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Evaluating national energy efficiency using hybrid DEA-Cross efficiency and machine learning models

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Abstract Energy efficiency is critical for the attainment of sustainable development, as it optimizes resource utilization and reduces environmental impacts. This study evaluates the energy efficiency of 28 countries from 1995 to 2021 using a hybrid methodology, Data Envelopment Analysis (DEA)-Cross-Efficiency and machine learning models. DEA was utilized to compute efficiency scores by analyzing inputs including population and total energy consumption, with output such as total energy production. The scores underwent additional analysis employing six machine learning models: LightGBM, XGBoost, KNN, Random Forest, Decision Tree, and SVR. This approach aimed to reveal intricate relationships between the inputs and efficiency ratings, in addition to forecasting future efficiency trends. LightGBM demonstrated outstanding performance, achieving $R^2 = 0.9820$, MSE = 0.0008, and MAE = 0.0155. This performance can be attributed to its capacity to manage large datasets, optimize memory utilization, and implement sophisticated tree-based algorithms for precise predictions. Analysis of feature importance indicated that gas and coal production per capita are significant factors influencing energy efficiency. The findings offer policymakers practical insights for optimizing resources and highlight the effectiveness of machine learning in improving conventional efficiency evaluations. In the assessment of the countries, Australia and Canada exhibited the highest energy efficiency scores, indicative of their proficient resource management and energy policies. These insights provide a framework for other nations to implement comparable strategies aimed at enhancing energy efficiency and fostering sustainable development.

Keyword: Energy Efficiency; Data Envelopment Analysis; Machine Learning; Performance Analysis

1 Introduction

Energy is a fundamental necessity of contemporary human existence, significantly influencing economic, social, and technical advancement. In fact, Energy serves as the fundamental catalyst for economic advancement in countries [1]. The increasing global demand for various energy resources, particularly fossil fuels, has created substantial issues

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for governments around. The swift rise in population, urban development, and industrial expansion has resulted in an unparalleled surge in energy demand, placing significant pressure on current resources and infrastructure [2]. The environmental repercussions of energy generation and use, including greenhouse gas emissions and climate change, have emerged as urgent global concerns. This challenge emphasizes the pressing necessity for efficient energy management techniques that balance human demands with environmental sustainability [3]. Consequently, evaluating the efficacy of countries in energy management is a crucial responsibility for policymakers, prompting governments to perpetually pursue optimal practices and pinpoint inefficiencies within the energy system [4].

Data Envelopment Analysis (DEA) is a non-parametric technique for assessing the efficiency of decision-making units [5]. DEA evaluates the efficiency of decision-making units by comparing several units based on distinct inputs and outputs. DEA has emerged as a formidable instrument for assessing the effectiveness of decision-making units across diverse sectors, including healthcare, education, and finance [6]. DEA approach is often categorized into two types: output-oriented and input-oriented. The output-oriented strategy aims to enhance outputs while maintaining constant inputs, whereas the input-oriented approach focuses on minimizing inputs while preserving constant outputs [7]. Conventional DEA methodologies exhibit some weaknesses, including bias in performance assessment, as each unit is solely compared to the optimal unit, resulting in non-comprehensive outcomes [8]. Diverse models have been suggested to address the shortcomings of conventional techniques. This study employs the cross-efficiency approach. This strategy involves comparing each decision-making unit not just with the optimal unit but also with all other units, resulting in more dependable outcomes [9]. This strategy enables policymakers to enhance decision-making on resource allocation and efficiency optimization.

Although DEA is regarded as an effective instrument for assessing the effectiveness of decision-making units, its models are constrained to retrospective analysis and cannot forecast future trends or elucidate intricate connections [10]. To overcome this weakness, it is advisable to employ machine learning approaches in conjunction with DEA. This method facilitates the identification of intricate patterns and variables influencing efficiency ratings [11]. Machine learning (ML), a subset of Artificial Intelligence (AI), concentrates on creating algorithms capable of learning from data, recognizing patterns, and making predictions and assessments autonomously, without explicit programming [12]. In contrast to conventional statistical approaches, ML algorithms are engineered to enhance their performance progressively as they encounter fresh data. This versatility renders machine learning a potent instrument for predictive modeling, allowing it to reveal linkages that may not be evident through traditional analysis [13]. In efficiency assessment, ML may enhance data envelopment analysis by offering predictive insights, identifying critical performance determinants, and simulating the effects of policy modifications [14].

This study evaluated the energy production performance of 28 countries from 1995 to 2021 with the DEA-Cross technique. The efficiency scores are analyzed using five machine learning models: XGBoost, KNN, Decision Tree, Support Vector Machine, Random Forest, and LightGBM, with their performance assessed in terms of accuracy. The determinants influencing efficiency ratings have been found and examined.

