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Comparative Analysis of Predictive Models for Carbon Emission in Major Countries: A Focus on Linear Regression and Random Forest

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Abstract: ***This study employs advanced predictive modeling techniques to examine carbon emissions across significant countries. Utilizing a comprehensive dataset from 1757 to 2017, it delves into the emission patterns of countries with the highest and lowest emissions. The study compares the efficacy of Linear Regression and Random Forest Regression models in predicting carbon emissions for Bangladesh, China, India, and the United States. The results, favoring the Random Forest model based on reduced Mean Squared Error, also project future emissions for these countries over the next 50 years. This research contributes to the discourse on sustainable environmental practices and policy-making by providing a solid foundation for understanding and forecasting carbon emission dynamics.***

Keywords: Carbon Emission, Predictive Modeling, Linear Regression, Random Forest Regression, Sustainability

1. Introduction

Carbon emissions, a major contributor to environmental problems, require thorough examination in light of growing concerns about climate change and its devastating global effects. It is critical to comprehend the historical trend of carbon emissions as countries work to strike a balance between ecological practices and economic growth. This study aims to investigate the complex trends that countries have demonstrated over this long period of time by analyzing data on carbon emissions from 1757 to 2017. The necessity of identifying the variables affecting carbon emissions and laying the groundwork for well-informed, ecologically responsible policy is what makes this study so urgent. In light of this [1], our study aims to clarify the dynamics of carbon emissions for both top and bottom-ranking countries. The variation in national emission levels highlights the necessity of customized approaches to tackle the worldwide climate emergency. In light of the global community's struggles with carbon emissions, this research attempts to provide insightful analysis of past patterns that will guide the development of sustainable practices and policies. Our study aims to close knowledge gaps and establish the groundwork for well-informed decision-making in the quest for a more sustainable future by thoroughly evaluating the carbon emission landscape.

By tackling the complex problem of carbon emissions, this study aims to bring new perspectives and approaches to the corpus of current knowledge. Our main area of interest is the use of sophisticated predictive modeling methods; in particular, we will be comparing the Linear Regression and Random Forest Regression models. We focus on four key countries: Bangladesh, China, India, and the United States in order to identify the underlying processes and patterns that define each country's trajectory in terms of carbon emissions [2]. The research has importance not just for revealing past emission patterns but also for offering a prospective outlook that projects carbon emissions for the ensuing half-century. Policymakers and environmental scientists can get nuanced insights by utilizing both linear and non-linear modeling methodologies, which allow for a comprehensive knowledge of the processes driving carbon emissions. By demonstrating how machine learning techniques may be used to anticipate and comprehend carbon emissions, our study adds to the current conversation about sustainable development. We provide a useful tool for academics and policymakers who are trying to make judgments about environmental sustainability by pointing out that the Random Forest Regression model has a better predictive performance than Linear Regression. Our research aims to be a pillar at the nexus of environmental science and data-driven decision-making as we work through the complexities of carbon emissions.

The parts that follow include a thorough analysis of the literature, including a thorough overview of earlier studies on carbon emissions, predictive modeling, and sustainable practices. Going ahead, the methodology section outlines the strategy used for gathering data, preparing it for analysis, and using prediction models. The empirical findings are then presented in the Results and Analysis section, which also provides a thorough analysis of carbon emission patterns and the relative effectiveness of the regression models used. Lastly, the Conclusion summarizes the entire story of this study by summarizing the results, talking about their implications, and suggesting possible directions for further research.

Range of factors are included in these criteria, including land use, population, income, block size, possible forms of transportation, land price, and traffic infrastructure. After that, the simulated traffic flow is used to determine the geographical distribution of carbon emissions using conventional automobile emission factors from the Intergovernmental Panel on Climate Change (IPCC).

Application of the study [6] is concentrated on Xiamen Island, where commuters' movement during rush hour on a regular weekday is simulated.

Through the introduction of a thorough carbon emission supervision system designed specifically for low-carbon city building, this study [7] adds to the conversation. This document outlines the carbon emission supervision system's conceptual framework, role, contents, and building methodologies. This cutting-edge device is made to effectively control carbon emissions and energy use as we move toward a low-carbon world. In order to meet their carbon reduction goals, cities that have started low-carbon city plans can successfully use the suggested strategy. The establishment and promotion of carbon-intensive department emissions within the environmental protection supervision system is one of the key elements and techniques highlighted. This is an important area for a significant decrease in carbon emissions.

