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Innovation, Crude Oil Prices, Fossil Fuel Energy Consumption and Climate Sustainability in Egypt: Using the Gradient Boosting Machine Learning Algorithm

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ABSTRACT

The present paper analyses the predictions of yearly carbon emissions and the impacts of innovation, crude oil prices, fossil fuel energy consumption, urbanisation, and economic growth on climate sustainability in Egypt from 1990 to 2024 using a gradient-boosting machine learning algorithm. The models' performance was assessed using root mean square error (RMSE), mean absolute error (MAE), R-squared, accuracy, precision, recall, F1 score, area under the curve (ROC AUC), and confusion matrix accuracy. The findings demonstrated that a gradient-boosting algorithm attains nearly flawless performance across all assessment metrics for carbon emission prediction. Moreover, the analysis revealed that fossil fuel demand is dominant in explaining carbon emissions in Egypt. It means fossil fuel consumption is the most influential factor at 22.3%, followed by economic growth at 20.2%, innovation at 15.6%, crude oil prices at 14.8%, renewable energy consumption at 14.2%, and finally urban population at 12.9%. The document offers substantial implications for policymakers and academics in mitigating CO_2 emissions. The findings suggest that it is necessary to implement a comprehensive policy package that emphasises demand management, enhances energy efficiency programs, accelerates clean energy deployment, and promotes green innovation in pursuit of a more sustainable energy mix in Egypt in the long term.

Keywords: Carbon Emissions, Fossil Fuel Energy Consumption, Innovation, A Gradient-boosting Algorithm
JEL Classifications: O24, Q4, Q5

1. INTRODUCTION

Energy and climate issues have been increasingly present in economic and environmental literature over the past few decades, due to their direct connection to the phenomenon of climate change and its implications for economic growth and sustainable development. Numerous studies have proven that fossil fuel consumption is the most significant source of greenhouse gas emissions, while technological innovation and the shift to renewable energy are key tools for reducing these emissions (Sadorsky, 2010; Acheampong, 2018). Other research has shown that fluctuations in global oil prices do not only affect economic activity but also extend to impact the environmental commitments of both developing and developed countries alike (Hamilton, 2013). At the same time, the economic literature confirms that economic growth and urbanisation exert increasing pressure on total energy demand and, consequently, carbon emissions (Shahbaz et al., 2014). However, the literature tends to focus on advanced or major emerging economies such as China and India, leaving a knowledge gap regarding developing economies like Egypt.

In Egypt, carbon dioxide emissions represent a significant environmental challenge that threatens climate sustainability and exacerbates environmental degradation associated with biodiversity loss, natural resource depletion, and the greenhouse effect, which is a global phenomenon facing all countries. These environmental challenges and risks pose a significant obstacle to achieving sustainable development goals (Selmey et al., 2025). Economic growth is viewed as a crucial driver for the development of all sectors in both developing and developed countries, but it can also lead to increased climate change risks and higher greenhouse gas emissions (Rashdan and Ibrahim, 2024). The main reason for this rise is Egypt's heavy reliance on fossil fuels to meet its energy needs. Fossil fuels are still Egypt's main source of energy, making up a large part of the country's total energy use. This makes global warming, climate change, and the environmental and economic effects that come with them worse. Egypt holds the title of being the largest oil consumer in Africa (Wesseh and Lin, 2018). This makes Egypt a suitable case for studying the potential to mitigate the impacts of replacing different fuel types, as well as the actual effects of energy consumption on economic growth and climate sustainability. Kraft and Kraft (1978) conducted a robust analysis of the importance of energy consumption, concluding that high economic growth necessitates higher energy consumption. Studies by Adebayo et al. (2021), as well as Karaaslan and Camkaya (2022), have confirmed the role of energy consumption in exacerbating climate change. It can also be said that the importance of the Egyptian economy as a case study comes from being one of the largest developing economies in the Middle East and Africa in terms of population and GDP, with a relatively large dependence on fossil fuels to meet energy needs. This makes Egypt more susceptible to fluctuations in global oil prices, while the state strives to balance the demands of rapid growth with environmental sustainability goals through its energy transition plans within the "Egypt Vision 2030" (Ministry of Planning, 2016). This disparity between growth requirements and environmental commitments puts Egypt in a favourable position to study the dynamics of the relationship between innovation, oil prices, fossil fuel consumption, and climate policies.

In this study, the Gradient Boosting Algorithm was adopted as an advanced quantitative tool for predicting carbon dioxide emissions in Egypt. This algorithm is characterised by its ability to handle nonlinear relationships and complex interactions among variables, surpassing the limitations of traditional models and classical economic measurement methods (Friedman, 2001). The results indicated that the boosted gradient outperformed other algorithms in terms of prediction accuracy. The analysis also revealed that fossil fuel consumption was the most influential factor at 22.3%, followed by economic growth at 20.2%, innovation at 15.6%, crude oil prices at 14.8%, renewable energy consumption at 14.2%, and finally urban population at 12.9%.The results indicate the dominance of fossil fuel demand in explaining carbon emissions in Egypt and practically point towards a policy package that focuses on demand management, improving energy efficiency, accelerating the deployment of clean energy, and stimulating green innovation.

Based on the above, the focus of this paper is on the question: How do oil prices, the level of innovation, and energy consumption affect climate sustainability in Egypt? And what role can machine learning algorithms, specifically the gradient boosting model, play in analyzing this complex relationship and providing accurate predictions that enhance the effectiveness of public policies related to energy and climate?. In this study, we explore and evaluate the impact of innovation, rising global oil prices, economic growth, and energy consumption on climate sustainability in Egypt.

