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Role of Economic Expansion, Energy Utilization and Urbanization on Climate Change in Egypt based on Artificial Intelligence

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ABSTRACT

This study employs machine-learning algorithms (ML), specifically Random Forest (RF) and Gradient Boosting (GB), to assess the impact of various factors, including Gross Domestic Product (GDP) growth, urbanization, and energy consumption, on carbon dioxide emissions (CO_2). The research underscores the RF algorithm's superior accuracy in determining independent variables' influence on CO_2 emissions compared to GB. Furthermore, the study reveals that natural gas is the most significant contributor to CO_2 emissions in Egypt, accounting for 49.7% of the total, followed closely by oil at 46.7%. The effect of other variables on CO_2 emissions is relatively minimal. The findings also establish a strong positive correlation between the consumption of natural gas, oil, and coal and CO_2 emissions in Egypt. Additionally, a negative relationship is observed between GDP growth, suggesting a positive trend in environmentally friendly economic expansion and urbanization on CO_2 emissions in Egypt. This unique scenario, where urban expansion appears to have an inverse relationship with CO_2 emissions, sets Egypt apart from many other countries and signifies a favorable environmental outcome.

Keywords: Climate Change, CO_2 Emissions, GDP Growth, Energy Consumption, Urbanization, Machine Learning
JEL Classifications: C63, C80, C81, C87

1. INTRODUCTION

Concerning comprehending climate change, there exists a prevailing perspective that attributes alterations in the climate to the dynamics of economic activity rather than the other way around. Nevertheless, it is crucial to recognize that the direction and nature of this causality may vary among different countries and regions. Two different angles can be used to analyze the complex relationship between GDP growth and CO_2 emissions (Jaunky, 2011).

One perspective posits that financial gain is the primary driver of environmental degradation, with the notion that increasing economic prosperity can be the universal solution to environmental pollution issues. From the perspective of consumers, this approach may seem suboptimal. In contrast, the second perspective emphasizes that emissions are the primary causal factor, while income levels play a secondary role. Here, emissions are regarded as an inherent cost of production that must be incurred in the pursuit of economic prosperity. It is important to note that variations in energy use are closely linked to economic expansion, but it is not a one-way street. While economic growth may lead to increased energy consumption, improved efficiency measures can also reduce energy demands.

Energy consumption is a central component of this complex relationship and significantly influences environmental contamination. CO_2 emissions, economic growth, and the use of fossil fuels are inherently interconnected. An alarming statistic reveals that more than 60% of global direct emissions can be attributed to CO_2 emissions, as measured by the yearly greenhouse gas (GHG) index. Over three decades, from 1990 to 2020 (Butler and Montzka, 2017), this type of pollution witnessed a staggering 45% increase. Urban areas, in particular, are significant contributors to this problem, generating over 70% of the world's CO_2 emissions (Mitchell et al., 2018). With more than half the global population residing in urban centers steadily increasing, cities have become pivotal in the climate change narrative (The World Bank. 2012). Furthermore, cities are estimated to be responsible for 75% of worldwide CO_2 emissions, with transportation and construction activities as two of the largest sources (Giro, 2021).

The Egyptian economy's CO_2 intensity declined by nearly 23% between 2005 and 2019. In 2019, it reached an unprecedented high of 884 g of CO_2e per US dollar, 56% more than the global average. Thanks to structural economic changes and improvements in energy use in the industrial sector, Egypt's GDP and population growth have become increasingly decoupled. In 2019, the service industry contributed 51% of Egypt's GDP. Egypt has the largest economy in North Africa, accounting for 0.5% of global GDP (World Bank data). Therefore, to further reduce CO_2 emissions in Egypt, it was necessary to determine connections between economic expansion, urbanization, energy consumption, and climate change have prompted economists and policy professionals to prioritize energy consumption and CO_2 emissions as key drivers that can stimulate, hinder, or potentially offset economic development. However, the results of various studies exploring this relationship exhibit inconsistency due to variations in the aspects of the economy examined, the timeframes considered, the econometric techniques employed, and the proxy variables utilized in their estimation. This underscores the importance of continuous research, and current policy recommendations should be viewed as evolving based on the causality element, which can be assessed in terms of energy efficiency, pollution mitigation, and cost-effectiveness.

In light of this intricate interplay between economic forces, urbanization, energy consumption, and their impacts on climate change, the urgency of addressing this global concern has never been more apparent. The consequences of global warming, including extreme weather events and rising sea levels, are increasingly evident and pose significant threats to human lives, ecosystems, and economies. As a response to these challenges, this research, titled "Role of Economic Expansion, unrenewable Energy Utilization and Urbanization on Climate Change in Egypt," seeks to provide a comprehensive understanding of these complex relationships and to shed light on potential strategies and policies that can mitigate the adverse effects of these forces on climate change while fostering sustainable socio-economic growth.

Moreover, this research harnesses the transformative capabilities of Artificial Intelligence (AI) to analyze vast datasets, model intricate relationships, and forecast future climate scenarios with unprecedented accuracy. By focusing on the case of Egypt, this paper endeavors to provide valuable insights into the role of economic expansion, urbanization, and energy consumption in driving climate change, ultimately contributing to the global effort to combat this pressing challenge. The implications of this research extend to policymakers, businesses, and communities worldwide, as it aims to inform evidence-based decisions and actions to mitigate climate change while advancing sustainable development and environmental stewardship.

In the following sections, we delve into the methodologies, findings, and policy implications of our research, shedding light on the complex nexus between economic expansion, urbanization, energy utilization, and climate change in Egypt and how AI-driven insights can contribute to a more sustainable future for the nation and the planet at large.

