Abd El-Aal, Mohamed F.; Mahmoud, Hasan Amin Mohamed; Abdelsamiea, Abdelsamiea Tahsin et al.

Article

Leveraging machine learning to assess the impact of energy consumption on global GDP growth : what actions should be taken globally toward environmental concerns?

International Journal of Energy Economics and Policy

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2024, 14(4), 108-115.

Leveraging Machine Learning to Assess the Impact of Energy Consumption on Global GDP Growth: What Actions should be taken Globally toward Environmental Concerns?

Mohamed F. Abd El-Aal[1]*, Hasan Amin Mohamed Mahmoud[2], Abdelsamiea Tahsin Abdelsamiea[3], Marwa Samir Hegazy[3]

[1]Department of Economics, Faculty of Commerce, Arish University, North Sinai, Egypt, [2]Department of Economics, Faculty of Commerce, Aswan University, Egypt, [3]Department of Economics, Faculty of Commerce, Mansoura University, Egypt.
*Email: mohammed.fawzy@comm.aru.edu.eg

Received: 09 January 2024 **Accepted:** 25 April 2024 **DOI:** https://doi.org/10.32479/ijeep.15833

ABSTRACT

The study aims to explore the impact of renewable, nonrenewable, and nuclear energy consumption on global gross domestic product (GDP) growth through machine learning algorithms. The findings reveal that renewable energy consumption is the most influential variable, contributing to a predicted 67.5% global GDP growth. In contrast, nuclear energy consumption contributes 17.8%, and non-renewable energy consumption contributes 14.6%. Notably, the relationship between nuclear energy consumption and global economic growth is positive; there is a negative relation in conjunction with renewable energy consumption. However, the association with non-renewable energy is consistently fixed. These results suggest that an increased reliance on renewable energy may necessitate a trade-off, potentially leading to a reduction in global GDP growth despite the positive contributions from renewable sources.

Keywords: Machine Learning, Renewable Energy, Nonrenewable Energy, Nuclear Energy, Global Gross Domestic Product
JEL Classifications: C63, C80, C81, C87

1. INTRODUCTION

This article delves into the complex interplay between energy consumption—from renewable, nonrenewable, and nuclear sources—and its effect on the global Gross Domestic Product (GDP) in light of the growing global need for energy and worries about environmental sustainability. In order to understand the complex interplay between energy consumption, economic development, and ecological sustainability, this study employs state-of-the-art machine learning methods.

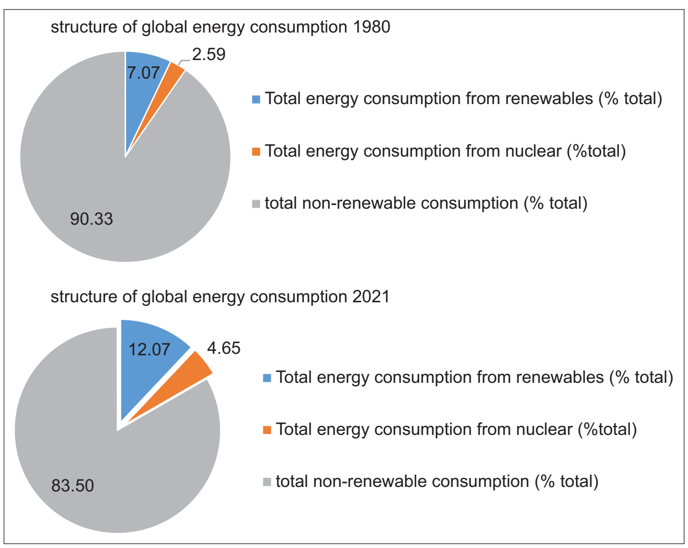
The proliferation of energy consumption, derived from diverse sources ranging from renewables to non-renewables and nuclear, has emerged as a critical driver of global economic activities. Against the backdrop of intensifying climate change concerns, understanding the ramifications of different energy consumption patterns on the global GDP becomes imperative. This research endeavors to bridge the gap in current understanding by leveraging machine learning methodologies to unravel the intricate relationships that govern this complex interplay.

Renewable energy, characterized by its sustainability and lower environmental impact, stands alongside nonrenewable and nuclear sources, each presenting unique challenges and opportunities. As nations grapple with choices concerning their energy portfolios, this paper delves into the consequential effects on global economic growth. By employing advanced machine learning tools, the study aims to discern patterns, forecast trends, and identify key determinants linking energy consumption to global GDP variations.

Most of the world's greenhouse gas emissions come from the energy industry. Nuclear, renewable, and non-renewable power comprise the global energy consumption structure. Compared to renewable and nuclear power, the environmental impact of the world's primary energy source, non-renewable, is far higher. Non-renewable energy consumption represented about 90.33% of the total energy consumed globally in 1980, followed by renewable energy at 7% and nuclear energy at 2.59%. Non-renewable energy remained at the forefront of global energy consumption at a rate of 83.5% (its contribution decreased compared to the year 1980 to account for the other two types of energy), followed by renewable energy at a rate of 12.07%, then nuclear energy at a rate of 4.65% (EIA database, 2024). This is shown in Figure 1.