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2 Literature Review

Energy efficiency has emerged as a crucial and essential concern in sustainable development. Nevertheless, escalating energy use and reliance on fossil fuels have engendered significant difficulties, including climate change and environmental contamination [15]. This context suggests enhancing energy efficiency as a viable approach to concurrently decrease energy usage, lower expenses, and safeguard the environment [3]. An important part of energy efficiency is using energy resources wisely so that the same level of service or production can be achieved with less energy. This notion is seen as an essential requirement for companies, governments, and the global society in pursuit of sustainable development [16]. However, it is not easy to achieve energy efficiency, especially in underdeveloped nations.

In these countries, the lack of proper infrastructure, restricted access to sophisticated technology, and insufficient expenditures frequently impede progress toward the effective use of energy [17]. These challenges highlight the need for countries to work together and share technology in order to close the divide between developed and impoverished countries. Furthermore, the absence of appropriate rules and regulations makes it much more difficult to improve energy efficiency in these places [18]. Moreover, the importance of sophisticated data analysis and big data has grown in the effort to improve energy efficiency. Policymakers and organizations may use big data and sophisticated analytics to acquire a better understanding of energy usage trends, detect inefficiencies, and provide targeted remedies [19]. This data-driven method not only helps improve decision-making but also increases the accuracy of energy efficiency assessments, making it an essential tool for contemporary energy management techniques [20].

2.1 Traditional methods for evaluating energy efficiency

Conventional methods for assessing energy efficiency have long been used to evaluate the performance of energy systems and identify areas for improvement. Among these approaches, DEA has gained significant attention due to its ability to handle multiple inputs and outputs without requiring predefined functional forms. Energy efficiency research widely uses DEA to evaluate the performance of various industries and geographical areas. For instance, a research by [21] employed Super efficiency DEA to evaluate regional energy efficiency in China, indicating large discrepancies across the eastern (0.812), central (0.534), and western areas (0.349). The study employed the Theil index to demonstrate that regional disparities have diminished over time, with inter-regional inequalities being the primary contributors to total inequality. Another study by [22] employed a two-stage network DEA model to assess the energy efficiency of energy-intensive firms in Korea.

The study found that while energy efficiency significantly impacts financial performance, firms with higher pure-energy efficiency do not always achieve better financial outcomes. Additionally, the study highlighted that improving both pure-energy and economic efficiencies simultaneously is challenging, suggesting that firms must strategically prioritize their efficiency goals based on their specific circumstances. Additionally, a study conducted by [23] utilized both conventional DEA and a bargaining game cross-efficiency DEA methodology to assess the energy, environmental, and economic (E3) efficiency of fossil fuel exporting nations. The results indicated notable variations in efficiency, with China, Oman, and Bahrain achieving the highest rankings, whereas Gabon, Saudi Arabia, and Albania occupied the lowest positions. These results emphasize the necessity of acknowledging

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multidimensional heterogeneity in the formulation of energy policies and highlight the efficacy of DEA in pinpointing inefficiencies across varied contexts.

2.2 Machine Learning Approaches in Energy Efficiency

Machine learning (ML) has become a powerful tool for evaluating intricate datasets and detecting patterns that conventional approaches may ignore. In the field of energy efficiency, machine learning methods like XGBoost and LightGBM are being used more and more to predict energy performance, improve resource distribution, and figure out the most important factors that affect efficiency. Research by [24] combined DEA with machine learning methods, such as back-propagation neural networks (BPNN), genetic algorithms (GA), and SVR, to assess and forecast the efficiency of Chinese manufacturing firms. The study got an average prediction accuracy of 94%, which shows that hybrid models can improve the accuracy and usefulness of performance evaluations. Another research [25] similarly presented a framework that integrates DEA, Artificial Neural Networks (ANN), and Deep Learning (DL) to assess the performance of the Indian pulp and paper sectors. The research indicated that the combined DEA-DL methodology attained a mean squared error of 0.08 relative to actual efficiency values, underscoring the efficacy of merging DEA with sophisticated machine learning approaches for precise performance forecasting .

A research [26] employed Fuzzy DEA (FDEA) and machine learning methods, including SVR and RF, to assess the efficiency of paddy growers in rural Eastern India. The FDEA model offered adaptability for evaluating performance across various potential levels, whilst SVR and RF were employed to determine critical aspects affecting efficiency. The research indicated that the hybrid method surpassed conventional DEA in managing ambiguous data and yielded more exact forecasts of agricultural efficiency.