2. Methodology

This study's methodology involves a thorough analysis of carbon emissions, with a major focus on four important nations: Bangladesh, China, India, and the United States. The procedure begins with the use of a carbon emissions dataset spanning several years. Then, patterns and trends between the top and bottom 10 nations in terms of carbon emissions are identified using data visualization tools. From now on, only the Random Forest and Linear Regression models are used for the four previously stated nations. To reach peak performance, the models go through extensive training and tuning processes.

3. Data Collection

3.1 Overview of Dataset

Data on greenhouse gas emissions for 231 nations from 1757 to 2017 are included in the dataset that is being examined. With a major focus on carbon dioxide (CO2), the emissions are measured in tons of greenhouse gasses. The dataset acknowledges its importance in comprehending how humans affect climate change and is sourced from reputable sources.

3.1.1 Source of Data

The dataset highlights how crucial human activity is in causing climate change and is derived from ourworldindata.org [8]. Global temperatures are known to be significantly influenced by greenhouse gas emissions from human activity, namely the production of CO2. The dataset highlights the importance of CO2 as the main cause of climate change and offers a thorough analysis of the relationship between global

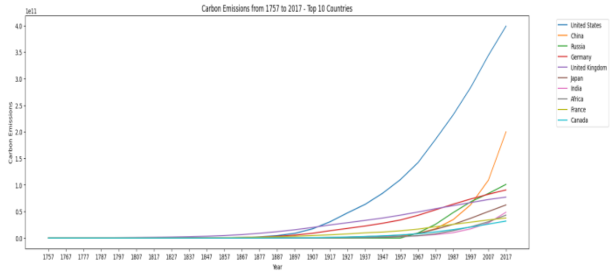

Figure 3: Carbon Emissions from 1757 to 2017 - Top 10 Countries

The top ten nations' historical carbon emissions from 1757 to 2017 are displayed in this line graph of figure 3. Since each nation is represented by a different line, it is possible to do an extensive examination of the patterns in emissions over time.

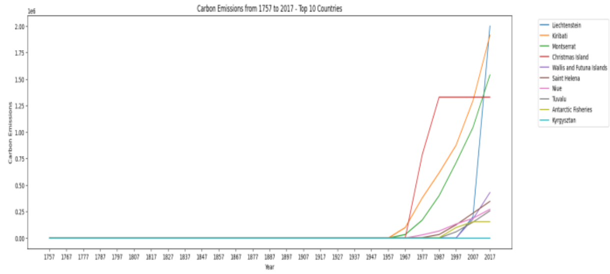

Figure 4: Carbon Emissions from 1757 to 2017 - Last 10 Countries

This line graph in figure 4, which is similar to figure 3, shows the historical carbon emissions of the last nations from 1757 to 2017. Emission trajectories throughout time may be compared thanks to the visualization.

3.2 Feature Selection and Workflow Analysis:

A careful feature selection is essential to the goal of comprehending and forecasting carbon emissions [10]. Using a feature selection technique, the study concentrated on the US, China, India, and Bangladesh as a subset of nations. The use of a targeted methodology enabled a more comprehensive examination of the carbon emission patterns of these countries, hence mitigating dataset complexity and maintaining the wealth of information relevant to major contributors to world emissions [11]. These chosen nations' historical emission trajectories from 1757 to 2017 were succinctly and clearly summarized by the detailed line graph that represented the carbon emissions for these nations throughout time. This thoughtful feature selection guaranteed a targeted analysis of important contributors, facilitating a more efficient workflow for the next regression analyses.

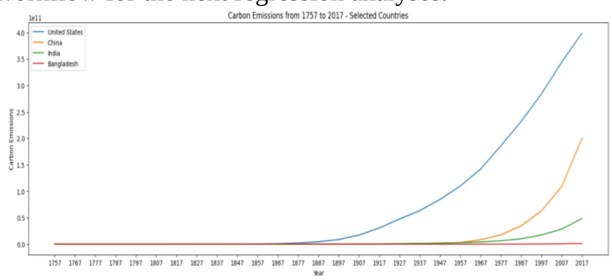

Figure 5: Carbon Emissions from 1757 to 2017 - Selected Countries

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This figure 7 illustrates the step-by-step progression of the research workflow. It encompasses data collection, preprocessing, visualization, and predictive modeling using Linear Regression and Random Forest techniques, leading to comprehensive metric analysis and the identification of the best-performing model, which collectively informs the research's conclusion and suggests avenues for future work.