2. LITERATURE REVIEW

The threats of climate change and global warming are now recognized as urgent problems on a global scale (Lin and Raza, 2019). Numerous elements, such as population size, culture, wealth, climate, finances, and cultural activities, contribute to the energy consumption of individual countries. This is visible in several energy sources, especially fossil fuels, electrical power, and modern technologies (Cassarino et al., 2019). There are quarterly and seasonal fluctuations in energy use across all of these departments. Rapid economic and social changes in recent decades have increased energy demand (Gong et al., 2020). The world faces energy scarcity, pollution, and climate change challenges. Full energy consumption, global urbanization, and increased CO_2 emissions result from increased industrial production (Rosenberg et al., 2018). Using fossil fuels has resulted in greenhouse gas emissions and climate change (Tsai et al., 2016; Wu et al., 2017). According to the Intergovernmental Panel on Climate Change, the emission rates of various energy sources vary and are affected by energy use patterns (Eggleston et al., 2006; Elsherif, 2023). Multiple empirical studies, including developed and developing nations, have examined the pooled fundamentals of multiple energy types or the variables contributing to energy consumption.

Table 1 shows the several studies related to climate change that are relevant to the research paper in question:

3. EMPIRICAL FRAMEWORK

In this paper, we can determine the effect of GDP growth, Urbanization, and energy consumption (coal, natural gas, and oil) on CO_2 emissions in Egypt. The following equation shows the practical framework of the paper, which will be implemented in Egypt:

$$CO_2 = GDPg + Ur + Co + NG + OL$$

Where;

CO_2 = carbon dioxide emissions

GDPg = Gross Domestic Product growth

Ur = Urbanization

Co = Coal

NG = Natural Gas

OL= Oil

Table 1: Empirical studies on the relationship between economic expansion, urbanization, and energy consumption on climate change

Author	Year	Results
Osobajo et al.	2020	Population size, capital stock, and economic growth were found to have a bidirectional causal link with CO_2 emissions. In contrast, energy consumption was found to have only a unidirectional association, as expected from the Granger causality tests. Similarly, the cointegration test results demonstrated a long-run link between the variables under investigation (energy consumption, GDP growth, and CO_2 emissions)
Abdallh and Abugamos	2017	CO_2 emissions and urbanization have an inverse U-shaped connection. However, GDP and EC are significantly related to CO_2 emissions. Using a semi-parametric model, the population indicates a positive effect. However, it is only significant at a 5% level.
Mirza and Kanwal	2017	A short- and long-term causal relationship exists between EC and GDP, CO_2.
Nain et al.	2017	CO_2 emissions, economic growth, and energy use all have a long-term relationship with one another. At the aggregated or disaggregated levels, there is no feedback causality in the short or long run.
Rehman and Rashid	2017	A correlation exists between GDP, energy use, and CO_2 emissions. The correlation between GDP and CO_2 emissions is inverse U-shaped.
Dogan and Aslan	2017	The variables used correlate in the long run. Consuming energy results in more CO_2 emissions, but tourism and actual income reduce this.
Esso and Keho	2016	A causal link exists between GDP, EC, and CO_2 emissions over the long term. However, the variables have a short-run causation relationship for Ghana, Congo DR, Benin, Nigeria, and Senegal.
Cian and Wing	2016	The paper shows that climate change has a regressive effect on energy demand, with the majority of increasing demand occurring in low- and middle-income nations. This raises the possibility that climate change will exacerbate energy poverty.
Kasman and Duman	2015	Energy use, GDP, CO_2 emissions, urbanization, and economic freedom are all interconnected in the long run. CO_2 emissions and real income also have an inverse U-shaped connection.
Saidi and Hammami	2015	CO_2 has a markedly beneficial effect on energy use. Similarly, an expanding economy boosts energy usage.
Dritsaki and Dritsaki	2014	Energy use, GDP, and CO_2 emissions all correlate over time. At the same time, Greece and Spain have a positive and statistically significant association between EC and CO_2 emissions, while in Portugal, there is a positive and statistically significant relationship between GDP and energy consumption.
Hwang and Yoo	2014	There is a unidirectional causation between economic output (GDP) and environmental cost (EC), a causality between CO_2 emissions and GDP, and a bidirectional relationship between CO_2 and EC.
Omri	2013	Energy consumption and GDP both cause and are caused by one another. Furthermore, CO_2 and GDP have a direct and causative link.
Akpan and Akpan	2012	According to a sector-by-sector examination of GHG emissions, the transportation sector (mostly road transport) and the energy and heat sectors of the economy are the two worst offenders.
Auffhammer and Mansur	2012	This work surveys previous research on how weather patterns affect the energy industry. Specifically, we focus on empirical publications from scholarly economics journals that examine the relationship between weather and energy costs and use. How individuals react to sudden changes in the weather (the intensive margin) and how they adjust to these changes over time (the extended margin) will impact the amount of energy they use. Further study using household and firm-level panel energy consumption data could show how energy users worldwide react to weather shocks if conducted along the intense margin.
Alam et al.	2011	Short-term CO_2 emissions and income are correlated. Furthermore, short- and long-term Granger causation occurs between CO_2 emissions and EC. Aside from this, there is no link between energy use and financial well-being. The GIRF technique does, however, reveal a short-term correlation.
Hossain	2011	Long-term energy use results in more CO_2 being released into the atmosphere. In contrast to the favorable effects of urbanization on GDP growth, trade openness has an adverse impact. However, it does not amount to much in the grand scheme.
Wang et al.	2011	GDP, EC, and CO_2 emissions all have a long-run causal link. CO_2 emissions and GDP also show a U-shaped relationship.
Menyah and Wolde-Rufael	2010	Capital, energy use, labor, and CO_2 emissions have interconnected short- and long-term dynamics. In addition, GDP and CO_2 emissions are positively and significantly related.

