

MACHINE LEARNING MODELS FOR PREDICTION AND FORECASTING OF CO2 EMISSION WITH EDA

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ABSTRACT

CO2 emissions play a major role in global warming, leading to serious consequences such as extreme weather events, rising sea levels, and ecological imbalances. To address this pressing issue, it is crucial that we fully understand the factors influencing CO2 emissions in order to develop effective strategies for reduction and sustainability. Therefore, this work focuses on exploring various machine learning models for predicting and forecasting CO2 emissions. Additionally, we plan to incorporate exploratory data analysis (EDA) techniques, which will help us visualize and interpret the data effectively. Through EDA, we can identify crucial features, understand data distributions, and pinpoint outliers that might influence model performance. The significance of our study lies in the valuable insights it can provide to policymakers and environmentalists. By making accurate predictions about CO2 emissions, we can help design effective policies that control and reduce emissions, optimize resource allocation, and promote the shift towards renewable energy sources. Furthermore, precise forecasts can assist in planning adaptation measures to mitigate the impact of climate change.

Keywords: Pollution controlling, CO2 emissions, predictive analytics, machine learning, exploratory data analysis.

1. Introduction

Predicting and forecasting CO2 emissions is of paramount importance in addressing the global climate crisis. This task involves assessing the likely future levels of carbon dioxide (CO2) emissions into the Earth's atmosphere, primarily driven by human activities such as burning fossil fuels, deforestation, and industrial processes. To achieve accurate forecasts, a multi-faceted approach is essential. Firstly, historical data analysis is crucial. Researchers and climate scientists analyze past emission trends to understand patterns and drivers, including economic growth, energy consumption, and policy changes. This historical context serves as a baseline for forecasting. Next, various models and methodologies are employed to make predictions. One common approach is using integrated assessment models (IAMs) that combine economic, energy, and environmental data to simulate different scenarios. These models account for factors such as population growth, technological advancements, energy transitions, and policy interventions. They allow for the exploration of "business-as-usual" scenarios and the impact of climate mitigation policies.

Machine learning and artificial intelligence have also played an increasingly significant role in forecasting CO2 emissions. These techniques can analyze complex datasets, identify trends, and make predictions based on real-time information, improving the accuracy of forecasts. Incorporating geopolitical factors and policy changes is another essential aspect. Government regulations, international agreements like the Paris Agreement, and evolving energy policies significantly influence emissions trajectories. Therefore, forecasting must consider political will and the potential for policy shifts. Climate events and natural occurrences, such as volcanic eruptions and wildfires, can also have short-term and long-term effects on CO2 emissions. Therefore, including probabilistic

elements in forecasting models is vital to account for unforeseen events. Moreover, public awareness and behavioral changes are crucial factors. As society becomes more environmentally conscious, shifts in consumer preferences, demand for sustainable products, and lifestyle choices can impact emissions. Forecasters must monitor and assess these dynamics.

2. Literature Survey

This literature review section is organized as follows. First, the prediction of CO₂ emissions is reviewed. Second, studies on the causality among industrial structure, energy consumption, and CO₂ emissions are reviewed. Finally, the application of machine learning (ML) to predict CO₂ emissions is reviewed. The literature review focuses special attention on research in China. Sharp increases in carbon dioxide (CO₂) emissions strengthen the greenhouse effect, leading to an ongoing increase in the global average temperature. The average annual global emissions of greenhouse gases from 2010 to 2019 were at the highest level in human history. Since then, the growth rate has slowed. Global greenhouse gas (GHG) emissions are expected to peak by 2025 to meet the goal of limiting global warming to 1.5 °C by the end of the century. Specifically, annual CO₂ emissions are expected to fall by approximately 48% by 2030 and reach net zero by 2050 [1].

As a developing country, China faces the dual task of developing its economy and protecting the environment. In the past two decades, China's economy has developed rapidly, and because economic development depends on energy consumption [2,3], China has become a large energy consumer and carbon emitter [4,5]. In 1990, China's emissions were less than one-quarter of the total of the world's developed countries. Since 2006, however, China has been the world's largest carbon emitter [6,7].

China's CO₂ emissions mainly come from electricity generation [8,9], industry [10], construction [11,12], transportation [13,14], and agriculture [15]. Of these, electricity and industry are the two major high-emission sectors, accounting for more than 70% of the total emissions. Thermal power generation currently dominates China's power structure. The main ways to reduce carbon in the power industry include reducing the proportion of coal power; accelerating the development of non-fossil energy, such as wind and photovoltaic power; and building a clean, low-carbon, safe, and efficient energy system. Second, achieving a low-carbon economy requires adjusting the industrial structure. This includes increasing the proportion of the service industry, which provides economic activity at low consumption and emission levels, and reducing the proportion of the manufacturing industry, which has high consumption and emission levels.