3.3 Machine Learning Implementation

To forecast future carbon emissions for Bangladesh, China, India, and the United States, we apply two machine learning models in this section: Random Forest Regression and Linear Regression. Using historical carbon emission data from 1757 to 2017, the models are trained. The main goal is to evaluate and contrast these models' prediction abilities for the chosen nations**.**

3.3.1 Linear Regression Implementation

The basic regression procedure known as "linear regression" makes the assumption that there is a linear connection between the target variable and the input characteristics. We use the Linear Regression model to estimate the historical trend of carbon emissions for particular nations in the context of our work on carbon emissions forecast. When examining possible linear relationships between time (years) and carbon emissions, this model is especially useful.

The historical carbon emissions data from 1757 to 2017 are used to train the Linear Regression model independently for each nation. During the training phase, the model is fitted in order to identify the ideal linear coefficients that reduce the discrepancy between the actual and forecast carbon emissions. To summarize, Linear Regression is an effective technique for identifying linear patterns in data on carbon emissions. It offers a foundation for comprehending and forecasting the future course of emissions for individual nations. The forecasts derived by this model aid in our comparison study of machine learning methods.

3.3.2 Random Forest Regression

An ensemble learning method called Random Forest Regression creates a large number of decision trees in order to provide a forecast that is more reliable and accurate. Random Forest Regression is a potent substitute for Linear Regression in the context of our study on the prediction of carbon emissions because it can capture intricate correlations between input characteristics and target variables.

For every chosen nation, the dataset is split into characteristics (X) and the target variable (y). In order to properly segregate the input characteristics (years) and related carbon emissions for model training and assessment, this step is necessary. The train_test_split function from scikit-learn is used to further split the data into training and testing sets. By evaluating the Random Forest Regressor model's prediction ability using hypothetical data, this guarantees a thorough assessment of the model. To summarize, the process of implementing Random Forest Regression entails building and honing unique models for every nation that is chosen. Through the use of ensemble learning, the

3.3.2.1 Mean Squared Error (MSE) Analysis:

The Mean Squared Error (MSE) of the Random Forest and Linear Regression models are meticulously contrasted in figure 8. An extensive knowledge of the models' predicted accuracy is provided by the bar plots that show the performance indicators for each nation. Red bars indicate Linear Regression, and blue bars indicate Random Forest.

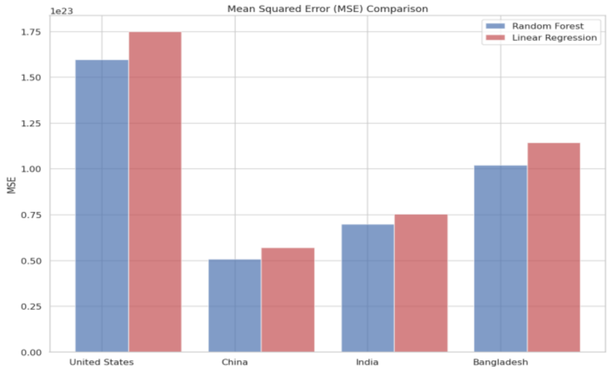

Figure 8: Mean Squared Error (MSE) Analysis--studies on carbon emissions, predictive modeling, and sustainable practices. Going ahead, the methodology section outlines the strategy used for gathering data, preparing it for analysis, and using prediction models. The empirical findings are then presented in the Results and Analysis section, which also provides a thorough analysis of carbon emission patterns and the relative effectiveness of the regression models used. Lastly, the Conclusion summarizes the entire story of this study by summarizing the results, talking about their implications, and suggesting possible directions for further research.

4. Literature Review

Previous study, as demonstrated by [3], used the empirical mode decomposition (EMD) approach to address the complex nature of carbon emissions across different countries. Using this technology, national carbon emissions time-series data may be successfully dissected to identify high-frequency modes that indicate short-term interferences and trend modes that indicate long-term trajectories. The study was noteworthy since it examined the particulars of carbon emissions for different nations and found some interesting trends. As an example, the research revealed that England's carbon emissions are trending downward, mostly due to short-term causes. On the other hand, long-term trends are mostly responsible for the increasing carbon emissions in nations like the US, China, Japan, Australia, and Canada.

Building on the comparative research framework, as demonstrated in [4], the author carried out an extensive investigation with a focus on the top CO2 emitting nations. The results emphasized an important realization: the reduction of carbon emissions as a whole requires persistent, long-term cooperation across countries, subject to the viability of each country's implementation plan.

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This highlights the need for coordinated efforts and specialized techniques to achieve significant and long-lasting reductions in CO2 emissions and highlights the interdependence of states in tackling the global problem of carbon emissions.

