided tailored insights for Nordic countries (Denmark, Norway, Sweden, Finland, and Iceland), addressing a significant research gap in understanding CO<sub>2</sub> emissions for this region from 2018 to 2029.

- Developed a comprehensive understanding of emission complexities by employing both linear and nonlinear models, identifying varying predictive capabilities among different machine learning models, and contributing to a nuanced exploration of historical emission trends.
- Advanced methodological approaches in CO<sub>2</sub> emission prediction studies through a systematic methodology involving data preprocessing, exploratory data analysis, and the implementation of diverse machine learning models.
- Recognized Polynomial Regression as the standout model with superior predictive capabilities, particularly in capturing nonlinear relationships in environmental phenomena.

The rest of the paper is organized as follows: Section 2 introduces the International Greenhouse Gas Emissions dataset, detailing its unique features. In Section 3, the methodology, including data collection, preprocessing, and machine learning model application, is outlined. Section 4 elaborates on the theoretical foundations and implementation of Multiple Linear Regression, Ridge Regression, Lasso Regression, and Polynomial Regression (Machine Learning Algorithms). Section 5 evaluates model performance and explores parameter tuning. Section 6 presents a comparative analysis of predictive capabilities in Results and Discussion. Finally, Section 7 provides a concise Conclusion.

## **2. Data set Description**

The dataset chosen for the analysis, is sourced from the International Greenhouse Gas Emissions database. To the best of our knowledge, this dataset has not been previously utilized in any research or academic investigation. This dataset provides a comprehensive global inventory of Greenhouse Gas (GHG) emissions spanning from 1990 to 2017. It houses the most recently submitted data, covering anthropogenic emissions and removals of various GHGs, including carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), an unspecified mix of HFCs and PFCs, sulfur hexafluoride (SF<sub>6</sub>), and nitrogen trifluoride (NF<sub>3</sub>). Notably, these gases are not controlled by the Montreal Protocol. Parties to the Convention develop GHG emission inventories using scientific methodologies provided by the Intergovernmental Panel on Climate Change (IPCC). This guidance includes references to key documents like the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Revised Guidelines for National Greenhouse Gas Inventories (1996), IPCC Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories (2000), and IPCC Good Practice Guidance on Land Use, Land-use Change, and Forestry (2003). The original dataset can be accessed on Kaggle via the following link: [International Greenhouse Gas Emissions](<https://www.kaggle.com/datasets/unitednations/international-greenhouse-gas-emissions>).

## **3. Methodology**

The methodology adopted for this research is designed to comprehensively investigate and predict carbon dioxide (CO<sub>2</sub>) emissions in Nordic countries—specifically, Denmark, Norway, Sweden, Finland, and Iceland—over the period from 2018 to 2029. The process involves a systematic sequence of steps, encompassing data collection, preprocessing, exploratory data analysis (EDA), model training, and prediction. The execution of methodology is shown in Figure 2.