3 Methods

This study employed a hybrid methodology, using Cross-DEA and Machine Learning, to assess the energy efficiency of various countries. We have used the DEA-derived performance ratings as target variables in machine learning models to identify and predict trends in energy efficiency. Each of the employed approaches is thoroughly elucidated below:

3.1 Data envelopment analysis- Cross-efficiency

The Cross-efficiency DEA model was introduced by Sexton to discern variations among efficient units. We presume that N decision-making units are assessed based on m inputs and s outputs. Let x_{ij} and y_{ij} represent the input and output values for $i=1,...,m$, $r=1,...,s$ and $j=1,...,n$. The efficiency of N decision-making units is assessed utilizing the CCR model as delineated in model (1):

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$$
\begin{aligned}
& Max\theta = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
& s.t \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \qquad j = 1,\dots,n \\
& u_r, v_i \ge 0 \qquad r = 1,\dots,s \qquad i = 1,\dots,m
\end{aligned} \tag{1}
$$

In equation (1), v_i and u_r are referred to as input and output weights. Charnes and Cooper transformations enable the nonlinear model (1) to be expressed linearly according to formula (2):

$$
\begin{aligned}
& Maxz = \sum_{r=1}^{s} u_r y_{ro} \\
& s.t \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad j = 1,\dots,n \\
& \sum_{i=1}^{m} v_i x_{io} = 1 \\
& u_r, v_i \ge 0
\end{aligned} \tag{2}
$$

Model (2) is solved sequentially for each DMU, resulting in *N* sets of input and output weights for the DMUs. Consequently, each DMU will possess (*N-1*) cross-efficiencies one CCR efficiency. The efficiencies are presented in the cross-efficiency matrix depicted in Table (1):

Table 1 Cross-efficiency matrix

DMUS	1	2	. . .	k	cross efficiency
1	θ_{11}	θ_{12}	. . .	θ_{1k}	$\frac{1}{n}\sum_{k=1}^{n}\theta_{1k}$
. . .	. . .	. . .	. . .	. . .	. . .
n	θ_{n1}	θ_{n2}	. . .	θ_{nk}	$\frac{1}{n}\sum_{k=1}^{n}\theta_{nk}$

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3.2 Extreme Gradient Boosting (XGBoost)

XGBoost technique first presented by [27], is based on the concept of gradient boosting, where the predictions of weak learners are successively amalgamated to form a strong model. This approach accommodates both linear and nonlinear models, provides considerable flexibility via various parameter settings, and is recognized for its rapid data processing capabilities. The initial model is trained on the complete input dataset, while succeeding models are developed in succession to rectify the mistakes of their forerunners. This recurrent procedure persists until a predetermined stopping requirement is satisfied. The ultimate forecast is derived by consolidating the outputs of all separate models.

3.3 Decision Tree (DT)

DT was first developed by [28]. It is extensively employed as a supervised learning instrument for classification and regression applications. These trees create a hierarchical framework by recursively dividing the dataset into smaller subsets, with each node representing a feature and each branch denoting a possible value of that feature. The main goal is to attain an ideal division at every step, guaranteeing maximal differentiation between groups. Metrics like entropy or the Gini Index are frequently employed to determine the most informative feature for partitioning. Ultimately, each leaf node signifies a conclusive conclusion or categorization result.

3.4 Random Forest (RF)

RF algorithm introduced by [29] was developed to enhance the decision tree methodology. RF leverages the ensemble learning technique by utilizing multiple decision trees as base models for prediction. This method trains each tree in the forest on a different set of input features and data samples. This makes sure that the predictors are all different and work on their own. For prediction, the results of all trees are added together. For classification tasks, the final prediction is chosen by a majority vote, and for regression tasks, it is found by taking the average of all the tree predictions. This method works well with complicated and nonlinear models because it can handle noise and overfitting without losing its effectiveness.

3.5 K-nearest neighbors (KNN)

KNN algorithm was introduced by [30]. Both classification and regression tasks utilize this supervised learning algorithm. KNN does not make any assumptions about the underlying data distribution, making it a non-parametric method. The algorithm’s predictions are based on the similarity between the new data point and the k nearest neighbors in the training set. The user chooses the value of k, which determines the number of neighbors considered. This method is simple yet effective, relying on the proximity of data points to infer the category or value of new instances.

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3.6 Light Gradient Boosted Machine (LightGBM)

LightGBM is an open-source framework for supervised machine learning employed in regression and classification problems [31]. The technique is an enhanced variant of gradient boosting, engineered to be more memory-efficient and to expedite training. LightGBM employs a tree learning method and gradient-based optimization to reduce the error function. We construct the tree model by incrementally incorporating decision trees, training each subsequent tree to correct the mistakes of its predecessors. LightGBM employs a leaf-wise tree construction technique that develops the tree incrementally, minimizing the number of splits necessary to attain a certain depth. This approach yields shallower and more equilibrated trees. LightGBM has features like Gradient-Based One-Way Sampling (GOSS), which lowers computational demands by utilizing a subset of data with bigger gradients. Moreover, exclusive feature bundling (EFB) consolidates features with like values into a singular feature, hence lowering the feature count and enhancing model accuracy. These attributes render LightGBM exceptionally efficient for extensive, high-dimensional datasets.