This paper does not solely seek to analyze; it aspires to contribute actionable insights to guide global policymakers. In probing the question of what actions should be taken on a global scale to address environmental concerns tied to energy consumption, the study positions itself at the intersection of empirical research and the imperative for sustainable development. The ensuing sections will unfold the research methodology, unveil key findings, and delve into the implications of leveraging machine learning to fathom the impact of renewable, nonrenewable, and nuclear energy consumption on global GDP growth. From this standpoint, we can use machine-learning algorithms to determine which of the three types of energy used in the study impacts global economic growth. If clean energy has the greatest impact, there will be no sacrifice but increased use. However, if polluting energy has the greatest impact on global economic growth, the world will be forced to sacrifice part of its growth to preserve the environment.

Figure 1: Structure of global energy consumption (1980, 2021)



2. LITERATURE REVIEW

According to Lorente et al. (2023), renewable energy reduces geopolitical risk and significantly impacts financial markets. The existing literature has found a unidirectional, bidirectional, or neutral effect for these three factors. Begum et al. (2015) examined Malaysia as an example of empirical data obtained in the literature. The research demonstrated that energy and GDP (economic growth) affect carbon emissions using an ARDL bound test. Neither of these variables affects GDP growth; in fact, they do not, according to the results of applying Granger causality to the link between energy, GDP growth, and carbon emissions (Zhang and Cheng, 2009). According to a study by Saidi and BenMbarek (2016), which involved nine industrialized nations, energy consumption has a short-term unidirectional causal influence on GDP growth. However, carbon emissions have a long-term bidirectional causation effect. To find out how energy consumption, CO_2 emissions, and real GDP in the South Caucasus countries relate to one another, Magazzino (2016) performed a causality test. According to the findings, Armenia's energy consumption and carbon dioxide emissions were both enhanced by real GDP. According to Cai et al. (2018), no co-integration was observed between clean energy utilization, greenhouse gas emissions, real GDP per capita, and Canada, France, and Italy. However, Japan and Germany exhibited different results. In the United States, Canada, and Germany, renewable energy only affects GDP per capita in one direction, as shown in the research. In addition, although renewable energy sources have a unidirectional causality impact in the United States, a feedback causal effect is observed in Germany. An analysis of 170 nations' carbon emissions revealed that energy, GDP growth, and urbanization all play a role (Wang et al., 2018). Growth in urban areas, renewable energy, economic development, CO_2, and the agro-industry were the subjects of ARDL test co-integration runs conducted by Malaysian academics between 1978 and 2016. According to Ridzuan et al. (2020), carbon emissions are boosted by urbanization and economic growth, and aquaculture, grown plants, and renewable energy sources dramatically reduce them. Another study found that unpredictability in economic policy increases emissions initially but decreases them later on (Syed and Bouri, 2021). More so, according to the World Uncertainty Index, the ten nations with the largest carbon emissions also have the least clear economic policies (Anser et al., 2021). This uncertainty negatively impacts carbon emissions in the short and long term.

In order to determine the correlation between economic growth and the confirmation of thermal power use from 1970

Table 1: Statistics and a description of all indicators

Variables	Abbreviation	Source of data	Mean	Sum	Min	Max	Mode	SD
Global domestic product growth	GDPg	World bank dataset	2.94	123.66	−3.07	6.20	−3.07	1.58
Renewable energy	REC	U.S energy dataset	8.36	351.08	7.07	12.10	7.07	1.33
Nuclear energy	NEC	U.S energy dataset	5.23	219.84	2.59	6.52	2.59	1.00
Non-renewable energy	NREC	U.S energy dataset	86.47	3631.90	83.42	90.33	83.42	1.36

Source: Compiled by the author.

to 2018, (Magazzino et al., 2020) conducted a contextual analysis of Switzerland. Useful factors included capital, labor thermal power, GDP, and fare. The VAR model determines the relationships between variables to evaluate the data. The paper showed that the thermal power loss will negatively affect GDP growth in the future. From 1971 to 2014, (Vo et al., 2020) outlined the CPTPP nations' contextual inquiry into the role of renewable and nuclear energy and solutions for reducing carbon emissions. These elements were used: CO_2, thermal power, power derived from petroleum products, and sustainable power. Information was assessed using the model (FMOLS). Worldwide warming results from increased CO_2 emissions; one possible solution is to switch to cleaner energy sources to reduce CO_2. From 1981 to 2019, researchers in Pakistan examined how green financial development affected GDP growth (Nawaz et al., 2021). Green financial development—including green loans, securities, insurance, investments, and FDI—has a favorable effect on Pakistan's economic growth, according to ARDL's empirical studies. The contextual inquiry in the link was described by (Abbasi et al., 2020) to find energy consumption and urbanization effects on carbon dioxide discharge: evidence from Asian-8 nations using board data analysis from 1982 to 2017. An ordinary least squares model is available for use. Y stands for per capita GDP, EU for energy use, FD for financial developments, UR for urbanization, and TO for exchange receptiveness; the factors utilize carbon dioxide (CO_2) emissions. The study's findings indicate a one-way causal relationship between CO_2 emissions and energy use, and the study's methodology provides substantial recommendations for reducing emissions from fossil fuels. The contextual examination of Pakistan was examined by (Naqvi et al., 2021) to find evidence of a sustainable power climate through monetary events, renewable energy, and the biological impact nexus. A Kuznets curve derived from pay bunch analysis from 1990 to 2017. To evaluate the data, an OLS model was employed. The criteria were renewable energy sources, real GDP growth per capita, and GDP growth with environmental impacts. Researchers' findings put policymakers in a pivotal position to prevent environmental disasters by influencing the development and use of sustainable power.