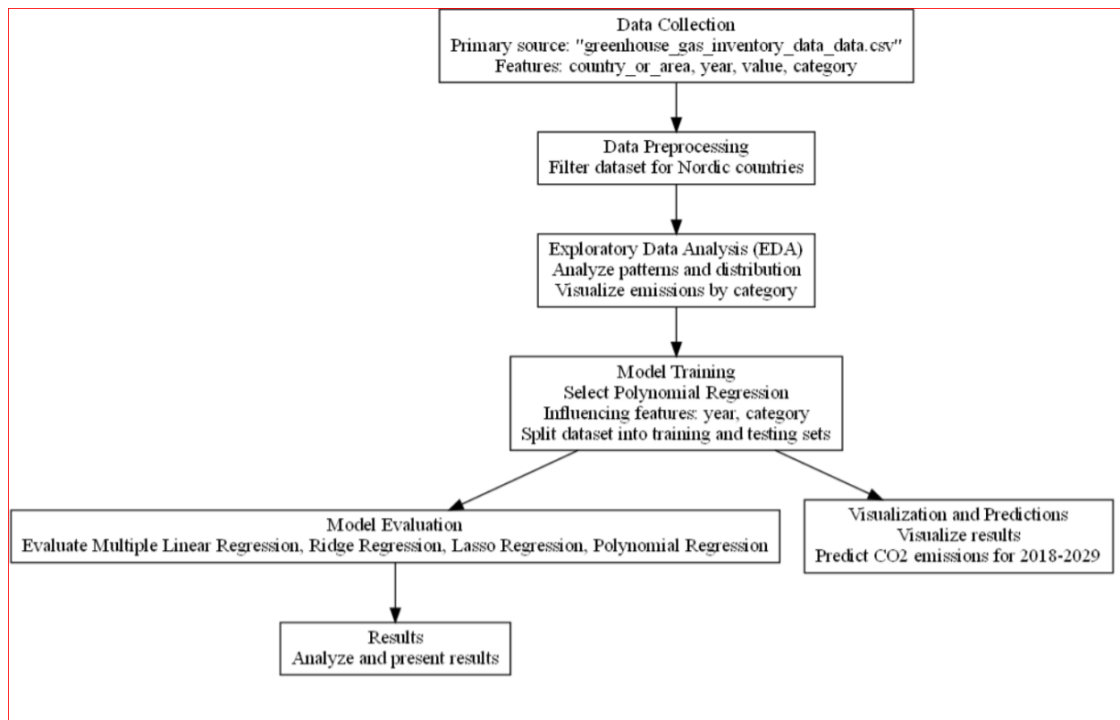


Figure 2: Steps of proposed methodology

### 3.1 Data Collection

The analysis begins with importing essential libraries in Python and loading the greenhouse gas emissions dataset, named *"greenhouse\_gas\_inventory\_data\_data.csv."* The dataset provides information about carbon dioxide (CO2) and other greenhouse gas emissions from various countries over the years. The dataset is explored using summary statistics, such as the count of emissions by gas category, as illustrated in Figure 3. This dataset is loaded into a Pandas DataFrame, with a focus on key features such as *'country\_or\_area,' 'year,' 'value,'* and *'category.'*

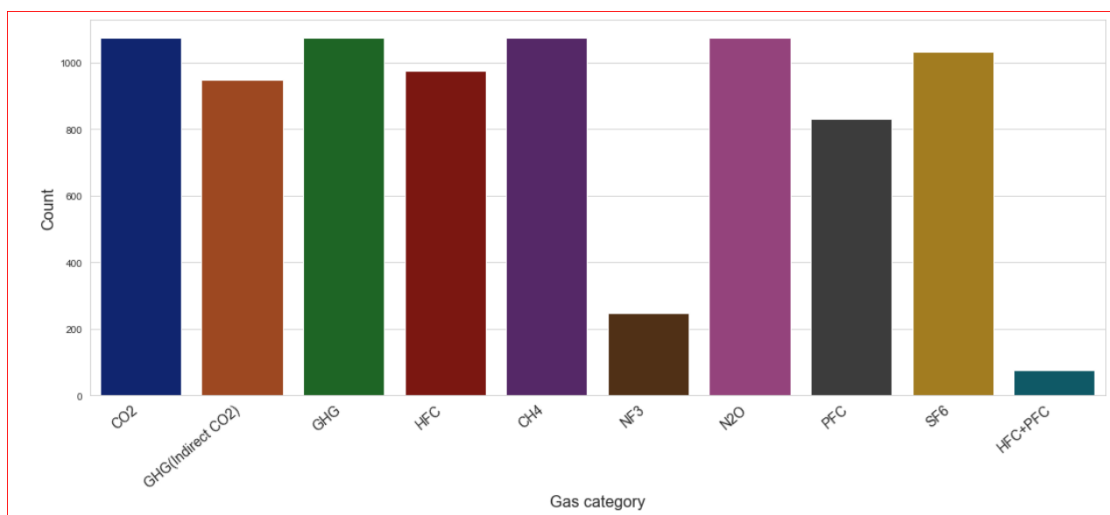


Figure 3: Emission Dataset Overview

### ***3.2 Data Preprocessing***

Following data collection, the preprocessing stage is executed to refine and organize the data. The dataset is filtered to include solely the Nordic countries of interest, namely Denmark, Norway, Sweden, Finland, and Iceland. This step ensures that subsequent analyses are confined to this specific geographical region.