4. DATA AND METHODOLOGY

This section was divided into two parts: the first part represents a description of the data used statistically and graphically, and the second part is specific to the methodology used in the paper.

4.1. Data

The World Bank database collects data discussed in Section 3 of this paper. For a statistical description and breakdown of the data mentioned above, Table 2. In addition, the violin plot (Figure 1) shows the distribution of each dependent and independent variable.

4.2. Methodology

This research uses GB and RF methods from machine learning (ML). Each of these models is a supervised ML model, which means it takes in existing data, analyzes it, and then applies the findings to forecast new data. Scikit-Learn is a Python module used by all ML methods described in this article (Abd El-Aal, 2023).

4.2.1. The ML algorithms

4.2.1.1. The gradient boosting algorithm (GB)

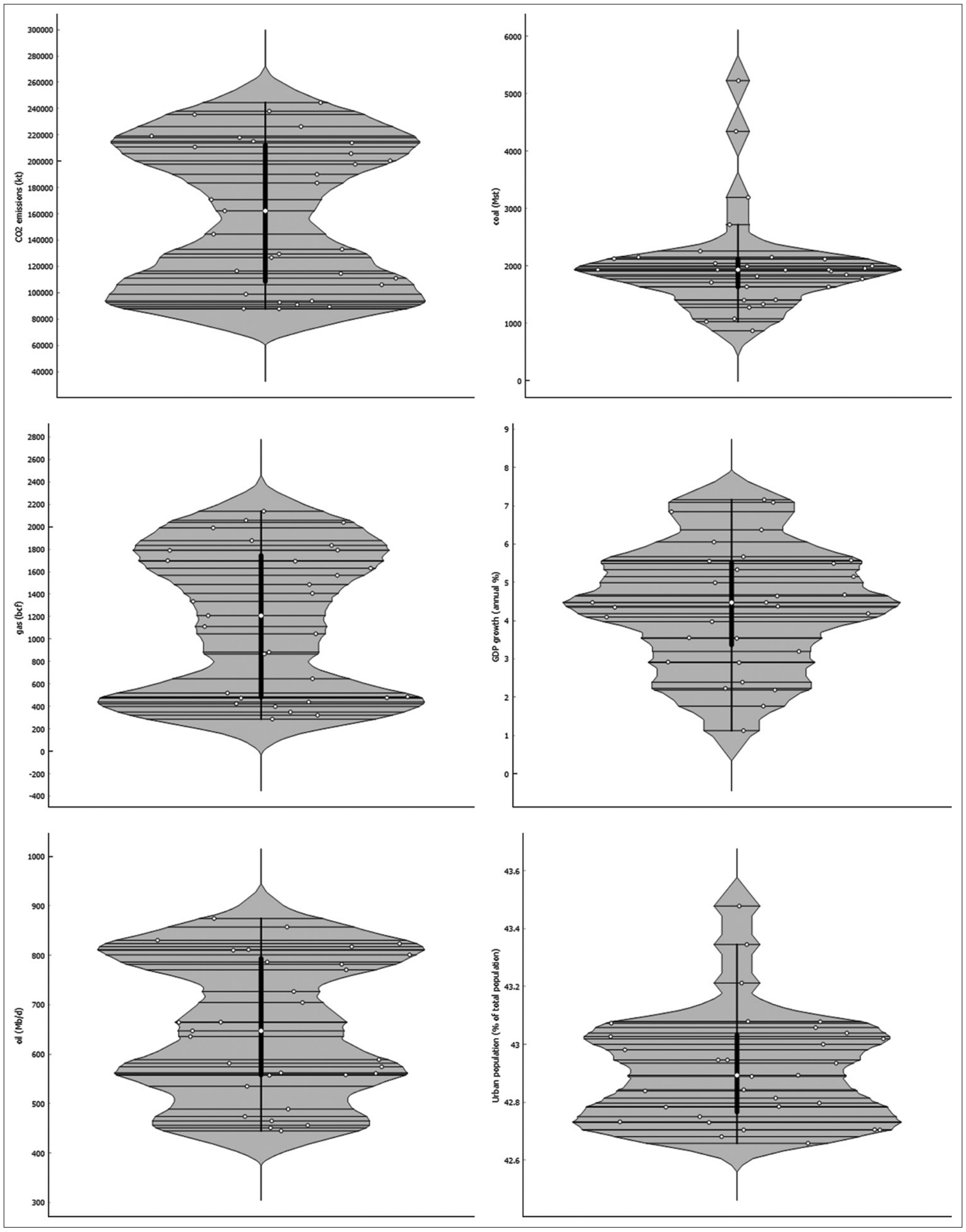
The GB algorithms are a variant of the ensemble ML that Friedman (2001) developed. The GB paradigm combines several relatively ineffective learners into a highly competent one.