This study offers three main contributions to academic literature and economic policy. First, advanced machine learning algorithms are employed to analyse the determinants of emissions in a developing economy, filling a gap in the literature that has traditionally focused on advanced economies. Secondly, the results confirm that reliance on fossil fuels remains the most influential determinant of Egyptian carbon emissions, guiding policymakers towards the necessity of accelerating the transition to sustainable alternatives. Thirdly, the results reveal promising roles for innovation and the expansion of renewable energy as complementary pathways to reshaping the Egyptian energy mix.

The study's results are expected to contribute to the expansion of relevant literature and provide practical recommendations for policymakers in Egypt and developing countries, enhancing the sustainability of the energy transition and reducing climate risks. It also opens up possibilities for employing artificial intelligence algorithms in energy and climate research. In the end, to achieve that purpose, the study is divided into several sections in addition to the introduction, which are the research methodology and the data used, then the results and discussion, and finally the study conclusion.

2. REVIEW OF THE LITERATURE AND HYPOTHESIS SYNTHESIS

This section examines the research investigating the link between innovation, fossil fuels energy consumption, oil prices and climate sustainability.

2.1. Fossil Fuel Energy Consumption and Climate Sustainability

Fossil fuels are the primary sources of energy worldwide; however, extracting, processing, and burning them significantly harm the environment and negatively affect climate sustainability (Ortega-Ramírez et al., 2022; Allen et al., 2012). Furthermore, natural resources such as oil, coal, and natural gas are limited in quantity and rare in nature, as fossil fuels are a finite resource that depletes quickly. With the increasing scarcity, the importance of finding and providing alternative energy sources arises. Burning fossil fuels can lead to air pollution, acid rain, and water pollution. Therefore, efforts should be made to conserve these resources and reduce reliance on fossil fuels through various means, including the use of renewable energy sources such as solar energy, wind energy, and geothermal energy; increasing energy efficiency; and using energy-saving devices (Díaz et al., 2019; Tawiah et al., 2021). The relationship between energy generated from fossil fuels and the environment is a research topic that attracted the attention of many researchers: Friedrichs and Inderwildi (2013), Narayanan and Steinbuks (2014), Al Mamun et al. (2018), Martins et al. (2019), Inumaru et al. (2021), and Liu et al. (2024). Further research, such as Laurent and Espinosa (2015), Sarwar et al. (2017), Shahbaz et al. (2017), and Ozturk and Al-Mulali (2019), has examined the role of energy consumption and its impact on economic growth and environmental sustainability. Some research has focused on measures aimed at combating the environmental damage associated with fossil fuels, like Sueyoshi and Goto (2013), De Souza et al. (2018), Perera (2018), Diaz et al. (2019), Anser et al. (2020), Solarin (2020), Salleh et al. (2024), and Wang and Pang (2025). The Ortega-Ramírez et al. (2020) study indicated that the exploitation of fossil fuels leads to environmental pollution and damage to natural resources, necessitating the implementation of measures to prevent and mitigate these impacts. In short, numerous studies have indicated that carbon dioxide emissions from fossil fuel combustion are a major contributor to global warming and climate change. Both the Bach (1981) and Wang and Azam (2024) studies also indicated that the effects on the climate are especially worrisome because CO_2 emissions contribute to the greenhouse effect and could cause global temperatures to rise. climatic scientists present compelling scientific evidence that global warming and the consequent climatic alterations are predominantly attributable to the combustion of coal, oil, and other fossil fuels.There are numerous studies aimed at raising awareness about fossil fuel sources and their connection to environmental degradation, such as the studies by Fredericks and Inderwildi (2013), Chan et al. (2017), and De Souza et al. (2018). Additionally, Investments in research and the development of new technologies that can help create new sources of energy are essential. These initiatives may encompass sources of clean energy, including biofuels, and innovative technology, such as hydrogen fuel cells. The ecological consequences of fossil fuels necessitate actions to diminish our reliance on these restricted resources that cause more environmental degradation. We can progress towards a sustainable future by saving suitable resources, enhancing efficiency, and investing in research and development (Khan et al., 2022). Therefore, we can reduce fossil fuel use and carbon emissions by utilising cleaner energy sources through innovation and increased spending on research and development.

The aforementioned review reveals the links between energy derived from the use of fossil fuels and its impact on the environment and climate sustainability. Therefore, the following hypothesis can be formulated:

The consumption of fossil fuels energy significantly affects the sustainability of the climate in Egypt.