The phenomena of "carbon source transfer," as examined in this paper [5], provides insight into the complex dynamics involved in the migration of high-carbon businesses from Annex I to non-Annex I nations. It is believed that the worldwide carbon emissions trading system has fundamental weaknesses that are the cause of this movement. The study explores the methods and underlying causes of carbon source transfer against the backdrop of the Kyoto Protocol's "common but differentiated responsibilities" premise. The study shows that the growing carbon emissions of non-Annex I nations are, in part, a result of carbon source transfer from Annex I countries by analyzing the industrial transfer within the framework of "carbon flow" under market processes.

This research offers a thorough review in response to the growing urbanization in emerging nations and its ensuing effects on environmental well-being, especially in terms of carbon emissions from urban transportation. With urban design data as input parameters, the research simulates commute traffic flow over road networks using the TRANUS integrated land use and transport model. A wide temperatures and greenhouse gas concentrations. The value of the dataset comes from its capacity to clarify past patterns in temperature and their relationship to greenhouse gas emissions caused by human activity.

Dataset Visualization:

The top ten nations' 2017 carbon emissions are displayed in a bar plot with figure 1.

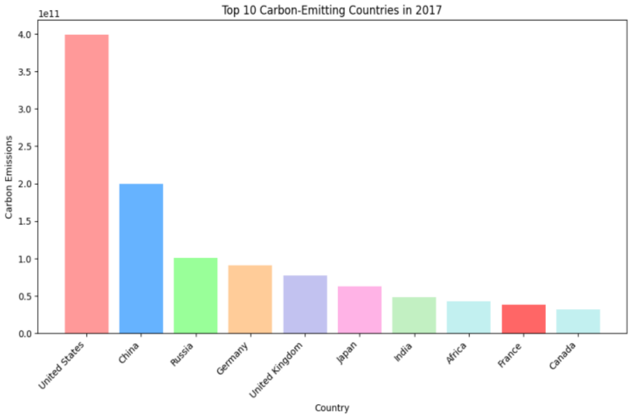

Figure 1: Top 10 Carbon-Emitting Countries in 2017

To emphasize their respective contributions, the nations—which include the US, China, Russia, Germany, the UK, Japan, India, Africa, France, and Canada—have been color-coded. The carbon emissions are represented on the y-axis, which allows for a visual comparison of various countries' emission levels.

This bar plot in figure 2, shows the carbon emissions of the last ten nations in 2017.

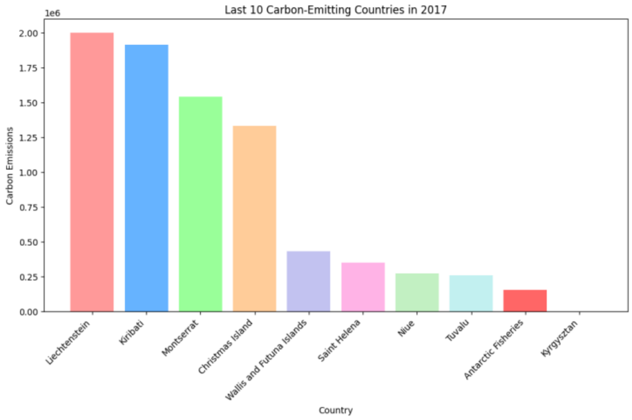

Figure 2: Last 10 Carbon-Emitting Countries in 2017

Highlighted are Kyrgyzstan, Wallis and Futuna Islands, Niue, Tuvalu, Liechtenstein, Kiribati, Montserrat, Christmas Island, Wallis and Futuna Islands, and Antarctic Fisheries. These countries' emission levels may be distinguished from one another because of their unique hues.

The line graph in figure 5 portrays the historical carbon emissions from 1757 to 2017 for a specific set of selected countries. Each country is represented by a distinctive line, offering a comparative analysis of their emission trends over the years. The x-axis denotes the years, while the y-axis represents the corresponding carbon emissions. This visualization provides insights into the diverse emission trajectories and patterns of the chosen countries.

Predictive modeling [9] was included in the approach, and the chosen dataset was subjected to both Linear Regression and Random Forest Regression. Interestingly, the Random Forest Regression performed better than the others, producing a smaller Mean Squared Error (MSE). The United States, China, India, and Bangladesh are now able to anticipate their carbon emissions for the next 50 years because of the effective application of these machine learning algorithms. The presentation of these future projections was made easier with the use of visualization tools like line charts. The research's efficiency was increased by this streamlined approach, which included feature selection and predictive modeling. This improved research provided insightful information on the carbon emission trajectories of individual countries as well as their possible future trajectories.