Table 2: Statistics and a description of all indicators

Variables	Abbreviation	Source of data	Mean	Mode	Median	Dispersion	Min	Max
Carbon dioxide	CO_2	World Bank data	159806.74	87745.4	162217.1	0.33	87745.4	244540.5
Gross domestic product growth	GDPg	World Bank data	4.39	1.125	4.47	0.35	1.125	7.15
Urbanization	*Ur*	World Bank data	42.92	42.7	42.89	0.004	42.65	43.47
Coal	Co	World Bank data	2022.06	866.95	1932.35	0.42	866.95	5229.57
Natural gas	*NG*	World Bank data	1169.72	286	1208.13	0.53	286	2138.3
Oil	*OL*	World Bank data	654.99	444.9	647.17	0.21	444.9	874.3

Source: Compiled by the author

Figure 1: Violin plots distribution of a dataset



The GB model can build regression trees with just one leaf. Instead of being used for classification, regression trees a subset of decision trees are trained to estimate continuous real-valued functions. The data is repeatedly partitioned into smaller and smaller pieces as the regression tree is built. All of the data is combined at the outset. Each split on each predictor is used to divide the data in half. Using Friedman's (2001) well-established Friedman MSE to quantify residual error, the analysis concludes that the predictor responsible for splitting the tree most effectively separates the observations into two categories.

The GB technique creates a new tree that fixes the problems in the old one. The GB method progressively increases the weight provided to the new tree to avoid overfitting based on the learning rate. This is done until the desired number of trees is reached, or the model can no longer be improved.

4.2.1.1.1. Regularized learning objective

To illustrate, consider a dataset with (n) observations and (m) features D = (x_i, y_i), (|D| = n, $x_i \in \mathbb{R}^m$, $yi \in \mathbb{R}$), Predicts findings by using K additive functions (Fafalios et al., 2020).

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{1}$$

where (*F*) is the CART (regression trees) space. Here, (*q*) stands for the hierarchy of each tree that connects a given instance to its matching leaf index. How many leaves a tree has is denoted by the symbol (*T*). Separate q and w values for each leaf in the tree are associated with each (f_k). Each leaf of a regression tree, in contrast to a decision tree, has a continuous score; we denote this score, (w_i), on the i-th node of the tree. The score in each leaf is used to determine the final prediction, and the trees' decision rules (represented by *q*) determine where the example goes. We minimize the following regularized goal to learn the model's collection of functions.

$$L(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k)$$

$$where\, \Omega(f) = \gamma T + \frac{1}{2}\lambda \| w \|^2 \tag{2}$$

Here, the error between the prediction ($\hat{y}_i$) and the target (y_i) is represented by the loss function (*L*), which is differentiable and convex. The second term (Ω) acts as a penalty for the model's (regression tree functions') complexity. The additional regularization term smoothes out the final learning weights to prevent over-fitting. It stands to reason that the regularized objective will favor a model that uses elementary and prescriptive operations.

Due to the presence of functions as parameters, the tree ensembles model in Eq. (2) cannot be improved using common optimization techniques in Euclidean space. Instead, the algorithm is trained in an additive manner. In mathematical notation, in order to minimize the following objective, f_t must be added to let ($\hat{y}_i^{(t)}$) represent the forecast of the (i-th) example at the (*t-th*) iteration.

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

According to Eq. (2), the (f_t) that provides the greatest benefit to the model is added. In this generic context, the aim is optimized rapidly using a second-order approximation[5].

$$L^{(t)} \simeq \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t)$$

Where, $g_i = \partial_{\hat{y}(t-1)} l\left(y_i, \hat{y}_i^{(t-1)}\right)$ and $h_i = \partial^2_{\hat{y}(t-1)} l\left(y_i, \hat{y}_i^{(t-1)}\right)$ are gradient statistics of the loss function at the first and second order. Then, the goal at a time (t) is simplified by eliminating the constant terms.

$$\tilde{L}^{(t)} = \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{3}$$

Where, $I_j = \{i \# q(x_i) = j\}$ as the instance of leaf j, rewriting equation (3) as shown:

$$\tilde{L}^{(t)} = \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

$$= \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} g_i \right) w_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) w_j^2 \right] + \gamma T \tag{4}$$

The ideal weight w j of leaf j can be calculated for a given structure q(x) by:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{5}$$

Then, derive the optimum value by

$$\tilde{L}^{(t)}(q) = -\frac{1}{2} \sum_{j=1}^{T} \frac{\left(\sum_{i \in I_j} g_i \right)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T \tag{6}$$

The quality of a tree structure (q) can be scored using Eq 6. This score is analogous to the impurity score in evaluating decision trees but is computed for a broader class of objective functions.

Most of the time, there are too many possible (q) tree architectures for us to be able to list them all. Instead, a greedy method is employed, which creates a tree from a single leaf and adds nodes to it in a series of iterations. After a split, we can think of (*IL*) and (*IR*) as the sets of left and right nodes, respectively. The loss reduction following the partition is given by ($I = I_L \cup I_R$). We let

$$L_{split} = \frac{1}{2} \left[\frac{\left(\sum_{i \in I_L} g_i \right)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{\left(\sum_{i \in I_R} g_i \right)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{\left(\sum_{i \in I} g_i \right)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma \tag{7}$$

4.2.1.2. Random forest algorithm (RF)

Breiman (2001) discovered another ensemble strategy equivalent to boosting models: the RF method. Dietterich (2000) claims that RF is a crucial and potent ML ensemble algorithm. The RF method also uses regression trees, just like the GB model. The RF model conducts individual training on each regression tree before averaging their collective forecasts.

In an RF, a random variable or combination of parameters determines the weight of each tree in the ensemble. The joint distribution is assumed to be unknown. $P_{XY}(X, Y)$ for a p-dimensional random vector $X = (X1,\ldots, Xp)$ denoting the input or predictor variables with real values and the response, represented by a random variable Y. The objective is to determine a function $f(X)$ for predicting variable Y. To minimize the expected loss, a loss function $L(Y, f(X))$ is used to determine the prediction function.

$$E_{XY}(L(Y, f(X)) \tag{8}$$

the subscripts represent probabilities based on how X and Y are distributed together.