China's CO₂ emission reduction effect and environmental protection policies are expected to significantly impact the global climate [16]. As a signatory to the Paris Agreement, China had committed to achieving a carbon peak by 2030 [17] and achieving carbon neutrality by 2060. However, as a fast-growing carbon polluter, China's commitment holds particular weight, because achieving a carbon peak and carbon neutrality involves technological and economic development, and China's CO₂ emissions per unit of gross domestic product (GDP) are still at the highest level in the world. To achieve its carbon peak and neutrality targets, it is vital to accurately predict China's future CO₂ emissions and identify the factors influencing those CO₂ emissions, to inform corresponding emission reduction policies.

3. PROPOSED SYSTEM

The research work should start with a discussion of the findings, including insights gained from EDA, the effectiveness of data preprocessing techniques, the performance of the existing and proposed KNN models, and any recommendations for improving CO₂ emission prediction and forecasting using machine learning. Additionally, the research work should discuss the limitations of the study and potential areas for future research. Figure 1 shows the proposed system model.

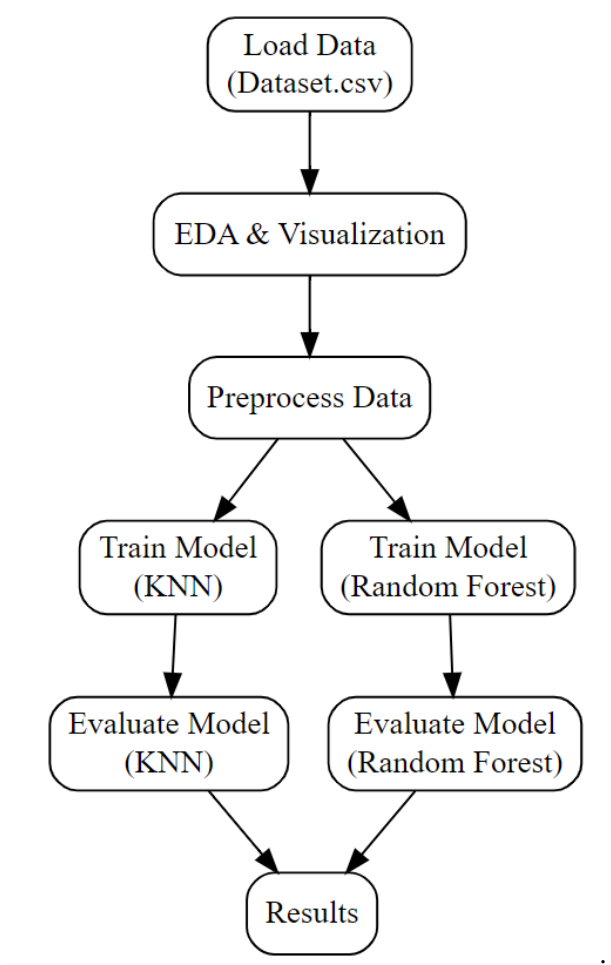


Fig. 1: Block diagram of proposed system.