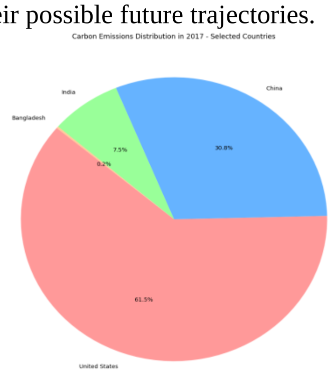

Figure 6: Carbon Emissions Distribution in 2017 - Selected Countries

The pie chart displays the distribution of carbon emissions among the selected countries specifically in the year 2017. Each country is represented by a segment of the pie, and the percentage labels provide a clear indication of their respective contributions. The colors distinguish between the selected countries, enhancing the visual representation of their relative emission shares.

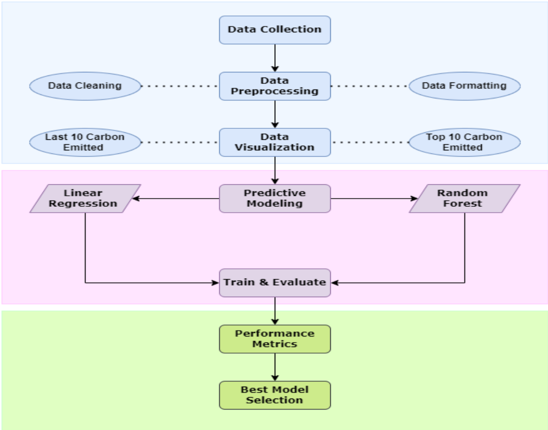

Figure 7: Research Workflow Diagram

prediction power is increased and complex patterns in the carbon emissions data are captured. The review of testing sets that follows adds to the thorough examination of machine learning methods for predicting carbon emissions.

3.3.2.1 Result and Analysis

An extensive study of the prediction models' accuracy in projecting carbon emissions for Bangladesh, China, India, and the United States may be found in the findings and analysis section. The study uses both Linear Regression and Random Forest Regression to analyze comparative measures, visualize historical data, and make predictions about the future. This section provides an in-depth analysis and visual aid to help understand how well machine learning techniques work for modeling and forecasting changes in carbon emissions. A comparative metrics study that follows validates the superiority of the Random Forest Regression model over Linear Regression in terms of R-squared values, Mean Squared Error (MSE), and Mean Absolute Error(MAE). The performance evaluation of the best model confirms its effectiveness in precisely predicting future carbon emissions, advancing environmental sustainability prediction modeling.

3.3.2.2 Evaluation Metrics

The evaluation of model performance in the classification of fetal health is dependent on an extensive set of critical indicators. The evaluation methodology is based on these parameters, which also include sensitivity, specificity, recall, accuracy, precision, F1 score, and AUC-ROC. While precision assesses the accuracy of positive predictions, accuracy gauges the overall soundness of the model's predictions. Recall, also known as sensitivity, measures how well the model can detect true positive cases; the F1 score finds a compromise between recall and accuracy. The model's ability to accurately detect positive and negative examples is further outlined by its sensitivity and specificity. The model's capacity for class distinction is measured by the AUC-ROC metric. In order to give a comprehensive picture of the model's performance in classifying fetal health and support well-informed decision-making in clinical settings, each statistic is essential. This thorough assessment guarantees a solid examination of the models' strengths and weaknesses in the crucial area of perinatal care.

3.3.2.3 Comparative Metrics Analysis

Analyzing the model's performance provides unique insights into how well Linear Regression and Random Forest estimate carbon emissions [12]. When compared to Linear Regression, Random Forest shows better accuracy worldwide in terms of Mean Squared Error (MSE). In particular, Bangladesh, China, India, and the US all have lower MSE values when using Random Forest. Mean Absolute Error (MAE) highlights Random Forest's higher predictive power and capacity to provide estimates that are more accurate. The comparative benefit of Random Forest is further reinforced by the examination of R-squared values. Higher R-squared values for every country show that Random Forest consistently performs better than Linear Regression, despite the inherent difficulties in estimating carbon emissions.

Random Forest's higher prediction accuracy when compared to Linear Regression is seen by its lower MSE values across all nations. The fact that Random Forest routinely attains lower error rates is noteworthy and highlights the model's ability to identify underlying patterns in the data on carbon emissions.

The Mean Squared Error (MSE) values for the Random Forest and Linear Regression models in the chosen countries are shown in Table 1. It is clear that Random Forest routinely beats Linear Regression in reducing the squared differences between projected and actual carbon emissions. Lower MSE values imply higher predictive ability.