(Chen and Zhou, 2021) looked into the impact of urbanization on energy intensity using panel data collected from 72 nations between 2000 and 2014, taking into account factors like the rate of urbanization and worries about energy security, among others. In order to find out how institutional efficiency affected the connection between urbanization and energy intensity, a panel threshold model was used. The data demonstrated that energy demand intensity increased as the number of metropolitan areas increased. After a certain level of institutional efficiency, the beneficial impacts of urbanization on energy intensity are reduced by 0.033, according to the study. The results show that as the pace of urbanization increases, so does the energy intensity. When institutional efficiency reaches a certain level, the research shows a small but significant decline of 0.033, representing urbanization's positive influence on energy intensity. As previously indicated, the institutional barrier greatly affected the fossil fuel business but had little to no effect on the renewable energy sector. Between 1978 and 2016, the impact of the province-level manufacturing structure distortion index on China's energy intensity was investigated (Shen and Lin, 2021). The data shows a noticeable decline in the distortion index of China's industrial structure from 1978 to 2016. This index was crucial for determining the energy power of each province. Energy costs, exports, and FDI impacted China's energy strength, while R&D spending had no such effect. China may reduce its energy intensity by using a market-based approach to factor price determination and eliminating the root causes of distortions in its industrial structure, as suggested in the report. (Wang and Wang, 2021) used data collected from 137 nations or regions between 2002 and 2012 to build a panel threshold regression (PTR) model that investigated the nonlinear influence of an aging population on carbon dioxide emissions. Urbanization and industrial structure were the explanatory variables in the PTR model, with the age of the population serving as the threshold variable. The variable that the PTR model explained was carbon emissions. The study also considered control variables like GDP growth, trade independence, financial position, and population size. In particular, the data show that as the population ages, there is a positive correlation between industrial structure and carbon emissions for low-income groups, a negative association for upper-middle-income groups, and a "U"-shaped reverse association for high-income groups. The associations between urbanization and carbon emissions are positive and nonlinear for middle-class, affluent, and upper-middle-class neighborhoods. On the other hand, as the population matures, the relationships adopt an inverted "U" shape.

Bashir et al. (2021) examined how GDP, energy consumption, carbon dioxide emissions, and Indonesia's rapidly expanding metropolitan areas are related. This information was culled from the World Development Indicators database, which had records of several development indicators spanning 1985-2017. The research used the vector error correction model to fix data mistakes. The foundation was a Granger causality test. According to real-world results, energy use and urbanization may soon contribute to CO_2 emissions. They also showed that urbanization could increase energy usage. In addition, there were long-term links between CO_2 emissions and energy consumption, urbanization, and economic expansion, among other findings. The EKC theory was validated by several studies, one of which looked at the correlation between GDP growth and CO_2 emissions in Indonesia. Based on these results, the researchers have concluded that regulations are required to lessen the harmful effects of urbanization through raising awareness and reducing energy consumption, thereby protecting the quality of the environment.

One or two nations have been the primary foci of studies examining the interplay between energy, economics, and the environment. They surveyed nations in the Middle East and North Africa (Farhani and Shahbaz, 2014). Their findings support the environmental Kuznets curve theory, which posits that growing economies directly cause increasing CO_2 emissions. According to panel data analysis, power consumption (renewable and non-renewable) and CO_2 emissions were causally related in the short run. A two-way causal relationship between power usage and CO_2 emissions exists in the long run. The Middle East and North Africa (MENA) area also found a short-run unidirectional relationship between energy use and CO_2 (Gorus and Aydin, 2019). However, the study finds no correlation between GDP growth and carbon emissions. Thus, it seems that conservation energy regulations do not hurt the MENA economies now or in the future.

A more recent study by Mensah et al. (2019) looked at 22 African states, some of which export oil and others that do not. They found that energy use, GDP growth, and carbon emissions were causally related. According to the long-term trend, there is a correlation between GDP growth and emissions for oil-exporting nations, even if the two sets of data exhibit different trajectories. Energy consumption and economic growth are positively correlated, according to both the long-term and short-term perspectives of non-oil exporters' examples.

To find out which of the three energy sources studied has the greatest effect on world GDP growth, we can apply machine learning techniques to this problem. Clean energy will be more widely used without any reduction in quality if it achieves its full potential (i.e., it does not slow down the expansion of the world economy). However, if polluting energy is the biggest factor in global economic expansion, the world will have to give up some economic growth to protect the environment.

Table 2: The ML accuracy

Model	CA	F1	Precision	Recall
GB	0.905	0.860	0.819	0.905
RF	0.857	0.835	0.814	0.857

Source: Compiled by author

3. EMPIRICAL FRAMEWORK

This paper trying to determine the effects of renewable, non-renewable, and nuclear energy on the global gross domestic product growth. The empirical framework is formulated as the eq.1:

$$GDPg = REN+NREN+NE \tag{1}$$

Where,
GDPg = global domestic product growth
REC = renewable energy consumption
NREC = non-renewable energy consumption
NEC = nuclear energy consumption.