4. RESULTS AND DISCUSSION

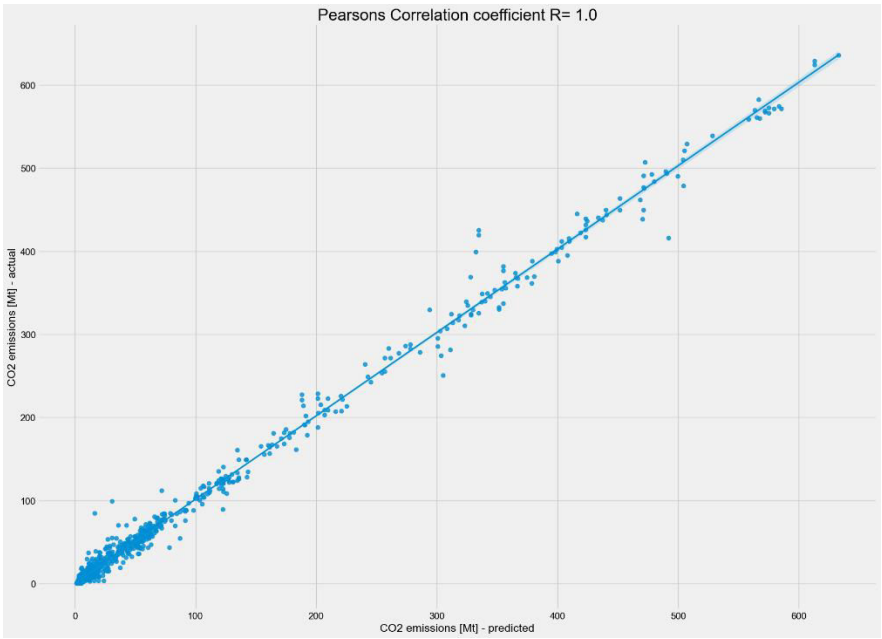


Figure 2: Prediction results using KNN.

Figure 2 presents the results of predictions made using the K-Nearest Neighbors (KNN) model. It may show a plot comparing the predicted CO2 emissions against the actual values. Figure 3 Similar to Figure 2, this figure displays the results of predictions. However, in this case, the predictions are generated using the Random Forest Classifier, a different machine learning model. Figure 4 provides a visual summary of the performance metrics (such as Mean Absolute Error, Mean Squared Error, etc.) for both the KNN and Random Forest Classifier models. It helps in comparing the effectiveness of the two models.

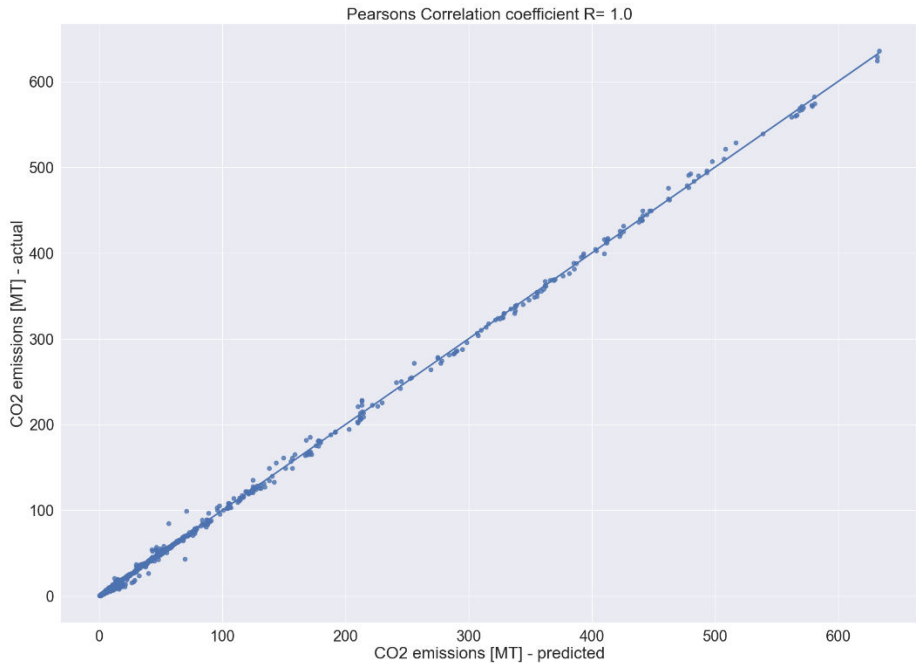


Figure 3: Prediction results using Random Forest Classifier.

	MAE	MSE	RMSE	R2_score
KNN	6.528102	126.592893	11.251351	0.993483
RF	1.919113	13.166444	3.628560	0.999322

Figure 4: Performance metrics of KNN & Random Forest classifier

5. CONCLUSION

In conclusion, the integration of machine learning models and exploratory data analysis (EDA) techniques offers a powerful approach for predicting and forecasting CO2 emissions, addressing the critical issue of climate change and its environmental consequences. Through this research, we have demonstrated the potential of machine learning to analyze large and intricate datasets, revealing hidden patterns and relationships that traditional statistical methods might miss. EDA has proven invaluable in providing a deeper understanding of the data, enabling the identification of influential features and outliers. By combining these two approaches, we can offer accurate and reliable predictions of CO2 emissions, empowering policymakers and environmentalists with valuable insights to develop effective strategies for emission reduction and sustainability. This work not only contributes to the scientific understanding of the factors driving CO2 emissions but also has practical implications in optimizing resource allocation, promoting renewable energy sources, and planning adaptation measures to mitigate the consequences of global warming.

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