To put it simply, $L(Y, f(X))$ penalizes $f(X)$ values that are extremely far away from Y. Common values for L consist of squared error loss. For regression, $L(Y, f(X)) = (Y f(X))^2$, and for classification, $L(Y, f(X)) = 0\text{-}1$:

$$L\left(Y, f\left(X\right)\right) = I\left(Y \neq f\left(X\right)\right) = \begin{cases} 0\, if\ Y = f(X) \\ 1\ \ otherwise \end{cases} \tag{9}$$

The conditional expectation is found by minimizing the squared error loss, which is denoted by $E_{XY}(L(Y, f(X))$.

$$f\left(x\right) = E\left(YX = x\right) \tag{10}$$

Also referred to as the regression equation. The classification problem can be solved by minimizing $EXY (L(Y, f(X))$ with zero-one loss, where Y is the set of all possible values of Y.

$$f\left(x\right) = \arg \max_{y \in \mathcal{Y}} P\left(Y = yX = x\right) \tag{11}$$

The "ensemble predictor" $f(x)$ is built from a collection of "base learners" $h_i(x)$., (x), which are then concatenated. Learners are averaged as a starting point in regression.

$$f\left(x\right) = \frac{1}{J}\sum_{j=1}^{J} h_j\left(x\right) \tag{12}$$

$f(x)$ is the class predicted the most frequently in classification.

$$f\left(x\right) = \arg \max_{y \in \mathcal{Y}} \sum_{j=1}^{J} I\left(y = h_j\left(x\right)\right) \tag{13}$$

In RF, the jth base learner is a tree denoted $h_j(X, \Theta j)$, where Θj is a collection of random variables, and the Θj's are independent for j = 1., J.

4.2.2. Crossvalidation

In this investigation, ML algorithms employ several hyperactive parameters. In order to fine-tune hyperactive parameters, k-fold cross-validation is frequently utilized in research such as this one. In k-fold cross-validation, the training set is divided into k-equivalent halves to assess the algorithm's fit to the dataset. In order to accommodate temporal variations in the data, K-fold cross-validation utilizes a training set and a test set characterized by distinct initiation and termination times. In order to ensure the accuracy of the forecasting model, it must not incorporate any information preceding the events that were utilized to suit the model (Tashman, 2000). By previous research (e.g., Molinaro et al. (2005)), we partition the training data into ten subgroups (k = 10) in order to calibrate and train the model.

Given that the RF models utilize trees generated by the bagging strategy, some have deemed cross-validation superfluous. However, since the out-of-bag procedure resembles cross-validation, it may be superfluous to employ cross-validation when working with an RF model. An important objective of our research is to conduct a comparative analysis of the efficacy of GB and RF models. Cross-validation was applied to the RF model to facilitate the most objective comparisons feasible for this investigation. Similar out-of-sample data were utilized for the GB and RF models to ensure an accurate comparison.

The cross-validation procedure aims to identify hyperactive parameters that reduce the mean squared errors across all ten test datasets. The cross-validation-determined hyperparameters will be implemented on the test dataset for predictive purposes. This study employs a grid search to ascertain the optimal values for hyperparameters. The GB and RF models consider every predictor, and the user can modify the depth of the trees through adjustments to the number of divisions. Cross-validation aims to determine which hyperparameter configurations produce the smallest MSE (Probst et al., 2019).

5. EMPIRICAL RESULTS

5.1. Model Evaluation

Accuracy metrics are fundamental for assessing the effectiveness of ML algorithms. Particularly for classification tasks algorithms. These metrics furnish valuable insights regarding the performance of a model and contribute to a holistic comprehension of its merits and demerits. The following accuracy metrics shall be introduced: AUC-ROC, F1 score, precision, and recall (Powers, 2020).

- Precision, also known as positive predictive value, is calculated by dividing the number of true positives by the sum of expected positives (true positives and false positives). It evaluates the accuracy with which the model generates predictions. The formula is:

Precision = TP/(TP + FP)

- Recall: The recall metric computes the ratio of accurately predicted positive events (true positives) to the total number of positive instances (true positives plus false negatives). Particularly crucial when attempting to capture the maximum number of positive instances is recall. Formula:

Recall = TP/(TP + FN)

- F1 Score: The F1 score is calculated by averaging the subscores for accuracy and memory. It effectively distinguishes between false positives and negatives due to its ability to reconcile precision and memory. F1 score performance is most pronounced when the distribution of courses is unbalanced. Formula:

F1 Score = 2 * (Precision * Recall)/(Precision + Recall)

- AUC-ROC: The model's efficacy is illustrated by the Area Under the ROC Curve (AUC-ROC) across different categorization criteria. The area under this curve is quantified by the area under the ROC curve (AUC-ROC) statistic. Comparing the performance of a model across various threshold values is particularly advantageous due to the comprehensive evaluation it offers regarding the model's capability to differentiate between classes. AUC-ROC values could be positive or negative. It is prudent to make an educated estimate if the AUC-ROC value of your model is less than 0.5; conversely, a value approaching 1 indicates exceptional discriminatory capability.

Table 3: The accuracy of an ML method using cross-validation to forecast CO_2

Model	Metrics			
	AUC	F1	Precession	Recall
RF	0.77	0.73	0.73	0.74
GB	0.70	0.57	0.57	0.58

Source: Compiled by the author

5.2. Algorithms Accuracy and Performance

The utilization of cross-validation Table 3 presents the accuracy ratings of the employed algorithms, which have been processed using Python.