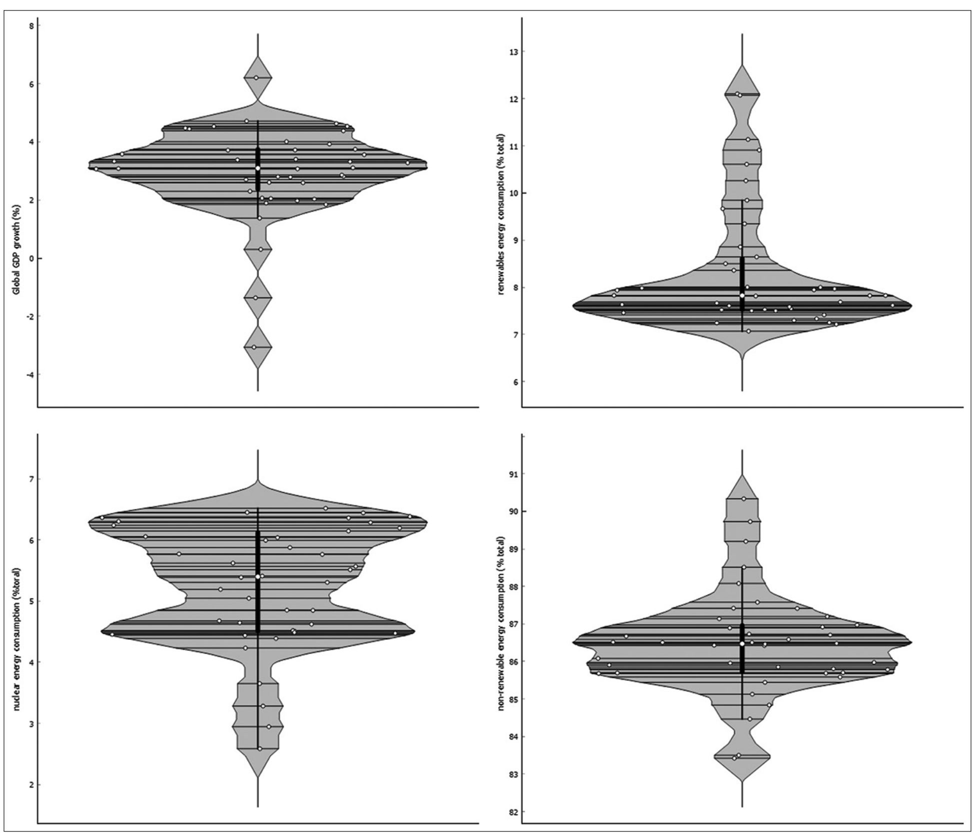
4. DATA AND METHODOLOGY

This Section is divided into two sub-sections; the first provides a statistical and graphical overview of the paper's data, while the second focuses on the methods employed.

4.1. Data

The data used in this paper was collected from the U.S. Energy Information Administration and the World Bank dataset. Refer to Table 1 for a statistical analysis and previous breakdown of the data. Furthermore, the distribution of each independent and dependent variable may be shown in the violin plot (Figure 2).

Figure 2: Violin plots distribution of a dataset



4.2. Methodology

4.2.1. The ML algorithms

One well-known ensemble learning approach that consistently produces accurate and reliable prediction models is the Gradient Boosting Regressor (GBR). With its origins in GB, GBR iteratively constructs a group of weak learners, usually decision trees, and then uses their predictions to build a powerful, high-performing model. According to AbdElminaam et al. (2023), GB has been an essential part of ML since its 2001 proposal by Jerome H. Friedman. It provides efficacy and versatility across many domains.

Because it is iterative, GBR can continuously improve forecasts, and its basic idea is to minimize the model's residuals. In order to fix the mistakes produced by the previous ensemble, the algorithm builds new trees, with each successive tree concentrating on the combined model's residuals. To handle complicated links within the data and adapt to subtle patterns, GBR employs an iterative approach and deploys weak learners.

Mathematically, the GBR algorithm can be expressed as:

$$F_m(x) = F_{m-1}(x) + v \cdot h_m(x) \tag{2}$$

Here, Fm (x) represents the ensemble's prediction at iteration m, F_{m-1} (x) is the prediction from the previous iteration, ν is the learning rate, and h_m (x) is the weak learner at iteration m. The algorithm aims to find the optimal values for the weak learners that minimize the loss function, thereby enhancing the overall predictive accuracy.

Regarding predictive modeling, the Random Forest Regressor (RFR) has received much praise for being a strong and flexible