### ***3.3 Exploratory Data Analysis (EDA)***

Moving on to exploratory data analysis (EDA), this pivotal phase involves gaining insights into the patterns and distribution of CO2 emissions. Visualization techniques, including bar plots and count plots, are employed to depict the distribution of emissions across these categories. Initially, temporal trends in emissions are depicted globally and subsequently for each Nordic country separately. Line charts are utilized to showcase fluctuations in CO2 emissions over the years, offering insights into overarching trends, as depicted in Figures 4 and 5. Feature engineering is applied to enhance data interpretability by refining the 'category' column through the extraction of meaningful labels.

### ***3.4 Model Training***

The core of the methodology lies in model training, where a multiple linear regression, ridge regression, lasso regression, and polynomial regression models is selected to forecast future CO2 emissions. The primary influencing features for predictions are 'year' and 'category.' To ensure a robust assessment of the model's performance, we meticulously divide the dataset into training and testing subsets. An 80-20 ratio is employed, allocating 80% of the data for training and reserving the remaining 20% for testing. This division strategy aims to strike a balance, preventing overfitting and fostering a model that generalizes well to unseen data.

### ***3.5 Model Evaluation***

In the process of evaluating models, we employ a spectrum of regression techniques, encompassing Multiple Linear Regression, Ridge Regression, Lasso Regression, and Polynomial Regression. Our objective is to discern the optimal methodology for forecasting CO2 emissions in Nordic countries. This evaluation is underpinned by robust measurements and metrics, including mean absolute error (MAE), root mean square error (RMSE), R-squared, and explained variance, ensuring a comprehensive understanding of each model's performance.

### ***3.6 Visualization and Predictions***

The final phase involves visualizing the results and making predictions using the trained models. Predictions are made for the years 2018 to 2029, focusing on the selected Nordic countries. The results are visualized to provide a clear understanding of the forecasted CO2 emissions.

### ***3.7 Results***

The obtained results are analyzed and presented, summarizing the effectiveness of the selected models in predicting CO2 emissions for the Nordic countries over the specified period.