Table 3 shows that the RF algorithm is more accurate than the GB algorithms regarding CO_2 prediction and its determinants in Egypt, where the AUC of the RF is 77% when the GB is 70%. We depend on the RF algorithm feature selection for Egypt shown in the next section, 5.3, in order to ensure that the RF algorithm is the most accurate in predicting CO_2 emissions using its determinants, which are GDP growth, Urbanization, and energy consumption (coal, natural gas, and oil), comparison between predicted values and actual values should be done as shown in Table 4.

Figure 2: The RF algorithm performance

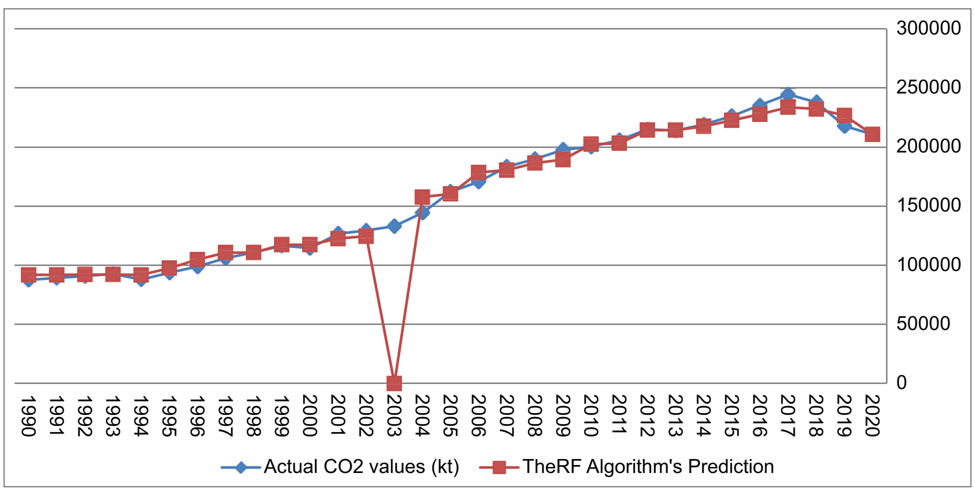


Figure 3: RF tree for Egypt

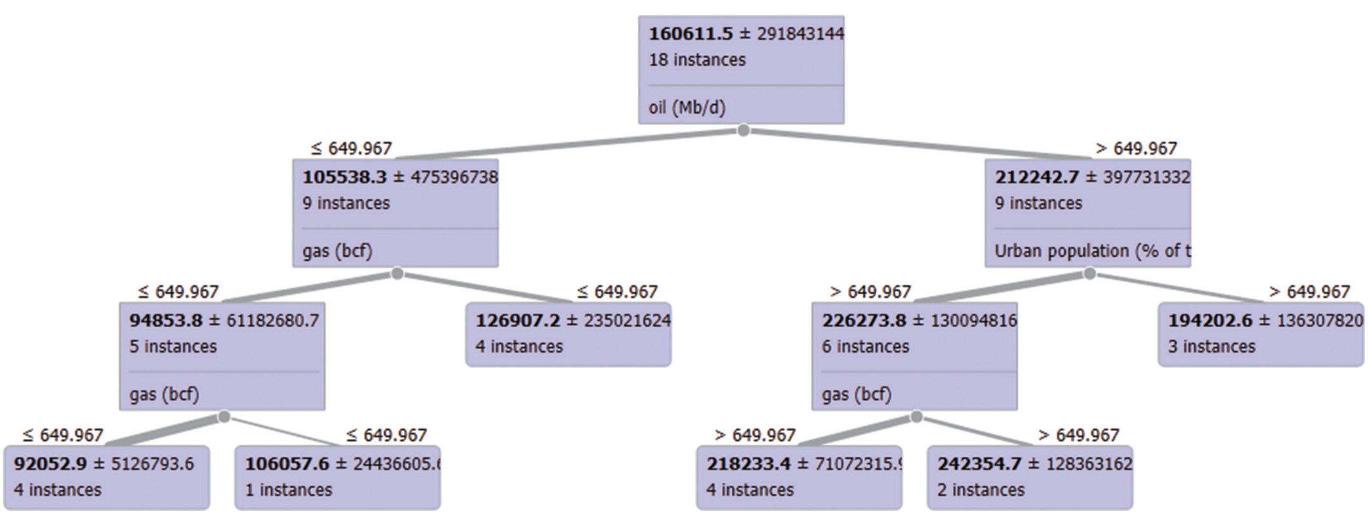


Table 4: Comparison between CO_2 actual values and predicted values according to independent variables

Year	Actual CO_2 values (kt)	The RF Algorithm's prediction
1990	87745.4	91884.2
1991	89369.5	91884.2
1992	90903.6	92200.5
1993	92661.9	92200.5
1994	87900.8	91884.2
1995	93722.3	97581.8
1996	98940.1	104780.7
1997	106057.6	110776.6
1998	110982.4	110776.6
1999	116535.3	117367.3
2000	114614.4	117367.3
2001	126704.4	122526.7
2002	129441.2	124542.2
2003	133020.4	132276. 8
2004	144503.9	157701.5
2005	162217.1	160387.7
2006	170745	178491.4
2007	183395.7	180501.9
2008	189935.2	186500.5
2009	197660.5	189363.7
2010	200313.3	202432.2
2011	205767.3	203247.2
2012	215000.9	214300.6
2013	213856.4	214300.6
2014	219121.1	217541
2015	226283.6	222653.3
2016	235425.8	227776.8
2017	244540.5	233764
2018	237983	232258.9
2019	217908.3	226729.2
2020	210752.3	210664.9

Source: Compiled by the author

Figure 2 shows more clearly how accurate the RF algorithm is in predicting CO_2 emissions, except for minor deviations that can be ignored.