2.2. Innovation and Climate Sustainability

It is widely recognized that innovation is a fundamental driver of climate sustainability, enabling economies and communities to transition toward low-emission and climate-resilient pathways (Matos et al., 2022). Innovation and technical advancement enhance the association between economic growth and the sustainability of the environment by facilitating the replacement of polluting and obsolete technologies and generating new, effective alternative energy sources (Mohamued et al., 2021). Global events in the past decade demonstrate the importance of creating strong incentives for innovation in the field of climate. In 2015, at the United Nations Climate Change Conference in Paris, twenty nations, including the UK, US, China, and India, pledged to double the public's investments in low-carbon technologies under the 'Mission Innovation' pact (Sanchez and Sivaram, 2017; Matos et al., 2022). At the same time, climate activists and non-governmental organisations, like Greta Thunberg, have influenced government policies that prioritise economic growth at the expense of environmental damage (O'brien et al., 2018; Sabherwal et al., 2021). On the other hand, the Acemoglu et al. (2023) study indicated that Innovation should be refocused on green technologies to address climate change while preserving long-run economic growth. Academics have been actively developing new technologies for decades (Burchardt et al., 2018). However, innovations in low-carbon technology have been so slow to meet the temperature targets established by the Paris Agreement (Höhne et al., 2020). Therefore, one of the main challenges is to understand the composition of factors that will help accelerate low-carbon innovations and halt high-carbon innovations. Matos's et al. (2022) study confirmed that innovation is expected to play a major role in mitigating climate change, but its development and dissemination are so slow that they cannot achieve climate stabilisation. Anadon's (2016) study indicated that institutional reforms to redirect innovation structures toward sustainable development could enhance the utilization of technological innovation to achieve climate sustainability. In short, the relationship between innovation and climate sustainability is complementary and reciprocal: the more societies advance in sustainable innovation, the more efforts to protect the environment accelerate, and the greater the climate challenges, the more the need to renew and deepen innovations in all sectors becomes. Finally, several studies have indicated that innovation is a key mechanism for addressing environmental challenges and supporting sustainable growth through renewable energy technologies, recycling systems, sustainable agriculture, and green technologies that reduce the carbon footprint.

The aforementioned review reveals the links between innovation and its impact on the environment and climate sustainability. Therefore, the following hypothesis can be formulated:

The innovation significantly affects the sustainability of the climate in Egypt.

2.3. Crude Oil Prices and Climate Sustainability

Crude oil prices, as a fundamental economic factor, play a pivotal role in influencing the issue of energy and climate sustainability. When oil prices rise, the cost of producing energy from fossil fuels increases, encouraging the search for more sustainable alternatives, such as renewable energy. Conversely, a decrease in oil prices may lead to an increased reliance on fossil fuels and reduce the incentives for investing in clean energy sources, hindering efforts to achieve climate sustainability (Katircioglu, 2017; Zaghdoudi, 2018; Abumunshar et al., 2020). Net oil-importing economies are particularly vulnerable to fluctuations in crude oil prices (Mahajan and Sah, 2025). When crude oil prices rise, the cost of importing it increases, leading to a decline in the trade balance and economic growth. However, when the price of crude oil decreases, the cost of importing oil decreases, which improves the trade balance and contributes to increased economic growth (Mahajan and Sah, 2025). The impact of oil prices on greenhouse gas emissions is asymmetrical between oil-exporting and oil-importing economies. Increases in oil prices in oil-importing countries lead to a reduction in greenhouse gas emissions; conversely, their impact increases emissions in oil-exporting countries. Therefore, oil-exporting countries lack the incentive to reduce emission levels due to rising oil prices (Mohamued et al., 2021). Furthermore, several empirical studies have indicated that carbon emissions are mainly affected by oil prices; for instance, McCollum et al. (2016) indicated that persistently low or high oil prices could significantly influence the global energy system and the emission of carbon dioxide. Jakada et al. (2020) indicated that the price of oil is negatively related to carbon dioxide emissions in the long run, meaning that an increase in the price of oil improves environmental quality in the long run. There is a two-way causal relationship between the price of oil and the amount of carbon dioxide emissions, meaning that changes in the price of oil affect environmental quality, and at the same time, changes in environmental quality affect the price of oil in Nigeria. Mousavi et al. (2021) indicated that high fuel prices in Iran lead to a decrease in carbon dioxide emissions, while increased individual production and energy consumption lead to an increase in emissions. Lastly, Wang et al. (2023) showed that rising oil prices enhance innovation in technologies used to mitigate the effects of climate change by reducing energy intensity, increasing the consumption of renewable energy, and promoting research and development in energy technology. The study also indicated that oil prices have a more notable effect on climate change mitigation technology's share in green innovation in oil-importing, high-income, and developed economies.

The aforementioned review reveals the links between Crude oil prices and its impact on the environment and climate sustainability. Therefore, the following hypothesis can be formulated:

The Crude oil prices significantly affects the sustainability of the climate in Egypt.

3. RESEARCH METHODOLOGY

This paper uses gradient boosting as a machine learning algorithm. The supervised machine learning models generate their prediction function data by analysing the training data. This paper relies on a machine learning model, such as gradient-boosting trees, to evaluate the features affecting climate sustainability and forecast emissions in Egypt based on annual data from 1990 to 2024. We rely on five models to evaluate their accuracy, then use the most accurate model to forecast CO_2 emissions while also identifying the fundamental factors that influence climate sustainability. Metrics such as accuracy, precision, recall, F1-score, and area under the curve (ROCAUC) analyse the performance comparisons of the algorithms (Itoo et al., 2021). This paper implemented a gradient boosting tree as a machine learning algorithm using the Scikit-Learn package in the Python programming language.

3.1. The Gradient Boosting Trees Algorithm

A gradient boosting technique is an ensemble machine learning methodology presented by Friedman in 2001 (Friedman, 2001). The fundamental idea of the gradient-boosting approach is to combine several weak learners to boost the robustness and accuracy of the final model (Yoon, 2021). The gradient boosting model initiates with the creation of a single leaf and the construction of regression trees. A regression tree is a decision tree specifically constructed to estimate a continuous real-valued function rather than serve as a classifier (Selmey et al., 2025).