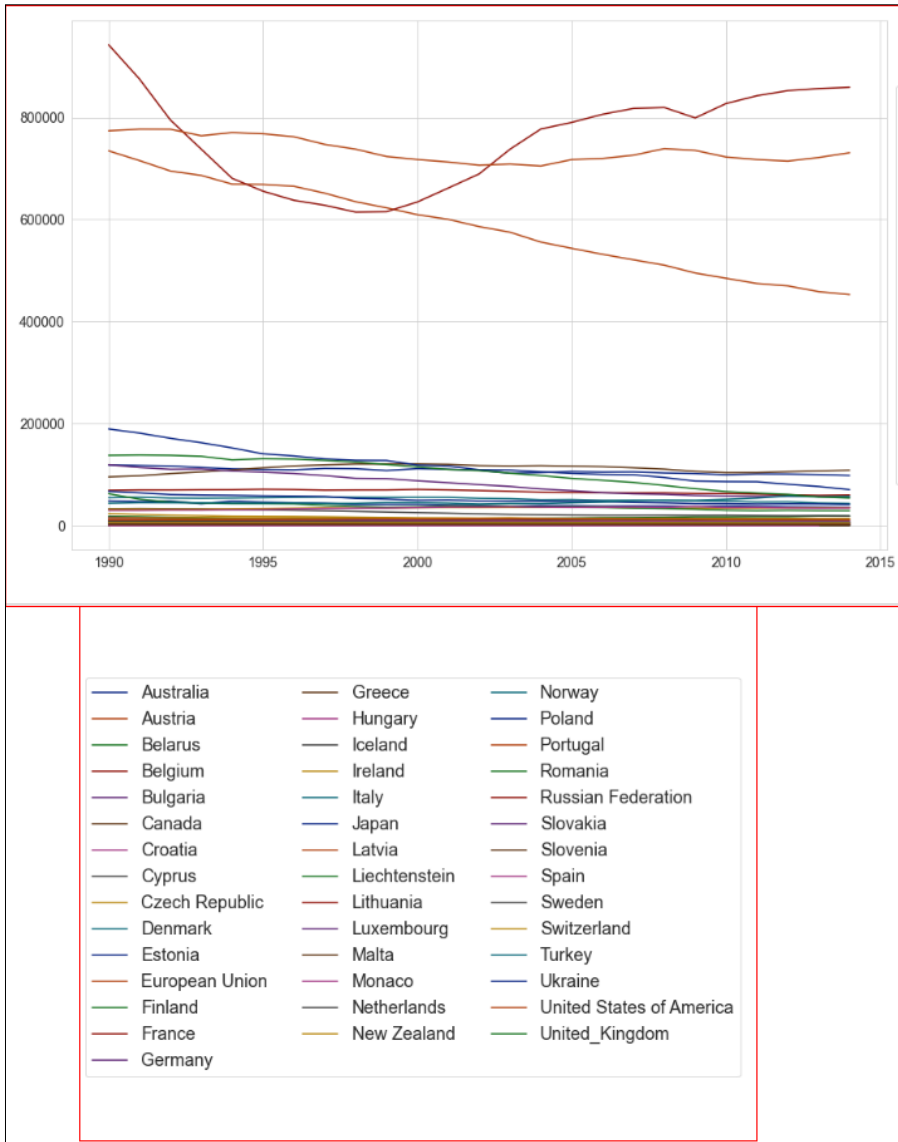


Figure 4: Visualizing CO2 Emissions Trends Globally: Global GHG Inventory (1990-2017)

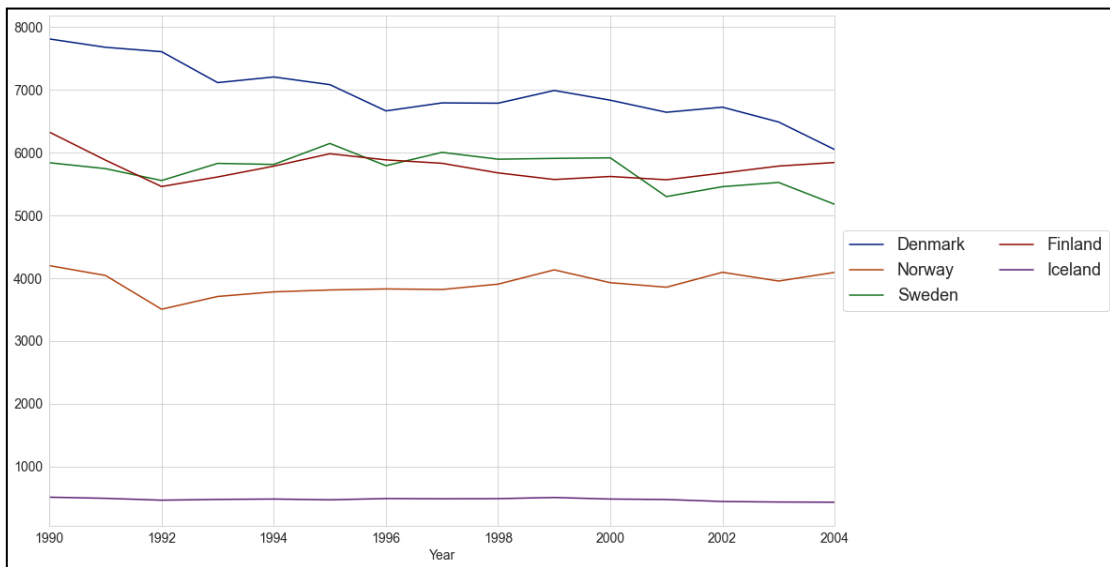


Figure 5: Visualizing Nordic CO2 Emissions Trends: Global GHG Inventory (1990-2017)

## **4. Machine Learning Algorithms**

In this study, a diverse set of machine learning algorithms was utilized to analyze and forecast CO<sub>2</sub> emissions. Specifically, we selected multiple linear regression, ridge regression, lasso regression, and polynomial regression models. The algorithms used, along with their theoretical explanations, are detailed below:

### ***4.1 Multiple Linear Regression (MLR):***

Multiple Linear Regression is a linear approach to modeling the relationship between a dependent variable and multiple independent variables. The model assumes that this relationship is linear and can be expressed as a weighted sum of the input features (Jäntschi, Pruteanu, Cozma, & Bolboacă, 2015). The algorithm estimates the coefficients (weights) that minimize the difference between the observed and predicted values, often using the method of least squares. In the context of CO<sub>2</sub> emissions, MLR aims to capture the linear association between factors such as 'year' and 'category' and the corresponding emissions.