5.3. GB and RF Algorithms Feature Importance

Unlocking the black capsule of ML models requires feature importance. The model's predictions or classifications are assessed, and the impact of each input variable or feature is measured and quantified. Data scientists acquire intimate knowledge of the underlying mechanisms of their models through the allocation of importance scores to these features. This understanding enables individuals to improve their models, stimulate progress, and generate more precise and comprehensible decisions.

This study examines the relevance of features, including their practical applications in diverse domains and the methodologies used to evaluate them. We cordially invite you to accompany us on an exploration into data-driven decision-making, where feature importance serves as a governing principle. In Table 5, the feature significance of the RF algorithms is displayed.

From Table 5, we find that according to the RF algorithms feature selection, the most influence on the CO_2emissions in Egypt is natural gas by 49.7%, then oil by 46.7%. Regarding other variables, influences are very limited. This is due to the small

Table 5: The RF algorithms FEATURE importance indicators

Variables	RF feature importance For high-income countries
NG	49.7
OL	46.7
Ur	2.6
Co	0.7
GDPg	0.3

Source: Compiled by the author

Figure 4: Scatter plot for a positive relationship between CO_2 emissions and other variables

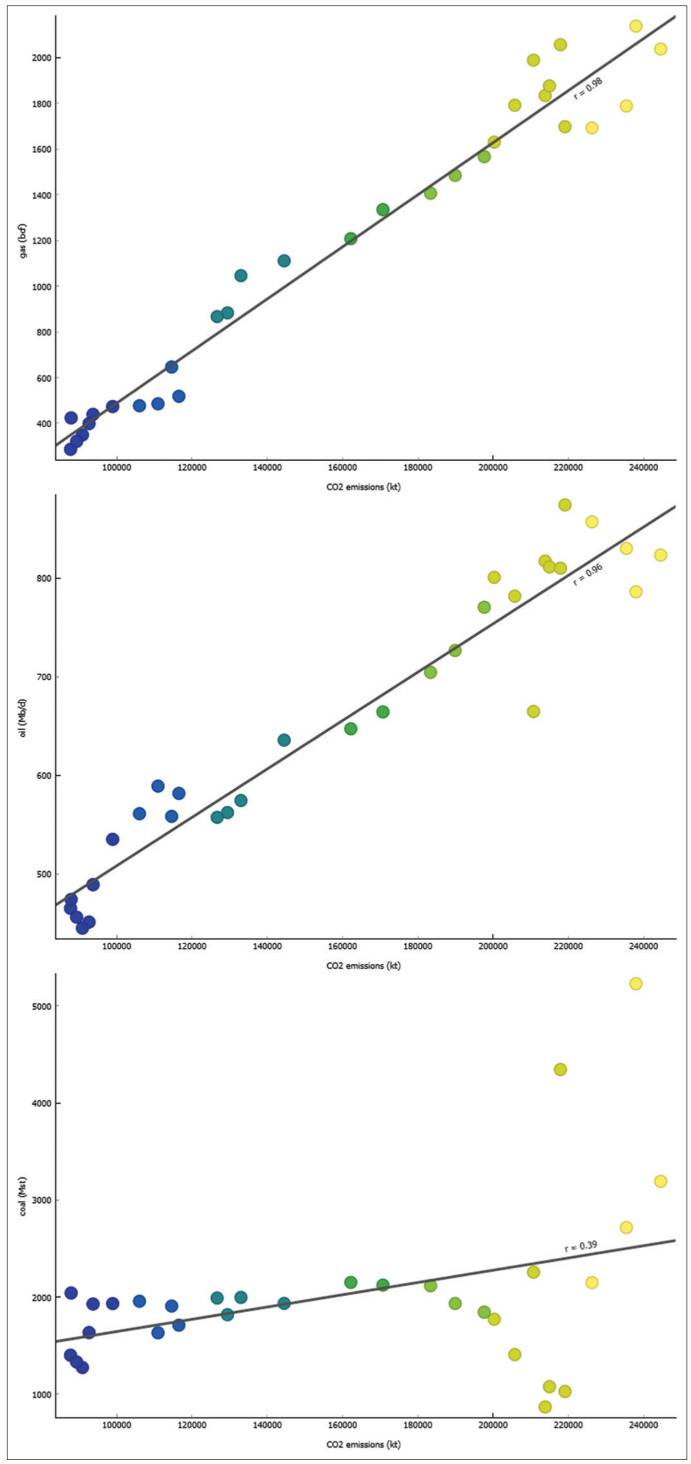
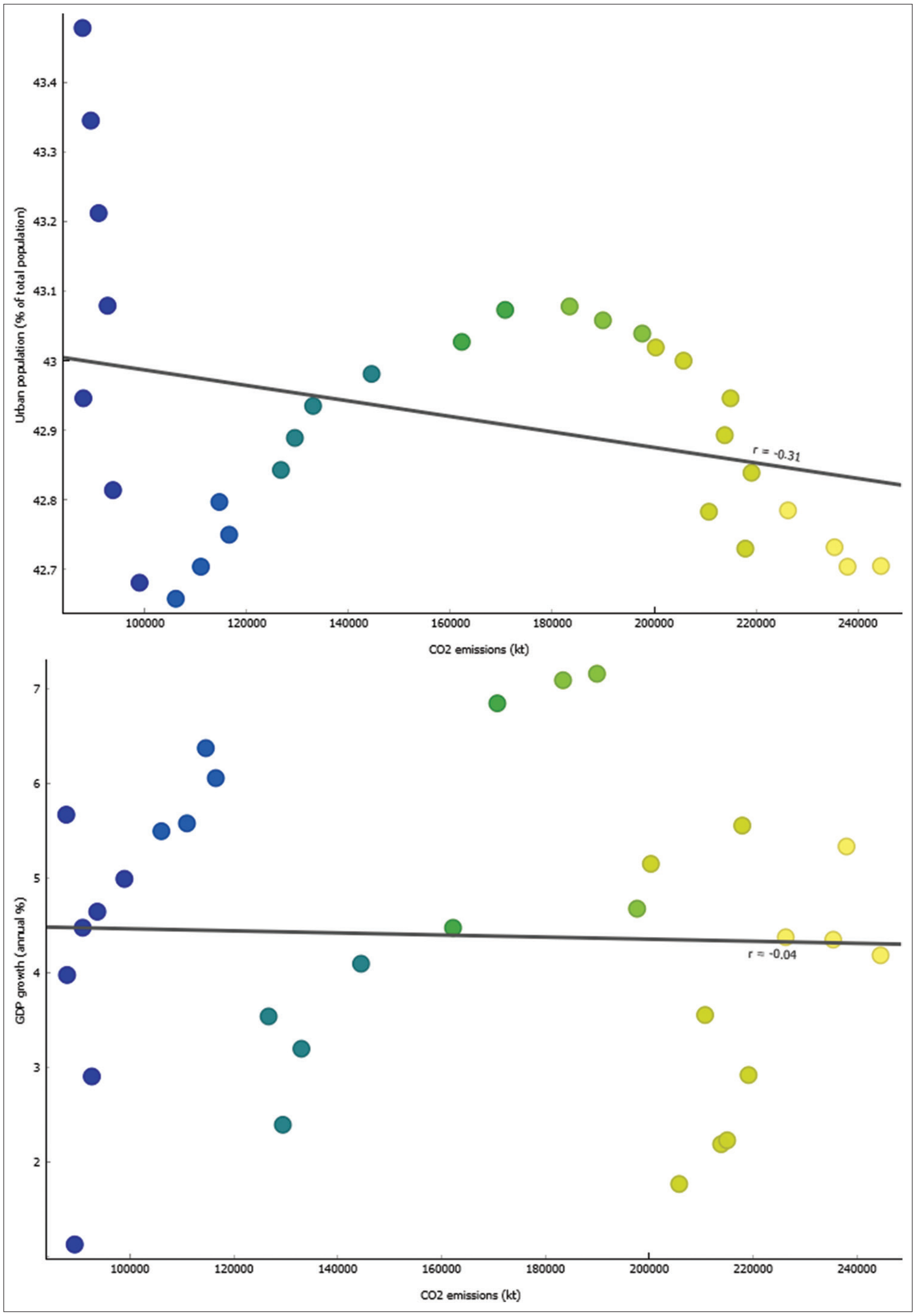