Table 1: Mean Squared Error (MSE)

Country	Random Forest (MSE)	Linear Regression (MSE)
United States	1.60e+23	1.75e+23
China	5.08e+22	5.69e+22
India	6.99e+22	7.53e+22
Bangladesh	1.02e+23	1.14e+23

The Mean Squared Error (MSE) values for the Random Forest and Linear Regression models in the chosen countries are shown in Table 1. It is clear that Random Forest routinely beats Linear Regression in reducing the squared differences between projected and actual carbon emissions. Lower MSE values imply higher predictive ability.

3.3.2.3.2 Mean Absolute Error (MAE) Analysis:

A thorough comparison of the Mean Absolute Error (MAE) between the Random Forest and Linear Regression models is shown in figure 9. The performance indicators for each nation are displayed in bar charts, which offer a thorough comprehension of the models' predicted accuracy. Whereas the red bars show Linear Regression, the blue bars reflect Random Forest.

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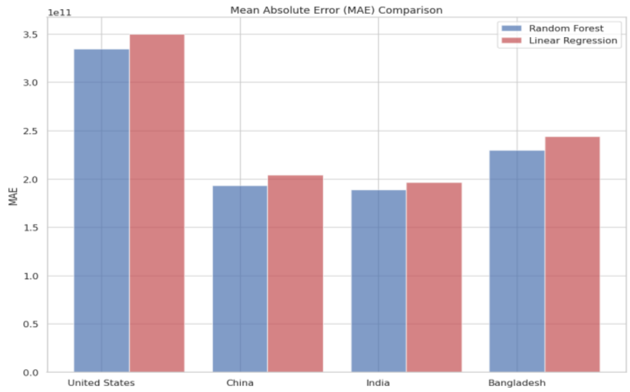

Figure 9: Mean Absolute Error (MAE) Analysis

In comparison to Linear Regression, Random Forest has better prediction accuracy, as seen by the lower MSE and MAE values for Random Forest across all nations. Remarkably, Random Forest continuously attains lower error rates, highlighting its ability to effectively identify the underlying patterns in the data on carbon emissions

Table 2: Mean Absolute Error (MAE)

Country	Random Forest (MAE)	Linear Regression (MAE)
United States	3.34e+11	3.50e+11
China	1.93e+11	2.04e+11
India	1.89e+11	1.96e+11
Bangladesh	2.30e+11	2.44e+11

The Mean Absolute Error (MAE) values for the Random Forest and Linear Regression models are shown in Table 2. Lower MAE levels are indicative of better predicting accuracy, much as MSE. The efficiency of Random Forest in obtaining reduced absolute errors across all nations is highlighted in the table.

3.3.2.3.3 R-squared (R2) Analysis:

The R-squared (R2) comparison of the Random Forest and Linear Regression models is shown in figure 10. An improved fit to the data is shown by higher R2 values, which are displayed in the bar plot as the variance explained by each model. As can be shown, Random Forest performs better than Linear Regression in terms of R2 in every nation, confirming its potential to offer a more thorough and precise depiction of trends in carbon emissions.—

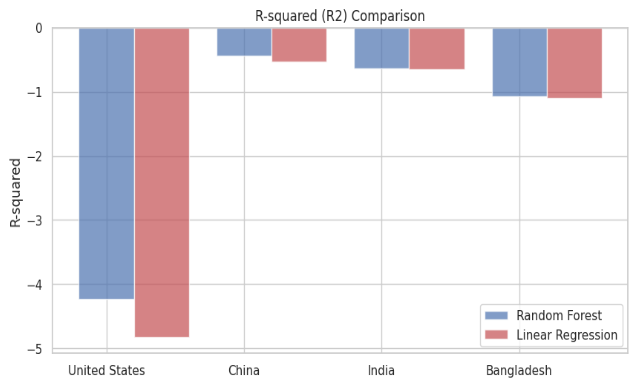

Figure 10: R-squared (R2) Analysis

The R-squared (R2) values for the Random Forest and Linear Regression models are displayed in Table 3.

Table 3: R-squared (R2)

Country	Random Forest (R2)	Linear Regression (R2)
United States	-4.23	-4.83
China	-0.43	-0.52
India	-0.63	-0.65
Bangladesh	-1.08	-1.09

A better fit to the data is shown by higher R2 values. Random Forest routinely exhibits comparatively better R2 values than Linear Regression, indicating its superior capacity to capture the variation in carbon emission patterns, even in the face of negative values that imply limitations in explanatory power.