Figure 3: The GB and RF ROC sensitivity

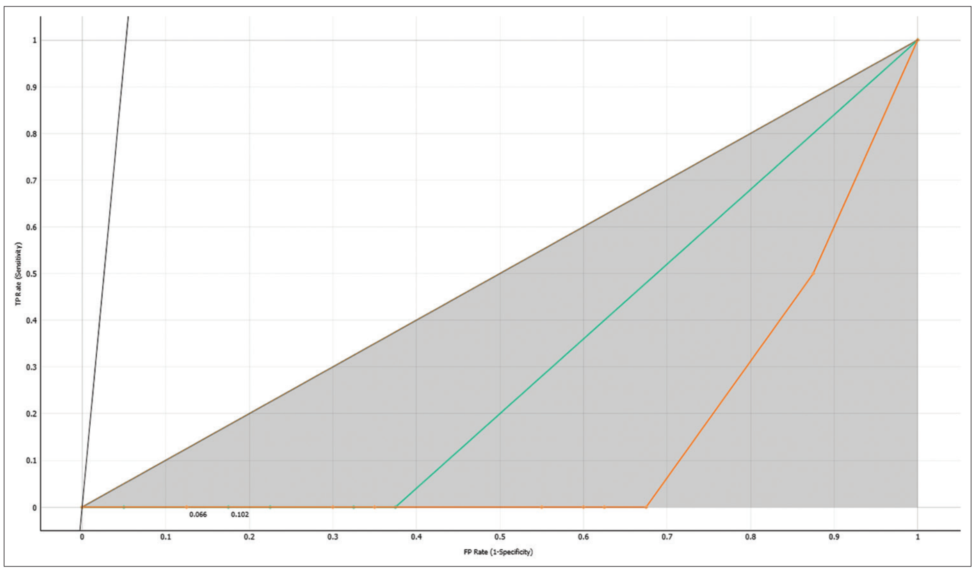
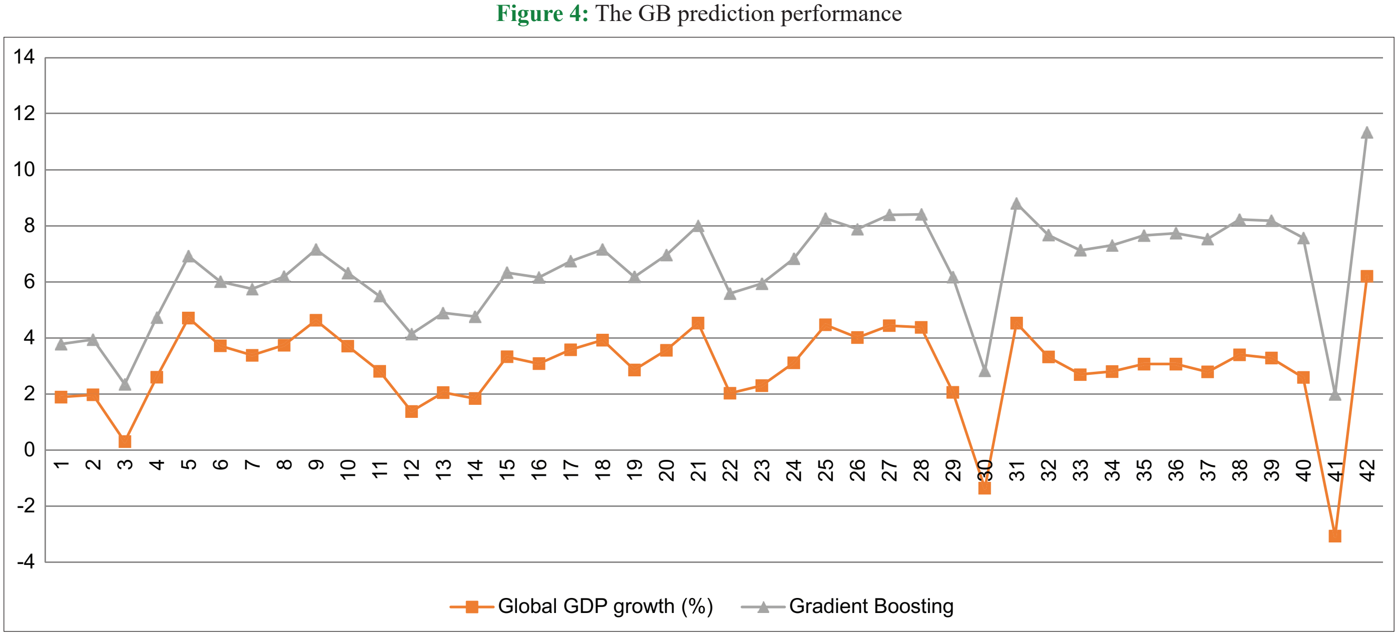


Figure 4: The GB prediction performance



Source: Compiled by author

Table 3: Comparison between global GDP growth actual values and predicted values according to independent variables