Figure 5: Scatter plot for the negative relationship between CO_2 emissions and other variables



contribution of the industrial sector to the gross domestic product and its expansion. Urbanization in Egypt is due to migration from regional cities to large cities such as Cairo. This migration is not followed by the industrial sector but is expanded in the construction sector.

This can be explained through an RF tree in Figure 3, which shows the relative importance of natural gas and oil's influence on CO_2 emissions.

We note from the tree of The RF that the contribution of oil and gas most influences climate change in Egypt.

Table 6: The correlation between the CO_2 emissions and the independent variables.

Variables	Relationship
NG	0.98
OL	0.96
Ur	−0.31
Co	0.39
GDPg	−0.04

Source: Compiled by the author

The stage assesses whether an entity's influence is positive or negative. Determine the correlation between the dependent and independent variables by consulting Table 6.

Table 6 shows a strong positive relationship between the consumption of natural gas, oil, and coal and CO_2 emissions in Egypt. There is also a negative relationship between urbanization and GDP growth (very weak in the case of output growth) and CO_2 emissions in Egypt. Figures 4 and 5 shows this in detail.

6. CONCLUSION

The key findings of this research underscore the profound impact of economic expansion, urbanization, and energy consumption on climate change in Egypt. With the nation's economic growth, there is a noticeable increase in greenhouse gas emissions, primarily driven by energy-intensive industrial activities. The study reveals that Egypt's Gross Domestic Product (GDP) influence on climate change is relatively limited, indicating a positive trend of environmentally friendly economic expansion. Unlike many other nations, urban expansion in Egypt appears to have an inverse relationship with CO_2 emissions, suggesting a unique and favorable scenario. These interconnected dynamics emphasize adopting a comprehensive and well-informed approach to address Egypt's environmental challenges.

Integrating Artificial Intelligence techniques in this study has proven to be a powerful asset in predicting future climate trends and unraveling complex environmental dynamics. The ML algorithms employed in the analysis provide precise forecasts and valuable insights, empowering policymakers, researchers, and stakeholders to make well-informed decisions and implement targeted strategies to mitigate the impacts of climate change in Egypt.

Furthermore, this research strongly underscores the urgency of adopting sustainable and environmentally conscious practices. It emphasizes the imperative transition to renewable energy sources, the enhancement of energy efficiency, and the promotion of sustainable urban planning as pivotal components in mitigating climate change in Egypt. The study also highlights the ongoing importance of research and innovation in Artificial Intelligence to continually refine predictive models and enhance mitigation strategies. This holistic approach is instrumental in steering Egypt toward a more sustainable and environmentally responsible future.

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