3.3.2.4 Best Model Performance:

The evaluation of model performance reveals that the Random Forest Regression consistently outperforms the Linear Regression model across various metrics. Notably, examining Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R2) values, Random Forest consistently demonstrates superior predictive accuracy.

representation showcases the temporal trends and projections of carbon emissions. The model's predictive power is evident in capturing the nuances of each country's emissions over the specified period.

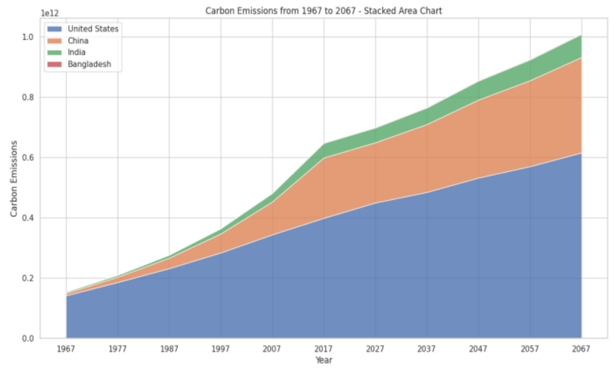

Figure 12: Carbon emissions from 1967 to 2067

Figure 12 presents a stacked area chart depicting carbon emissions from 1967 to 2067 for the United States, China, India, and Bangladesh. This visual representation emphasizes the cumulative contributions of each country to global carbon emissions over time. The stacked area chart offers a comprehensive overview of the relative magnitudes and trends in emissions.

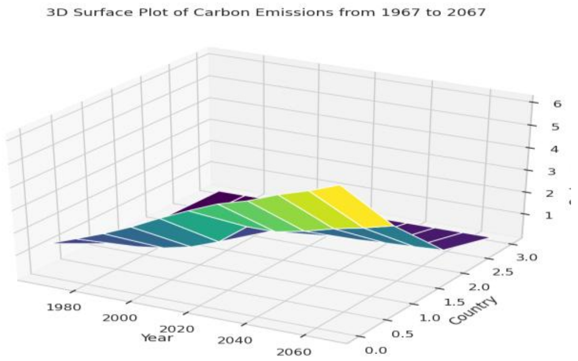

Figure 13: Surface plot

A three-dimensional surface plot in figure 13 visualizes carbon emissions across years and countries. This plot offers a dynamic perspective on the changing patterns of emissions, providing a clear representation of the dataset's structure in a spatial context.

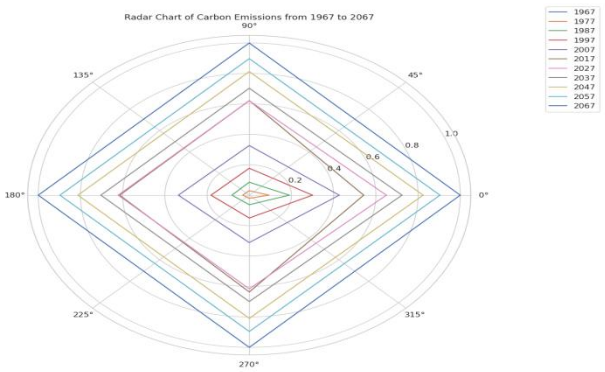

Figure 14: Radar plot

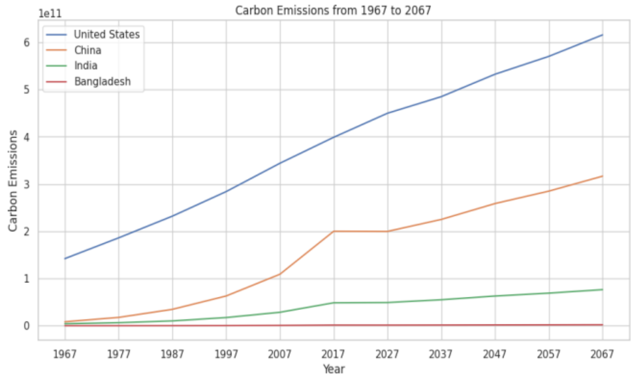

Figure 11: Carbon emissions from 1967 to 2067

The line chart in figure 11 illustrates carbon emissions from 1967 to 2067 for the selected countries. The visual
The radar chart in figure 14 is an innovative representation of carbon emissions. Each axis represents a country, and the distance from the center indicates the normalized emissions. This visual representation offers a unique perspective on the comparative performance of countries in terms of emissions over the specified years.