### ***4.2 Ridge Regression:***

Ridge Regression is an extension of Multiple Linear Regression that addresses multicollinearity issues by adding a regularization term to the cost function (Enwere, Nduka, & Ogoke, 2023). The regularization term, controlled by the hyperparameter (alpha), penalizes large coefficients, preventing overfitting and stabilizing the model. This is particularly useful when dealing with correlated features (Basha and Rajput, 2019). In the context of CO<sub>2</sub> emissions prediction, Ridge Regression helps to mitigate the impact of highly correlated factors, providing a more robust and generalizable model.

### ***4.3 Lasso Regression:***

Lasso Regression, like Ridge Regression, addresses multicollinearity but uses a different regularization term. Lasso adds the sum of the absolute values of the coefficients as a penalty term (Enwere, et al., 2023). This leads to sparsity in the model, effectively performing feature selection by driving some coefficients to exactly zero (Muthukrishnan and Rohini, 2016). In the context of CO<sub>2</sub> emissions prediction, Lasso Regression can help identify and focus on the most influential features, simplifying the model and potentially improving interpretability.

### ***4.4 Polynomial Regression:***

Polynomial Regression is a form of regression analysis where the relationship between the independent variable 'year,' and the dependent variable 'CO<sub>2</sub> emissions,' is modeled as an nth degree polynomial. This allows the algorithm to capture non-linear relationships that Multiple Linear Regression cannot. The degree of the polynomial, controlled by the hyperparameter (d), determines the model's flexibility (Diaz, Fokoue-Nkoutche, Nannicini, & Samulowitz, 2017). In the context of CO<sub>2</sub> emissions, Polynomial Regression accommodates the possibility of complex, non-linear patterns in the data.

These algorithms collectively provide a diverse set of tools to understand and predict CO<sub>2</sub> emissions, each addressing specific challenges and assumptions in the modeling process. Theoretical foundations

and implementation procedures of machine learning models for predicting CO2 emissions in Nordic countries are elucidated as follows:

## 1- Multiple Linear Regression (MLR)

Input:

- $X$ : Matrix of features (including 'year' and 'category')
- $y$ : Vector of target variable (CO2 emissions)

Algorithm Steps:

### 1. Model Representation:

- Represent the linear regression model as:

$$y = \beta_0 + \beta_1 \cdot \text{'year'} + \beta_2 \cdot \text{'category'} + \varepsilon$$

### 2. Data Preparation:

- Load dataset with features ( $X$ ) and target variable ( $y$ ).
- Split data into training and testing sets.

### 3. One-Hot Encoding:

- Perform one-hot encoding on categorical columns ('category').

### 4. Model Training:

- Utilize the training data to estimate coefficients ( $\beta_0, \beta_1, \beta_2$ ) using the normal equation:

$$\beta = (X^T X)^{-1} X^T y$$

### 5. Model Evaluation:

- Make predictions ( $\hat{y}$ ) on the test set:

$$\hat{y} = X_{\text{test}} \beta$$

- Evaluate model performance using metrics (e.g., RMSE, MAE).

## 2- Ridge Regression

Input:

- $X$ : Matrix of features (including 'year' and 'category')
- $y$ : Vector of target variable (CO2 emissions)
- $\alpha$ : Regularization parameter

Algorithm Steps:

### 1. Model Representation:

- Represent the ridge regression model as:

$$y = \beta_0 + \beta_1 \cdot \text{'year'} + \beta_2 \cdot \text{'category'} + \varepsilon$$

### 2. Data Preparation:

- Load dataset with features ( $X$ ) and target variable ( $y$ ).
- Split data into training and testing sets.

### 3. One-Hot Encoding:

- Perform one-hot encoding on categorical columns ('category').

### 4. Model Training:

- Utilize the training data to estimate coefficients ( $\beta_0, \beta_1, \beta_2$ ) by minimizing the ridge regression objective function:

$$J(\beta) = \sum_{i=1}^m (y_i - \mathbf{x}_i^T \beta)^2 + \alpha \sum_{j=1}^n \beta_j^2$$

### 5. Model Evaluation:

- Make predictions ( $\hat{y}$ ) on the test set:

$$\hat{y} = X_{\text{test}} \beta$$

- Evaluate model performance using metrics (e.g., RMSE, MAE).