The gradient boosting approach initiates with the creation of a single leaf and the construction of regression trees. The regression tree is created using a method that repeatedly divides the data into nodes or splits it into smaller sets of data. Initially, every observation is categorized into a single category. The data is subsequently divided into two parts, employing every conceivable split on each accessible predictor. The predictor that splits the tree divides the observations most clearly into two groups and decreases the residual error (Yoon, 2021).

Based on the errors of the previous tree, the gradient boosting approach builds a new tree and continues to generate more trees in this manner until it reaches the specified number or further improvement becomes unattainable (Yoon, 2021). To avoid overfitting issues, the gradient-boosting approach employs a learning rate to adjust the contribution of the new tree (Yoon, 2021). Essentially, every tree in this technique provides its prediction, which is aggregated with the predictions from preceding trees to improve the model's final prediction. Boehmke and Greenwell sum up this method using the following formula (Tenorio and Pérez, 2023):

$$F(x) = \sum_{z=1}^{Z} F_z(x)$$

Where z represents the total number of trees that cumulatively collect the errors from all preceding trees. The first tree is represented as y = F1(x), followed by the second tree defined as F2(x) = F1(x) + e1, and this process continues consecutively to minimize F(x) as expressed below (Tenorio and Pérez, 2023):

$$L = \sum_{z} L\left(y_z, F_z(x)\right)$$

Consequently, as new decision trees add up, the accuracy of the ultimate predict progressively enhances, yielding more precise forecasts for annual CO_2 emissions.

Additionally, The GBM technique yields superior results when the contribution of each additional decision tree is diminished at every iteration step through a shrinkage parameter known as the learning rate. The concept of the shrinking technique within the framework of GBM posits that an increased frequency of minor increments yields more precision compared to a reduced frequency of substantial increments. The learning parameter can assume a value between 0 and 1; a smaller value correlates with increased model accuracy. However, selecting a more substantial shrinkage (smaller) necessitates an increased number of iterations to attain convergence, as the value is inversely related to the iteration count (Touzani et al., 2018).

One method to enhance the predicted accuracy of the GBM algorithm is to incorporate randomisation into the fitting process

(Friedman, 2002). At each iterative step, instead of utilising the complete training dataset, a randomly selected subsample, typically chosen without replacement, is employed to fit the decision tree. When the number of observations is sufficiently large, the default proportion of data utilised at each iteration is typically 0.5, indicating that 50% of the dataset is employed in each iteration. One should assess multiple values of a subsample fraction to determine the effect of reducing the number of data points on the model's fitting quality. Nonetheless, it is essential to assess numerous values of a subsample fraction to determine the effect of reducing the number of data points on the model's fitting quality. Besides enhancing the accuracy of the GBM model, the subsampling possesses the beneficial impact of decreasing the algorithm's computing expense by a magnitude corresponding to the subsampling factor (Touzani et al., 2018).

The characteristics eventually evaluated for gradient boosting are (Bentéjac et al., 2021):

- The learning rate, also known as the shrinkage factor, is evaluated.
- The maximum depth of the tree (max_depth) refers to the same concept as in the trees produced by random forest.
- This refers to the rate at which the random samples are subsampled to determine their magnitude. In contrast to random forest, this is typically conducted without replacement (Friedman, 2002).
- This refers to the number of features that need to be evaluated in order to determine the optimal split (max_features), a method that random forest employs.
- The smallest number of samples required for partitioning an internal node (min_samples_split), similar to random forest, is also evaluated.

3.2. Assessment of Model Efficacy

The efficacy of the SVM technique and other soft computing models are evaluated using statistical markers, like root mean square error (RMSE), the mean absolute error (MAE), the coefficient of determination (R^2), and the Pearson correlation coefficient (r). Decreased values for these indicators indicate enhanced model fits (Mladenović et al., 2016; Yu et al., 2024; Selmey et al., 2025). It is represented by the following equations.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - O_i\right|$$

$$RMSE = \sqrt{\frac{\sum_{i1}^{n}\left(P_i - O_i\right)^2}{n}},$$

$$R = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)}$$

In this context, the experimental values are denoted as P_i, the predicted values as O_i, and the total number of test data is represented by n.

The term represents the number of observations, P_i signifies the actual value, O_i indicates the predicted value, and $\overline{O_i}$ defines the mean value. A higher R^2 indicates better fitting of the model, whereas increased MSE and MAPE values imply greater prediction errors. RMSE values can vary from 0 to ∞, with diminished values indicating better results. An RMSE value of 0 signifies that the method has produced no errors (Prayudani et al., 2019).

This paper also utilises critical metrics for evaluating the effectiveness of various algorithms, including accuracy, precision, recall, and F1-score. The metrics presented were computed for both training and testing datasets to guarantee a precise evaluation of model efficacy. The confusion matrix illustrates performance across many classes, facilitating the identification of true positives, false positives, true negatives, and false negatives. Additionally, visual tools such as ROC curves were generated to illustrate the balance between sensitivity and specificity, offering insights into model performance across various thresholds (Jain and Srihari, 2024; Selmey et al., 2025).

3.3. Variable Importance

Feature importance denotes the ranking and hierarchy of each feature's relative importance in forecasting carbon dioxide emissions. It is implemented using Python software. In an ensemble including K decision trees, x_j is calculated as (Yu et al. 2024; Selmey et al., 2025):

$$\text{Imp}\left(x_j\right) = \frac{1}{K}\sum_{k=1}^{K}\sum_{z\in\varphi_k} I\left(j_z = j\right)\left[\frac{n_z}{N}\text{''}\, i(z,s)\right]$$

Where z denotes the z^{th} non-terminal node of the decision tree φ_k, j_z denotes the feature identifier utilized to split node z, $I()$ denotes the indicator function, n_z indicate the number of samples arriving at node z, N represent the total number of samples, and $\Delta i\,(z, s)$ indicates to the reduction in the Gini coefficient at the z^{th} node after s-splitting.