5. Conclusion

Using both Random Forest Regression and Linear Regression models for forecasting, our research concludes with a thorough examination of carbon emissions. Strong assessment measures consistently demonstrate that Random Forest Regression outperforms Linear Regression in terms of predictive accuracy for key countries, including Bangladesh, China, India, and the United States. These results emphasize the need to use cutting-edge machine learning methods, particularly Random Forest Regression, to improve the precision of carbon emission estimates. The research findings provide valuable insights for the creation of more effective methods aimed at mitigating climate change, since carbon emissions continue to be a major worldwide concern.

Subsequent studies may investigate supplementary machine learning methods and ensemble methodologies to augment carbon emission prediction models. Furthermore, adding additional elements, such policy modifications and economic indicators, could offer a more comprehensive knowledge of the variables affecting carbon emissions. Finally, broadening the scope of the research to include a larger number of nations and areas would help to provide a more thorough and internationally representative view of changes in carbon emissions.

References

[1] X. Tong and K. Chen, "Correlation analysis of carbon emissions and influencing factors in China," The 26th Chinese Control and Decision Conference (2014 CCDC), Changsha, China, 2014, pp. 1413-1417, doi: 10.1109/CCDC.2014.6852388.

[2] Shengli Song, Huajun Cao and Hongcheng Li, "Evaluation method and application for carbon emissions of machine tools based on LCA," International Conference on Advanced Technology of Design and Manufacture (ATDM 2010), Beijing, 2010, pp. 74-78, doi: 10.1049/cp.2010.1263.

[3] M. Liu and G. Zhang, "Characteristics of Multinational Carbon Emissions Based on Empirical Mode Decomposition," 2013 Sixth International Conference on Business Intelligence and Financial Engineering, Hangzhou, China, 2013, pp. 458-462, doi: 10.1109/BIFE.2013.97.

[4] Li Muhan, Zhang Lianzhong and Chen Jianguo, "An comparative study based on leading CO2 emission countries," 2010 International Conference on Mechanic Automation and Control Engineering, Wuhan, 2010, pp. 4647-4649, doi: 10.1109/MACE.2010.5536478.

[5] J. -q. Bao, S. -h. Huang, Y. Miao and S. -y. Zhu Fang, "Carbon source transfer: The defect and strategy research of international carbon emissions trading market," 2011 International Conference on Materials for Renewable Energy & Environment, Shanghai, China, 2011, pp. 1917-1921, doi: 10.1109/ICMREE.2011.5930712.

[6] Q. Qiu, Y. Zhao, L. Chen and Y. Quan, "Utilization of Urban Form Information for Extracting Commuting Travel Carbon Emission on Urban Road Network," 2012 Ninth International Conference on Information Technology - New Generations, Las Vegas, NV, USA, 2012, pp. 895-895, doi: 10.1109/ITNG.2012.88.

[7] C. Jinyi, H. Yingjia, L. Jia, L. Nian and Z. Xiaomei, "Studies on the carbon emissions supervision system

of low carbon urban," 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet), Xianning, China, 2011, pp. 1687-1690, doi: 10.1109/CECNET.2011.5769377.

[8] H. Ritchie, M. Roser, and P. Rosado, "CO_2 and greenhouse gas emissions," Our World in Data, https://ourworldindata.org/co2-and-greenhouse-gas-emissions#why-do-greenhouse-gas-emissions-matter (accessed Nov. 30, 2017).

[9] Y. Yao, X. Chen and C. Han, "Cause Analysis of the Decoupling Elasticity between China's Carbon Emission and Economic Development: Based on LYQ Framework," 2011 Fourth International Joint Conference on Computational Sciences and Optimization, Kunming and Lijiang City, China, 2011, pp. 1168-1171, doi: 10.1109/CSO.2011.99.

[10] Lan Teng and Zhenji Zhang, "Container multimodal transport routing selection modeling considering carbon emission cost," 2015 International Conference on Logistics, Informatics and Service Sciences (LISS), Barcelona, Spain, 2015, pp. 1-6, doi: 10.1109/LISS.2015.7369770.

[11] X. Wang, M. Qiu, H. Ding, J. Dong and W. Wang, "A carbon capture and distribution network design problem for carbon emission reduction and utilization," Proceedings of 2010 IEEE International Conference on Service Operations and Logistics, and Informatics, QingDao, China, 2010, pp. 246-251, doi: 10.1109/SOLI.2010.5551571.

[12] W. Tian and P. Da Costa, "Inequalities in per capita CO2 emissions in European Union, 1990–2020," 11th International Conference on the European Energy Market (EEM14), Krakow, Poland, 2014, pp. 1-5, doi: 10.1109/EEM.2014.6861214.