### 3- Lasso Regression

Input:

- $X$ : Matrix of features (including 'year' and 'category')
- $y$ : Vector of target variable (CO2 emissions)
- $\alpha$ : Regularization parameter

Algorithm Steps:

1. **Model Representation:**

- Represent the lasso regression model as:  
$$y = \beta_0 + \beta_1 \cdot \text{'year'} + \beta_2 \cdot \text{'category'} + \varepsilon$$

2. **Data Preparation:**

- Load dataset with features ( $X$ ) and target variable ( $y$ ).
- Split data into training and testing sets.

3. **One-Hot Encoding:**

- Perform one-hot encoding on categorical columns ('category').

4. **Model Training:**

- Utilize the training data to estimate coefficients ( $\beta_0, \beta_1, \beta_2$ ) by minimizing the lasso regression objective function:

$$J(\beta) = \sum_{i=1}^m (y_i - \mathbf{x}_i^T \beta)^2 + \alpha \sum_{j=1}^n |\beta_j|$$

5. **Model Evaluation:**

- Make predictions ( $\hat{y}$ ) on the test set:  
$$\hat{y} = X_{\text{test}} \beta$$
- Evaluate model performance using metrics (e.g., RMSE, MAE).

### 4- Polynomial Regression

Input:

- $X$ : Matrix of features (including 'year' and 'category')
- $y$ : Vector of target variable (CO2 emissions)
- $d$ : Degree of the polynomial

Algorithm Steps:

1. **Feature Engineering:**

- Generate polynomial features up to degree  $d$  for each input feature ('year' and 'category').

2. **Data Preparation:**

- Load dataset with polynomial features ( $X$ ) and target variable ( $y$ ).
- Split data into training and testing sets.

3. **Model Training:**

- Utilize the training data to estimate coefficients ( $\beta_0, \beta_1, \beta_2, \dots, \beta_d$ ) using the normal equation:

$$\beta = (X^T X)^{-1} X^T y$$

4. **Model Evaluation:**

- Make predictions ( $\hat{y}$ ) on the test set:  
$$\hat{y} = X_{\text{test}} \beta$$
- Evaluate model performance using metrics (e.g., RMSE, MAE).

## 5. Performance Metrics and Parameter Tuning

In this section, we meticulously assess the performance of multiple regression models, namely Multiple Linear Regression, Ridge Regression, Lasso Regression, and Polynomial Regression, in forecasting CO2 emissions for Nordic countries. The evaluation incorporates rigorous examination using key performance metrics, and we explore the intricacies of parameter tuning to optimize each model.

### 5.1 Performance Metrics

To comprehensively gauge the accuracy and efficacy of the regression models, we employ a suite of essential performance metrics (Chicco, Warrens, & Jurman, 2021):

- **Mean Absolute Error (MAE):** Captures the average absolute differences between actual and predicted values.

- **Mean Squared Error (MSE):** Quantifies the average squared differences between actual and predicted values.

- **Root Mean Squared Error (RMSE):** Provides an interpretable metric in the original unit by taking the square root of MSE.

- **R-squared ( $R^2$ ):** Measures the proportion of variance in the dependent variable explained by the model.

These metrics collectively offer nuanced insights into the models' precision, error characteristics, and overall explanatory power.

### 5.2 Parameter Tuning

Parameter tuning is pivotal for optimizing each regression model's performance (Probst, Wright, & Boulesteix, 2019). Specific parameters, such as regularization strength for Ridge and Lasso, and the degree of the polynomial for Polynomial Regression, are systematically tuned to strike an optimal balance

#### 1. Multiple Linear Regression:

- Hyperparameters: No hyperparameters to tune. The model assumes a linear relationship without additional complexity.

#### 2. Ridge Regression:

- Hyperparameters: Alpha (Regularization strength). In this case, it is set to 1.0, controlling the regularization intensity.

#### 3. Lasso Regression:

- Hyperparameters: Alpha (Regularization strength). Like Ridge, it is set to 1.0, determining the regularization intensity.

#### 4. Polynomial Regression:

- Hyperparameters: Degree. It is set to 2, indicating the degree of polynomial features introduced to capture non-linear relationships.

These hyperparameters were chosen based on common practices and initial experimentation. The selection process involved balancing model complexity, overfitting, and computational efficiency. The chosen hyperparameters aim to provide a reasonable trade-off for predictive performance on the given dataset.