3.4. Sample and Variable Measurements

This paper uses annual time-series data from 1990 to 2024 to analyse the impacts of innovation, crude oil prices, and renewable energy consumption on climate sustainability in Egypt. This study incorporates crucial economic, social, and environmental variables to evaluate Egypt's climatic sustainability. Table 1 outlines the variables, their symbols, measurement units, and data sources. By incorporating these variables, the study seeks to evaluate the impact of technological, economic, demographic, and policy variables on the attainment of climatic sustainability.The data for this study were gathered mainly from the World Development Indicators (WDI) database, ensuring reliable and comprehensive information over the period 1990-2024. Carbon dioxide (CO_2) emissions, measured in million tonnes, serve as the dependent variable representing climate sustainability. Meanwhile, the explanatory variables

Table 1: Variable measurements

Variables	Symbol	Measurement	Source
Carbon dioxide (CO_2) emissions (total)	CO_2	Million tonnes of carbon dioxide	World Development Indicators
Innovation	INV	Patent applications, nonresidents and Patent applications, residents	World Development Indicators
Economic Growth	GDP	GDP, PPP (constant 2021 international $)	World Development Indicators
Renewable energy consumption	REC	Renewable energy consumption (% of total final energy consumption)	World Development Indicators
Fossil fuel energy consumption	FEC	Fossil fuel energy consumption (% of total)	World Development Indicators
Urbanization	Urb	Urban population (% of total population)	World Development Indicators
Crude oil prices	COP	Global price of Brent Crude	International Monetary Fund

Source: The authors

include: innovation, captured through the patent applications of both residents and non-residents; economic growth, measured by GDP at purchasing power parity (constant 2021 international dollars); renewable energy consumption as a percentage of total final energy use; fossil fuel consumption's share of total energy use; and urbanisation, reflected by the percentage of the urban population. Furthermore, crude oil prices, specifically the global Brent crude price, were extracted from the International Monetary Fund (IMF) database to include the external economic influence on the climate dynamics in Egypt. This well-rounded dataset allows for a detailed investigation of how various economic, technological and environmental factors interact to impact climate sustainability.

4. RESULTS AND DISCUSSION

This study presents a novel approach to examining the impact of innovation, crude oil prices, renewable energy consumption, economic growth, Fossil fuel energy consumption and urbanization on climate sustainability and predicting annual carbon emissions between 1990 and 2024 in Egypt using the gradient boosting trees algorithm as a machine learning approach. The machine learning models produce accurate predictions of annual carbon dioxide emissions and identify the most significant factors affecting climate sustainability in Egypt. In this part of our study, we present the main findings and explain why the gradient boosting trace algorithm is the most reliable and accurate among the machine learning algorithms.

4.1. Performance Measurements

The performance of five algorithms for predicting carbon dioxide emissions was evaluated using several metrics, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), as shown in Table 2. The gradient boosting algorithm showed a clear superiority in R^2 at 0.96, which is much higher than linear logistic regression, which recorded 0.91; random forests at 0.94; KNN at 0.95; and support vector machine (SVM), which scored −0.73. Additionally, gradient boosting recorded the lowest values for both RMSE and MAE, reflecting its ability to significantly reduce predictive errors, as shown in Table 2. Table 3 uses several important metrics for evaluating the performance of the five algorithms, which are precision, recall, F1 score, ROC AUC, and confusion matrix accuracy. These metrics provide a comprehensive understanding of the overall predictive power of each model, the balance of false positives and false negatives, and the accuracy of data classification. Table 3 demonstrates that all algorithms performed outstandingly, with all metrics equal to one, except for the SVM algorithm, which

Table 2: Performance measures of algorithms

Metrics	RMSE	MAE	Pearson correlation coefficient (r)	R-squared
Random forest	8.19	6.82	0.973	0.94
Logistic regression	7.84	6.42	0.952	0.91
SVM	43.91	39.31	0.940	-0.73
KNN	7.34	6.58	0.987	0.95
Gradient boosting	6.71	5.23	0.981	0.96

Source: Output by Python

performed worse. It means the other models, such as random forests, logistic regression, and KNN, also performed well, but gradient boosting performed slightly better. These results reflect the strength of the gradient boosting model in interpreting and predicting carbon emissions data with high accuracy. In short, regarding stability, Table 3 shows that the gradient boosting, linear logistic regression, KNN and random forest algorithms provide stable and comparable performances based on the results of the train-test data split, whereas the SVM suffers from greater performance fluctuations. Based on this data, the Gradient Boosting algorithm is the optimal choice for studying climate sustainability in Egypt. This outcome is due to the combination of high predictive accuracy and acceptable performance stability, which enhances the reliability of the results when analysing the impact of innovation, crude oil prices, economic growth, urbanisation, and energy consumption on climate sustainability in Egypt.