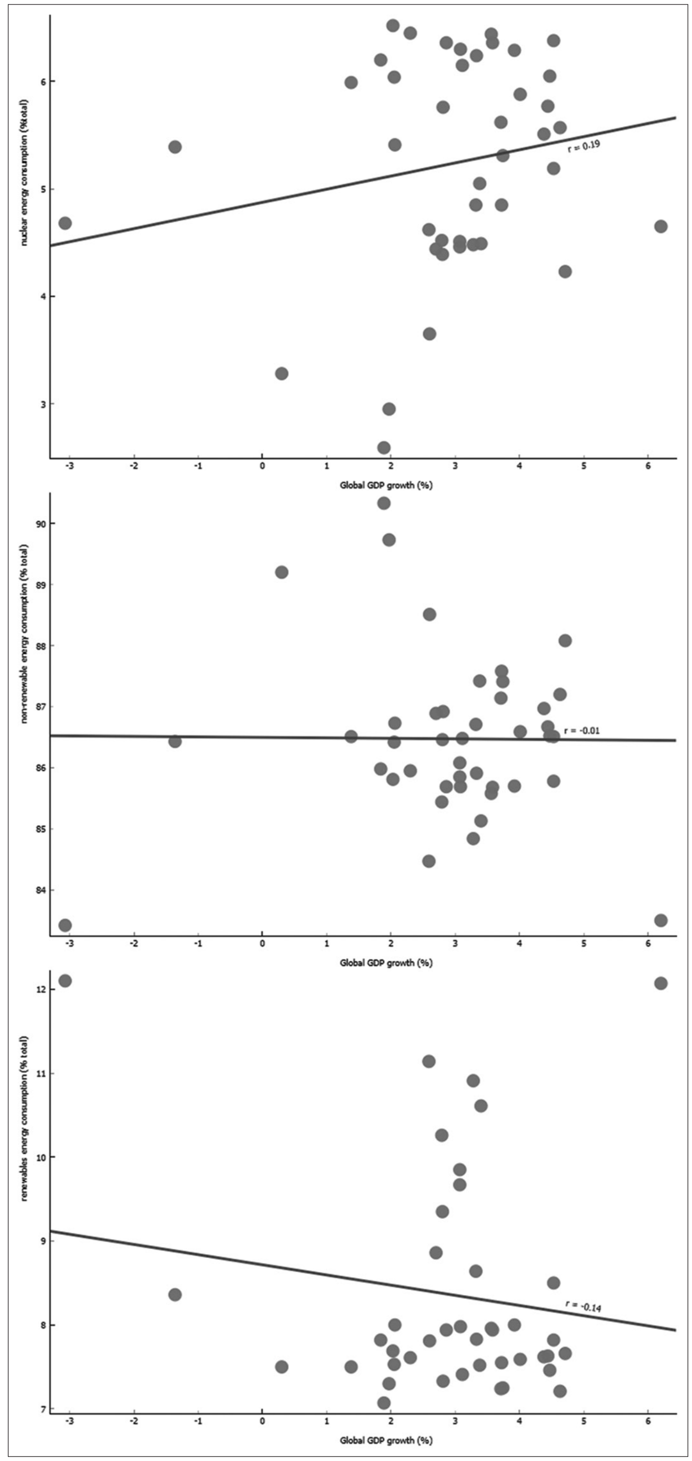
Year	Global GDP growth actual values (%)	Gradient boosting prediction values
1980	1.89	1.89
1981	1.97	1.97
1982	0.3	2.05
1983	2.6	2.13
1984	4.71	2.21
1985	3.72	2.29
1986	3.38	2.37
1987	3.74	2.44
1988	4.63	2.52
1989	3.71	2.60
1990	2.81	2.68
1991	1.38	2.76
1992	2.05	2.84
1993	1.84	2.92
1994	3.33	3.00
1995	3.08	3.08
1996	3.58	3.16
1997	3.92	3.24
1998	2.86	3.32
1999	3.56	3.39
2000	4.53	3.47
2001	2.03	3.55
2002	2.3	3.63
2003	3.11	3.71
2004	4.47	3.79
2005	4.01	3.87
2006	4.44	3.95
2007	4.38	4.03
2008	2.06	4.11
2009	−1.36	4.19
2010	4.53	4.27
2011	3.32	4.35
2012	2.7	4.42
2013	2.8	4.50
2014	3.07	4.58
2015	3.07	4.66
2016	2.79	4.74
2017	3.4	4.82
2018	3.28	4.90
2019	2.59	4.98
2020	−3.07	5.06
2021	6.2	5.14

Source: Compiled by author

machine-learning algorithm. Breiman presented RFR in 2001 as an expansion of the RF method, which was mainly developed for regression tasks and originated from the ensemble-learning paradigm. Because of its remarkable flexibility and performance, this method has become standard in many scientific fields (Abd El-Aal, 2023).

Central to the RFR is building an ensemble of decision trees and then using their combined predictions to improve accuracy and generalizability. In order to prevent overfitting and make the model more resilient, the technique makes all of the training data and characteristics examined at each split randomly generated. A robust and accurate regression model is produced by averaging the predictions of individual trees in the ensemble.

Figure 5: The correlation between dependent and independent variables



Source: Compiled by the author

Mathematically, the RFR combines the Predictions of N decision trees to produce the final output F(x):

$$F\left(x\right)=\frac{1}{N}\sum_{i=1}^{N}f_i\left(x\right)$$

The forecast of the i-th ensemble decision tree is represented here by fi (x). A robust ensemble model is achieved through training-related randomization techniques, such as bootstrapping and feature subsampling, guaranteeing tree diversity.

5. EMPIRICAL RESULTS

5.1. Model Evaluation

To evaluate ML algorithms, accuracy measures are essential. In particular, algorithms for classification jobs. These indicators help us understand the model's strengths and weaknesses by providing vital insights into its performance. According to Powers (2020), new accuracy metrics will be implemented, including AUC-ROC, F1 score, precision, and recall.

By dividing the total number of expected positive results (including real and false positives) by the number of actual positive results, one may determine the precision, also called positive predictive value. The accuracy of the model's predictions is assessed. Precision = TP/(TP + FP) is the formula.

The recall Metric calculates the proportion of correctly anticipated positive events, or true positives, to the overall number of positive occurrences, or the sum of true positives and false negatives. When trying to catch as many positive situations as possible, recall is really important. Remember: TP divided by (TP plus FN).