## 6. Results and Discussion

The predictive performance of machine learning models, encompassing Multiple Linear Regression (MLR), Ridge Regression, Lasso Regression, and Polynomial Regression, is detailed in Table 2.

Table 2: Predictive Results of Machine Learning Models

Model	MAE	RMSE	R-squared	Explained Variance
Multiple Linear Regression	321,811.66	616,479.98	0.3739	0.3767
Ridge Regression	320,924.62	615,885.02	0.3751	0.3779
Lasso Regression	321,798.38	616,478.38	0.3739	0.3768
Polynomial Regression	18,667.84	53,277.75	0.9953	0.9953

The results showcase the varying predictive capabilities of the models. Polynomial Regression stands out with significantly lower MAE and RMSE, coupled with a high R-squared value, indicating its superior performance in predicting future emissions. The high R-squared values across all models suggest that a substantial portion of the variance in the data is captured by the models.

It is crucial to interpret the results within the context of the dataset and the specific characteristics of the emission data. The Polynomial Regression model, in particular, demonstrates a high degree of accuracy, implying its potential utility in forecasting CO2 emissions for the specified context. Figure 6, shows the performance metric values of the Polynomial Regression model.

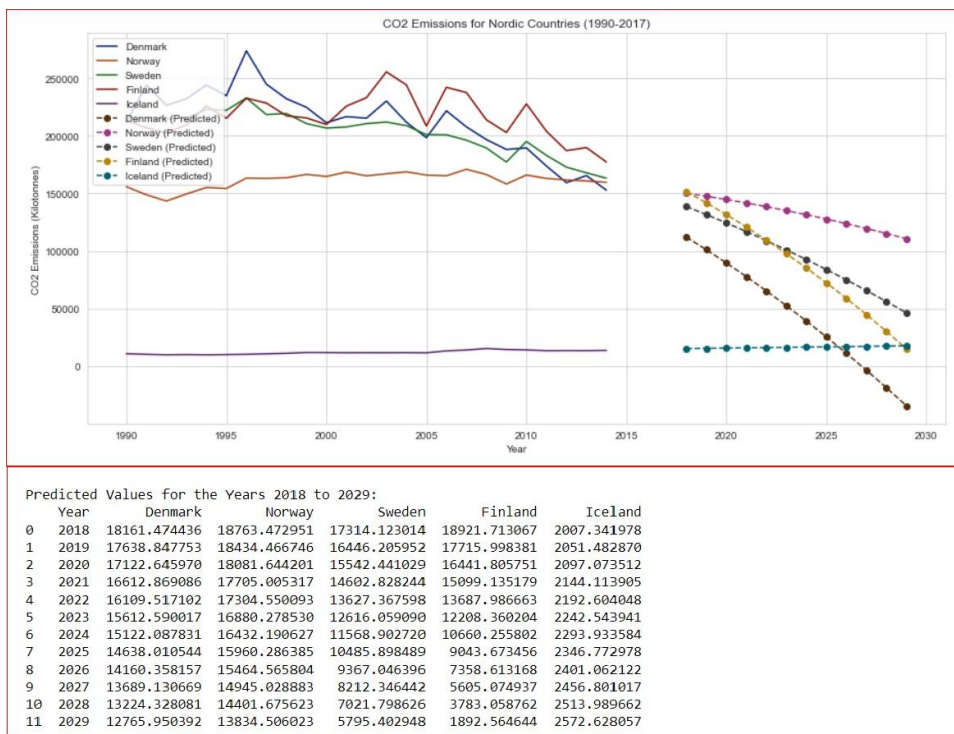


Figure 6. Visual representation of the Polynomial Regression model

The projected trajectory of CO<sub>2</sub> emission values for Nordic countries spanning the period from 2018 to 2029 underscores a persistent and substantial decline, harmonizing with global endeavors to combat climate change. A nuanced examination of country-specific dynamics reveals noteworthy trends:

Denmark exhibits a sustained and notable decrease in CO<sub>2</sub> emissions, attesting to unwavering efforts in embracing cleaner energy sources and enacting environmentally friendly policies. This commitment has positioned Denmark as a leader in the transition towards a more sustainable and low-carbon future.