4.2. The Features Importance in a Gradient Boosting Algorithm

Feature importance denotes the ranking and hierarchy of each feature's relative importance in forecasting carbon dioxide emissions. It is implemented using Python software. In an ensemble including K decision trees, x_j is calculated as (Yu et al. 2024; Selmey et al., 2025):

$$\text{Imp}\left(x_j\right) = \frac{1}{K}\sum_{k=1}^{K}\sum_{z\in\varphi_k} I\left(j_z = j\right)\left[\frac{n_z}{N}\text{"}\, i(z,s)\right]$$

Where z denotes the zth non-terminal node of the decision tree φ_k, j_z denotes the feature identifier utilized to split node z, $I()$ denotes the indicator function, n_z indicate the number of samples arriving at node z, N represent the total number of samples, and $\Delta i\ (z, s)$ indicates to the reduction in the Gini coefficient at the z^{th} node after s-splitting. The gradient algorithm relies on this method to determine the features that influence climate sustainability, as well as their relative importance in predicting carbon emissions.

Table 3: Performance measures of algorithms

Metrics	Accuracy	Precision	Recall	F1 Score	ROC AUC	Confusion matrix accuracy
Logistic regression	1	1	1	1	1	1
Random forest	1	1	1	1	1	1
SVM	0.29	0.0	0.00	0.00	1	0.29
KNN	1	1	1	1	1	1
Gradient boosting	1	1	1	1	1	1

Source: Output by Python

Table 4 and Figure 1 show a summary plot. We use this plot to determine the importance of various features according to the gradient boosting algorithm's feature importance values. The importance feature values of the gradient boosting algorithm provide a unified measure of feature importance by quantifying the contribution of each feature to the model's predictions. Based on the outcomes of Table 4 and Figure 1, we can determine the importance of the factors influencing climate sustainability and carbon emissions in Egypt. The results briefly showed that the consumption of fossil fuels has the most significant impact on emissions, followed by economic growth. As for the other factors, such as innovation, crude oil prices, renewable energy consumption, and urbanisation, they have a relatively lesser impact. Therefore, the first factor identified is fossil fuel consumption, which has a relative importance score of 22.3%. Thus, fossil fuel use is the predominant factor influencing the rise in carbon emissions in Egypt; consequently, alterations in primary energy consumption substantially impact the expected CO_2 emissions.

The consumption of fossil fuels is the most important factor affecting carbon emissions and climate sustainability in Egypt, as it constitutes the main source of energy used in industry, transportation, electricity production and residential activities, leading to substantial carbon dioxide emissions, causing severe environmental damage that negatively impacts climate sustainability in Egypt. This is consistent with the results of Raihan et al. (2023), which revealed that the use of fossil fuel energy contributes to environmental damage caused by cumulative carbon dioxide emissions in Egypt. Other studies also reached the same conclusion, such as Adebayo and Kalmaz (2021) and Shaari et al. (2020). The use of energy is the main and most significant cause of daioxide carbon emissions. Therefore, it is important to provide valuable insights to formulate policies that focus on enhancing energy efficiency, transitioning to clean energy sources, and supporting investments in the energy, transportation, production, and renewable energy sectors. Egypt has already explored renewable energy technology for several decades, although fossil fuel-based energy generation has remained constant. Egypt's Vision 2030 has been launched to address these challenges, aiming to reduce greenhouse gas emissions from the energy sector by 10% (Rayhan et al., 2023).

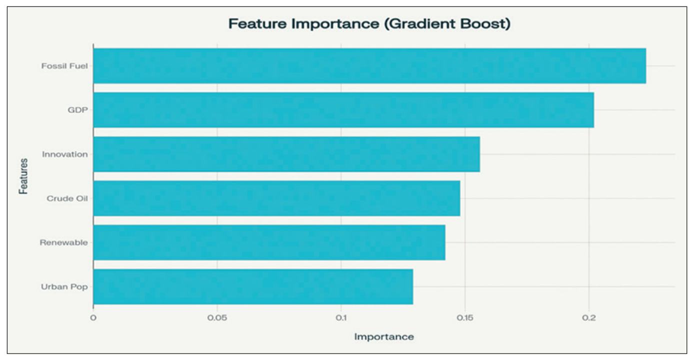
The analysis results show that the impact of GDP is the second most significant influencing factor on CO_2 emissions, after the impact of fossil fuel consumption, which has a relative importance value of approximately 20.2% according to the gradient boosting algorithm. According to the research study, increased economic activity is associated with decreased environmental sustainability in Egypt. This aligns with the results of Abdouli and Hammami

Table 4: Feature importance indicators

Features	Importance
Innovation	0.156
Crude oil prices	0.148
Renewable energy consumption	0.142
GDP	0.202
Fossil fuel energy consumption	0.223
Urban population	0.129

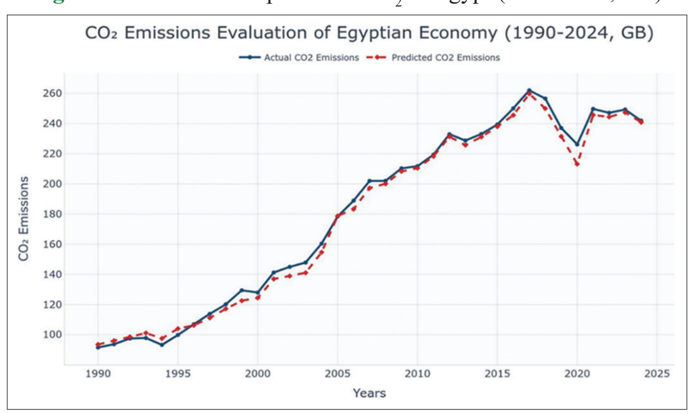
Source: Output by Python

Figure 1: Features importance using gradient boosting algorithm



Source: Output by Python

Figure 2: Actual versus predicted CO_2 of Egypt (1990-2023, GB)



Source: Output by Python

(2017), Sghaier et al (2019), Maku and Ikpuri (2020) as well as Adebayo and Klamaz (2021), Ebrahim et al (2025) confirmed the existence of a positive relationship between GDP and carbon dioxide emissions in Egypt. With the expansion of economic activity, productive and consumptive activities increase, leading to greater environmental pollution and the destruction of natural resources. Economic development contributes to meeting the needs of society thru spending and infrastructure growth, but it is accompanied by an increase in emissions and environmental waste.