The F1 score is determined by averaging the accuracy and memory subscores. Because it can balance accuracy with memory, it can easily tell the difference between true positives and false negatives. An imbalance in the distribution of courses has the greatest impact on F1 score performance. The F1 score is calculated by dividing the sum of the precision and recall by two, raised to the power of three.

The AUC-ROC, which measures the model's performance across many classification criteria, shows how effective the model is. One measure of its extent is the area under the ROC curve, often known as the AUC-ROC statistic. Because it thoroughly evaluates the model's capacity to distinguish between classes, comparing the model's performance across different threshold values is very beneficial. Values of AUC-ROC could be in the positive or negative range. If your model's AUC-ROC is <0.5, it is wise to make an educated guess; a number close to 1 shows great discriminatory ability, on the other hand.

Table 2 shows that the GB algorithms are more accurate than the RF by 90.5% versus 85.7%, as shown in the ROC sensitivity analysis in Figure 3. This leads to the analysis depending on the GB model in prediction and feature selection.

5.2. The GB Algorithm Prediction Performance

In order to determine the quality of gradient boosting prediction, we must compare the actual values with the predicted values, as shown in Table 3, which will be expressed in Figure 5.

Table 4: The GB algorithms feature importance indicators

Variables	GB feature importance
REC	67.5
NEC	17.8
NREC	14.6

Source: Compiled by the author

Figure 4 shows the Excellent prediction of the GB algorithm for global GDP growth dependent on Independent variables. So, the GB algorithm is optimized to determine Feature selection.

5.3. GB Algorithm Feature Importance

The dark box of ML models can only be unlocked by recognizing the significance of features. We evaluate the model's predictions or classifications and quantify the influence of each input variable or feature. Prioritizing these attributes with significance ratings helps data scientists understand their models' inner workings. With this knowledge, people may enhance their models, drive advancement, and make clearer and more accurate decisions. Table 4 shows the feature importance of the GB algorithm.

Table 4 shows that renewable energy consumption is the most influential variable for global GDP growth, predicted by 67.5%, nuclear energy consumption by 17.8%, and non-renewable energy consumption by 14.6%. This indicates that the more the world relies on renewable energy, the greater global economic growth. This leads to two probabilities: the effect is negative or positive; this is situated on the correlation coefficient between variables, as shown in Figure 5.

Figure 6 shows the positive and negative relationship between nuclear energy consumption and global economic growth with renewable energy consumption. The relation with non-renewable is a fixed relationship. Hence, increasing reliance on renewable energy will lead to a reduction in global economic growth and, on the contrary, the use of nuclear energy.

6. CONCLUSION

In navigating the intricate nexus of energy consumption, global GDP growth, and environmental sustainability, this study has employed advanced machine learning techniques to unravel patterns and forecast trends. The structure of global energy consumption, dominated by non-renewable sources, underscores the urgency of addressing environmental concerns associated with energy utilization. The findings reveal a shifting landscape in energy consumption, with a notable increase in the share of renewable energy over the years. However, the predominant reliance on non-renewable sources, particularly in the past, has contributed significantly to environmental challenges. As the world grapples with the imperative of sustainable development, it becomes crucial to analyze and prescribe actionable insights.

The study's unique contribution lies in its positioning at the intersection of empirical research and global policymaking. Moving beyond analysis, the focus shifts towards proposing actions that can guide policymakers in mitigating the environmental impact of energy consumption. The machine learning algorithms offer a nuanced understanding of the impact of renewable, nonrenewable, and nuclear energy on global GDP growth. As we envision a sustainable future, the study contemplates the actions needed globally. Renewable energy emerges as the primary driver of economic growth; the path is clear for increased adoption with sacrificing prosperity, where the relationship between renewable energy consumption and global GDP growth is inverse. However, if the study underscores the environmental toll of polluting energy on global economic growth, the call for sacrifice becomes evident.

REFERENCES

Abbasi, M.A., Parveen, S., Khan, S., Kamal, M.A. (2020), Urbanization and energy consumption effects on carbon dioxide emissions: Evidence from Asian-8 countries using panel data analysis. Environmental Science and Pollution Research, 27(15), 18029-18043.

Abd El-Aal, M.F. (2023), Analysis factors affecting Egyptian inflation based on machine learning algorithms. Data Science in Finance and Economics, 3(3), 285-304.

AbdElminaam, D.S., El-Aal, A., Abdellatif, A. (2023), Nowcasting Egypt GDP using machine learning algorithms. Journal of Computing and Communication, 2(1), 1-8.

Ahmed, K., Rehman, M.U., Ozturk, I. (2017), What drives carbon dioxide emissions in the long-run? Evidence from selected South Asian Countries. Renewable and Sustainable Energy Reviews, 70, 1142-1153.

Al-Mulali, U., Ozturk, I., Lean, H.H. (2015), The influence of economic growth, urbanization, trade openness, financial development, and renewable energy on pollution in Europe. Natural Hazards, 79, 621-644.

Anser, M.K., Apergis, N., Syed, Q.R. (2021), Impact of economic policy uncertainty on CO_2 emissions: Evidence from top ten carbon emitter countries. Environmental Science and Pollution Research, 28, 29369-29378.