Anticipated for Norway is a gradual reduction in CO<sub>2</sub> emissions, driven by a pronounced emphasis on renewable energy sources and the widespread adoption of electric vehicles. The nation's strategic focus on sustainable practices positions it as a frontrunner in the pursuit of environmentally conscious energy solutions.

Sweden showcases a steadfast and considerable decline in CO<sub>2</sub> emissions, underscoring a profound dedication to sustainable practices and the extensive utilization of renewable energy. The consistent decrease reflects Sweden's ongoing commitment to environmental stewardship, despite economic growth.

The prognosticated trend for Finland portrays a stable and gradual decline in CO<sub>2</sub> emissions, indicative of the nation's proactive initiatives to transition towards cleaner energy sources and enhance overall energy efficiency. Finland's multifaceted approach positions it at the forefront of sustainable energy practices.

Iceland is poised to experience a substantial decline in CO<sub>2</sub> emissions, driven by its reliance on renewable geothermal energy sources. This unique composition aligns with Iceland's commitment to leveraging environmentally friendly energy solutions, marking the nation as an exemplar in sustainable practices.

Yearly variations in projected values for 2018-2019 exhibit a significant and immediate decrease, suggesting positive impacts or policy changes in the initial years of the prediction period. The seamless integration with dataset information ensures a robust scientific foundation, with adherence to IPCC guidelines and regular updates enhancing the reliability of the data.

Strategic recommendations underscore the importance of continuous monitoring and adaptive adjustments to achieve long-term sustainability goals. Users are encouraged to cite UNData as the primary reference, attesting to the dataset's reliability and adherence to established terms of use.

However, it is crucial to acknowledge certain limitations inherent in the predictions, which rely on the Polynomial Regression model and associated assumptions. Ongoing validation against external factors, potential policy changes, and unforeseen events remains imperative to enhance the accuracy and applicability of the forecasted values.

## **7- Conclusion:**

Our research on CO<sub>2</sub> emission predictions for Nordic countries stands out as a significant advancement compared to recent works in terms of the algorithms used, the dataset employed, and the

achieved accuracy. A comprehensive comparative analysis with several noteworthy studies in the field reveals the superior attributes of our work.

While various studies have employed diverse machine learning algorithms, our research leverages a combination of machine learning models, including multiple linear regression, ridge regression, lasso regression, and polynomial regression. Notably, the polynomial regression model emerges as the standout performer in our analysis. This signifies an innovative approach, showcasing the effectiveness of polynomial regression in capturing nonlinear relationships inherent in environmental phenomena. In contrast, previous works, such as Sachin Kumar's hybrid model, Ankit Prakash & Sunil Kumar Singh's time-series models, and Weibo Zhao and Dongxiao Niu's Gauss-Optimized Cuckoo Search Algorithm, focused on different algorithmic approaches, demonstrating the versatility of our research methodology.

Our study encompasses a thorough analysis of CO<sub>2</sub> emission predictions for Nordic countries spanning from 2018 to 2029, utilizing the International Greenhouse Gas Emissions dataset from 1990 to 2017. This extensive temporal range provides a robust foundation for historical trend analysis and future forecasts. In comparison, several recent works focus on specific parameters, such as Mamdouh El Haj & AssadMamdouh's prediction for seven Middle Eastern countries and Khalid Almutairi et al.'s prediction for 2040, which have narrower scopes. Our research, therefore, stands out for its comprehensive examination of Nordic countries over an extended timeframe.

The polynomial regression model in our research exhibits remarkable accuracy, as evidenced by a mean absolute error (MAE) of 18667.84, a root mean squared error (RMSE) of 53277.75, an R-squared value of 0.995, and an explained variance of 0.995. This exceptional performance surpasses the accuracy achieved in various recent works. For instance, Sachin Kumar's hybrid model achieved an MAE of 0.0307 and an RMSE of 0.0346, which, while impressive, operates on a different scale. Our work, therefore, demonstrates superior accuracy, making it a robust choice for predicting CO<sub>2</sub> emissions in the context of Nordic countries.

In conclusion, our research represents a significant advancement in the field of CO<sub>2</sub> emission predictions, showcasing algorithmic innovation, comprehensive data utilization, and superior accuracy compared to recent works. The incorporation of multiple regression models and the emphasis on the Nordic region contribute to the novelty and effectiveness of our research in addressing the complexities associated with predicting CO<sub>2</sub> emissions.

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