From here, Egypt adopted the Green Transformation Strategy since 2011, integrating the principles of the green economy into its plans, where "Egypt Vision 2030" places sustainable development at the top of its priorities. The plan gives an environmental dimension that balances economic growth and environmental preservation, emphasizing the adoption of a low-carbon growth path to achieve sustainability (Raihan et al., 2023).

The analysis of feature importance using the Gradient Boost algorithm indicates that innovation ranks third among the factors influencing carbon emissions in Egypt, after fossil fuel consumption and GDP. This reflects that the heavy reliance on fossil fuels remains the main source of emissions, while economic growth affects the increase in activities that release carbon. As for innovation, it comes in third place, highlighting its role in improving energy efficiency and reducing emissions through the development of cleaner technologies. This aligns with the results of the Wesseh and Lin (2018) study, which shows that technological progress depends on inputs, and its maximum rate is <9%. These findings highlight the enormous opportunities for reducing carbon dioxide emissions that could arise from innovation in various energy technologies in Egypt, especially those related to electricity, natural gas, and petroleum. The study's results demonstrate this potential, showing a significant reduction in carbon dioxide emissions when replacing natural gas with petroleum. The concept is that as energy efficiency levels increase due to advancements in various energy technologies, greater benefits in reducing carbon dioxide emissions can be realised by substituting different types of fuels; high-emission fuel sources can be replaced with cleaner alternatives. Furthermore, Ibrahim (2020) examined the role of technological innovation in improving environmental quality in Egypt. It showed that environmental degradation leads to technological innovation. Similarly, the results of Ma and Qamruzzaman's (2022) study indicated that integrating clean energy and technological innovations into the economy reduces environmental hardships by lowering carbon emissions, which in turn improves climate sustainability in Egypt. Thereby, innovation is not only a driver of economic growth but also a key to achieving an effective reduction in carbon emissions, especially through improving energy efficiency and developing less polluting energy sources. In particular, EU countries have significantly reduced emissions due to innovation, followed by China and the United States (Mohamued et al, 2021).

Regarding the fourth factor in Table 4, Figure 1, the gradient algorithm results indicated that the relative importance of crude oil prices is 14.8%. Therefore, crude oil prices play a significant role in influencing climate sustainability in Egypt. Since the rise in oil prices drives up import costs and encourages the search for cleaner and more efficient energy alternatives, while a decrease in prices may lead to increased reliance on fossil fuels and their lower costs, raising emissions. This aligns with the findings of Mohamued et al. (2021), which indicated that there are significant impacts of oil prices and their volatility on greenhouse gas emissions. The impact of oil prices on greenhouse gas emissions is asymmetric between oil-exporting and oil-importing economies. Increases in oil prices in oil-importing countries lead to a reduction in greenhouse gas emissions; conversely, their impact increases emissions in oil-exporting countries. Wang et al. (2023) found that high oil prices drive innovation in technology for climate change mitigation by reducing energy intensity, increasing renewable energy, and enhancing research and development in energy technology. Moreover, Yang et al. (2023) indicated that oil price fluctuations negatively impact the financials of the oil industry and positively affect carbon emissions, suggesting the need for policies to encourage the transition to sustainable energy. Additionally, climate risk itself influences oil price dynamics through interdependent long-term relationships (Rufai et al., 2024). For Egypt, oil constitutes an important part of the energy mix, as price fluctuations significantly impact carbon emissions and investments in clean energy. Therefore, understanding the dynamics of oil prices is essential for planning sustainable environmental and economic policies that achieve emission reductions.

Table 4 and Figure 1 show that renewable energy consumption is the fourth most important factor in explaining climate sustainability in Egypt according to the results of the gradient boosting model, with its relative contribution being approximately 14.2% compared to the other studied factors. The ratio indicates the growing role of renewable energy sources in the Egyptian ecological system, as the percentage reflects the importance of gradually shifting away from traditional fuels toward less harmful and environmentally impactful options, despite the continued reliance on traditional energy sources like oil, which still hold a leading position. Historical data shows that fossil fuels remain the primary source of energy, significantly contributing to greenhouse gas emissions. Expectations indicate that carbon dioxide emissions in Egypt could increase by 125% between 2012 and 2035 if traditional energy generation methods continue to dominate, highlighting the importance of transitioning to renewable energy (Ibrahim, 2025). The Egyptian government is rapidly expanding renewable energy production through public-private partnerships to achieve sustainability goals. In short, increasing the usage of renewable energy helps Egypt reduce its reliance on fossil fuels, lower carbon emissions, and promote climate sustainability.