Anwar, A., Sarwar, S., Amin, W., Arshed, N. (2019), Agricultural practices and quality of environment: Evidence for global perspective. Environmental Science and Pollution Research, 26, 15617-15630.

Available from: https://data.worldbank.org

Available from: https://www.eia.gov

Bashir, A., Susetyo, D., Suhel, S., Azwardi, A. (2021), Relationships between urbanization, economic growth, energy consumption, and CO_2 emissions: Empirical evidence from Indonesia. The Journal of Asian Finance, Economics and Business, 8(3), 79-90.

Begum, R.A., Sohag, K., Abdullah, S.M.S., Jaafar, M. (2015), CO_2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41, 594-601.

Breiman, L. (2001), Random forests. Machine Learning, 45, 5-32.

Cai, Y., Sam, C.Y., Chang, T. (2018), Nexus between clean energy consumption, economic growth and CO_2 emissions. Journal of Cleaner Production, 182, 1001-1011.

Charfeddine, L., Kahia, M. (2019), Impact of renewable energy consumption and financial development on CO_2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. Renewable Energy, 139, 198-213.

Chen, Z., Zhou, M. (2021), Urbanization and energy intensity: Evidence from the institutional threshold effect. Environmental Science and Pollution Research, 28, 11142-11157.

Cheng, M., Liu, B. (2019), Analysis on the influence of China's energy consumption on economic growth. Sustainability, 11(14), 3982.

Farhani, S., Shahbaz, M. (2014), What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate CO_2 emissions in MENA region? Renewable and Sustainable Energy Reviews, 40, 80-90.

Gozgor, G., Lau, C.K.M., Lu, Z. (2018), Energy consumption and economic growth: New evidence from the OECD countries. Energy, 153, 27-34.

Lorente, D.B., Mohammed, K.S., Cifuentes-Faura, J., Shahzad, U. (2023), Dynamic connectedness among climate change index, green financial assets and renewable energy market, and renewable energy markets: Novel evidence from a perspective. Renewable Energy, 204, 94-105.

Magazzino, C., Mele, M., Schneider, N., Vallet, G. (2020), The relationship between nuclear energy consumption and economic growth: Evidence from Switzerland. Environmental Research Letters, 15(9), 0940a5.

Magazzino, C.T. (2016), He relationship among real GDP, CO_2 emissions, and energy use in South Caucasus and Turkey. International Journal of Energy Economics and Policy, 6(4), 672-683.

Mensah, I.A., Sun, M., Gao, C., Omari-Sasu, A.Y., Zhu, D., Ampimah, B.C., Quarcoo, A. (2019), Analysis on the nexus of economic growth, fossil fuel energy consumption, CO_2 emissions and oil price in Africa based on a PMG panel ARDL approach. Journal of Cleaner Production, 228, 161-174.

Naqvi, S.A.A., Shah, S.A.R., Anwar, S., Raza, H. (2021), Renewable energy, economic development, and ecological footprint nexus: Fresh evidence of renewable energy environment Kuznets curve (RKC) from income groups. Environmental Science and Pollution Research, 28, 2031-2051.

Nawaz, M.A., Hussain, M.S., Hussain, A. (2021), The effects of green financial development on economic growth in Pakistan. iRASD Journal of Economics, 3(3), 281-292.

Ozcan, B., Ari, A. (2017), Nuclear energy-economic growth nexus in OECD countries: A panel data analysis. International Journal of Economic Perspectives, 6(1), 138-154.

Pao, H.T., Tsai, C.M. (2010), CO_2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy, 38(12), 7850-7860.

Powers, D.M. (2020), Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation. arXiv preprint. arXiv:2010.16061.

Ridzuan, N.H.A.M., Marwan, N.F., Khalid, N., Ali, M.H., Tseng, M.L. (2020), Effects of agriculture, renewable energy, and economic growth on carbon dioxide emissions: Evidence of the environmental Kuznets curve. Resources, Conservation and Recycling, 160, 104879.

Saidi, K., Mbarek, M.B. (2016), Nuclear energy, renewable energy, CO_2 emissions, and economic growth for nine developed countries: Evidence from panel Granger causality tests. Progress in Nuclear Energy, 88, 364-374.

Syed, Q.R., Bouri, E. (2022), Impact of economic policy uncertainty on CO_2 emissions in the US: Evidence from bootstrap ARDL approach. Journal of Public Affairs, 22(3), e2595.

Vo, D.H., Vo, A.T., Ho, C.M., Nguyen, H.M. (2020), The role of renewable energy, alternative and nuclear energy in mitigating carbon emissions in the CPTPP countries. Renewable Energy, 161, 278-292.

Wang, Q., Wang, L. (2021), The nonlinear effects of population aging, industrial structure, and urbanization on carbon emissions: A panel threshold regression analysis of 137 countries. Journal of Cleaner Production, 287, 125381.

Wang, S., Li, G., Fang, C. (2018), Urbanization, economic growth, energy consumption, and CO_2 emissions: Empirical evidence from countries with different income levels. Renewable and Sustainable Energy Reviews, 81, 2144-2159.

Zhang, X.P., Cheng, X.M. (2009), Energy consumption, carbon emissions, and economic growth in China. Ecological Economics, 68(10), 2706-2712.