According to the gradient-boosting algorithm and the study results, urbanisation ranked as the least relatively important factor in climate sustainability in Egypt, at 12.9%. Although urbanisation increases energy demand and raises emissions, its relative impact is less because other factors such as fossil fuel consumption and innovation play a larger role in determining emissions, meaning that the impact of urbanisation is currently limited compared to the main factors. Studies have indicated that urbanisation increases energy demand and results in higher emissions, but due to the characteristics of urban growth in Egypt currently, its impact on emissions is relatively limited. This is consistent with the findings of Aldegheishem (2024), which indicate that urbanisation does not have a significant impact on carbon dioxide emissions in Egypt.

This chart below presents an analysis of 34 years of carbon dioxide emissions data, specifically for the Egyptian economy, comparing actual values with machine learning predictions using a gradient boosting model. The predicted carbon dioxide emissions closely match actual levels in Egypt. In most years, the differences between actual and predicted values were minimal, as shown in Figure 2. This indicates that the predictions were highly accurate and of high quality. This chart covers the period from 1990 to 2024, offering critical perspectives on economic and environmental impact trends in Egypt. Over this period, there is a clear upward trend in carbon emissions, reflecting the country's expanding economic activities and industrial growth. From 1990 to the mid-2000s, emissions increased steadily, coinciding with rising energy consumption and development. The rate of increase dramatically increased between the mid-2000s and 2017, a sign of both increased reliance on fossil fuels and rapid economic expansion. Energy efficiency efforts or external economic and environmental factors may have caused a temporary decline in emissions from 2017 to 2020, besides the COVID-19 pandemic. The COVID-19 epidemic was the principal cause of the reduction in carbon emissions until 2020. The decrease resulted from a deceleration in industrial and economic activities, along with lockdown measures that suspended air and maritime transit, culminating in a notable reduction in energy consumption and carbon emissions (Selmey et al., 2025). However, the economic recovery following the COVID-19 pandemic likely drove a surge in emissions from 2020 to 2022. From 2022 onwards, a slight reduction occurs, suggesting improvements in environmental policies or shifts toward cleaner energy sources. The predicted emissions closely track the actual data throughout, demonstrating the robustness of the gradient boosting approach in forecasting emission trends and supplying beneficial information for environmental planning and sustainability efforts in Egypt.

5. CONCLUSION

Climate sustainability represents one of the most pressing challenges of the 21st century, with the energy sector playing a pivotal role due to its heavy reliance on fossil fuels. The complex relationship between fossil fuel consumption, oil prices, and the pace of technological innovation has had a profound impact on global efforts to decarbonise and enhance environmental resilience. Egypt represents a realistic model that combines heavy reliance on crude oil and traditional energy with growing efforts in renewable energy and ambitious plans to reduce emissions. This paper assists in recognising shared drivers that impact emissions and could potentially affect environmental policies and sustainability initiatives. In light of this, the present paper analyses the predictions of annual carbon emissions and the impacts of innovation, crude oil prices, fossil fuel energy consumption, urbanisation, and economic growth on climate sustainability in Egypt from 1990 to 2024 using a gradient-boosting machine learning algorithm. The models' performance was assessed using root mean square error (RMSE), mean absolute error (MAE), R-squared, accuracy, precision, recall, F1 score, area under the curve (ROC AUC), and confusion matrix accuracy.

The findings demonstrated that a gradient-boosting algorithm attains nearly flawless performance across all assessment metrics for carbon emission prediction. The study found that the consumption of fossil fuels is the most important factor affecting carbon emissions and climate sustainability in Egypt, as it constitutes the main source of energy used in industry, transportation, electricity production, and residential activities, leading to substantial carbon dioxide emissions, causing severe environmental damage that negatively impacts climate sustainability in Egypt. This is consistent with the results of Rayhan et al. (2023), which revealed that the use of fossil fuel energy contributes to environmental damage caused by cumulative carbon dioxide emissions in Egypt. Other studies also reached the same conclusion, such as Adebayo and Kalmaz (2021) and Shaari et al. (2020). The analysis results indicate that the impact of GDP is the second most significant influencing factor on climate sustainability, after the impact of fossil fuel consumption, which has a relative importance value of approximately 20.2% according to the gradient boosting algorithm. This aligns with the results of Abdoli and Hamami (2017), Saghir et al. (2019), Mako and Ikebori (2020), and Adebayo and Klamaz (2021). Additionally, the findings indicated that innovation ranks third among the factors influencing climate sustainability in Egypt, highlighting its role in improving energy efficiency and reducing emissions through the development of cleaner technologies.

These findings highlight the enormous opportunities for reducing carbon dioxide emissions that could arise from innovation in various energy technologies in Egypt, especially those related to electricity, natural gas, and petroleum. Furthermore, the findings indicated that crude oil prices play a significant role in influencing climate sustainability in Egypt. According to the results, renewable energy consumption and urbanisation rank at the bottom of a list of important factors that affect climate sustainability in Egypt. This result indicates the growing role of renewable energy sources in the Egyptian ecological system, as the percentage reflects the importance of gradually shifting away from traditional fuels toward less harmful and environmentally impactful options, despite the continued reliance on traditional energy sources like oil, which still hold a leading position.

Finally, The study recommends the importance of accelerating the replacement of traditional fuels with renewable energy sources, intensifying investment in modern technologies, and directing economic policies to support low-carbon economic growth, achieving a balance between development requirements, environmental preservation, and climate change mitigation. It also emphasizes the necessity of building renewable energy infrastructure and implementing energy efficiency improvement programs, in pursuit of achieving a more sustainable energy mix in Egypt in the long term.

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