3.7 Support vector Regression (SVR)

SVR is a supervised machine learning method utilized for classification and regression purposes [32]. The main aim of this strategy is to discover a suitable hyperplane that separates data from different classes inside the feature space. SVR employ kernel functions to handle problems related to data that are not linearly separable. These functions transform the original data into a higher-dimensional feature space, enabling the separation of the data using a hyperplane. Prevalent kernels comprise the polynomial kernel, the Gaussian kernel (RBF), and the sigmoid kernel.

4 Results

In this section, at the first step, we use the first step is the use of the Cross-Efficiency technique to compute the performance ratings of 28 countries from 1995 to 2021. Secondly, we analyze the performance scores using machine learning methods.

4.1 Efficiency analysis using Cross-Efficiency-DEA

This section assesses the energy efficiency of 28 countries from 1995 to 2021 with the proposed Cross-Efficiency DEA model (data was obtained from the website databank.worldbank.org). Assessing the energy efficiency of nations from many perspectives, particularly energy production and consumption, is essential as it reveals the strengths and weaknesses of their energy systems. This research offers critical insights for policymakers to enhance energy efficiency and foster sustainable growth. The identification of input and output variables is a crucial phase in DEA applications. However, there is no consensus over which factors most accurately represent the energy efficiency of nations. This study utilizes population and total energy consumption as input factors, while total energy production serves as the output variable to evaluate the efficiency of each country. The Cross-Efficiency DEA method facilitates a more thorough assessment by incorporating efficiency ratings from

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the viewpoint of all nations, rather than relying on a singular benchmark. Figure 1 illustrates each country included in this study, and Table 2 presents a summary of the statistical data.

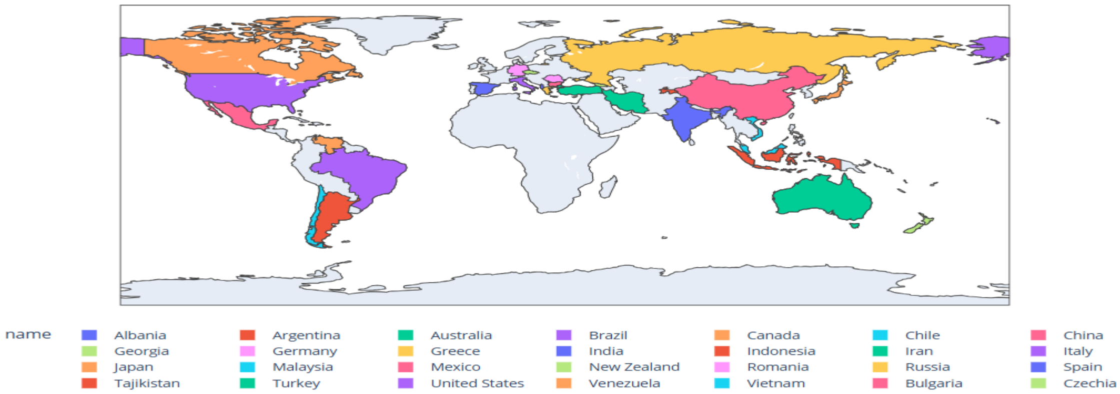

Fig. 1 Countries evaluated for energy efficiency

Table 2 Statistical summary of countries data from 1995 to 2021

Data	Inputs		Output
	Population	Total Energy Consumption	Total Energy Production
Mean	1.509799e+08	7.299590e+10	6.968535e+10
Standard deviation	3.146900e+08	1.445642e+11	1.571395e+11
Minimum	2.881000e+06	1.162700e+07	4.088400e+05
Maximum	1.434000e+09	8.834268e+11	9.613520e+11

Table 3 presents the analysis of the Cross-efficiency matrix for 28 countries. Efficiency scores, serving as a comparison metric among nations throughout several years, reveal substantial disparities in energy performance. Result indicates that Australia ranked first in 2019, followed by Australia in 2018 and Albania in 2011. Georgia received the lowest performance score in 2014.

Table 3 Cross-efficiency matrix for 28 countries

DMUS	Albania_1995	Albania_۱۹۹۴	. . .	Czechia_2021	cross efficiency
Albania_1995	0.2472	0.2714	. . .	0.0095	0.2115
.	.	.	.		.
.	.	.	.		.
.	.	.	.		.

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Albania_2011	0.1643	0.1753	. . .	0.0046	0.8463
Australia_2019	0.0268	0.0315	. . .	0.0006	0.9987
Australia_2018	0.2472	0.2714	. . .	0.0095	0.9514
. . .	. . .	. . .	. . .	. . .	. . .
Georgia_2014	0.2418	0.2659	. . .	0.0095	0.0001
Czechia_2021	0.2470	0.2712		0.0095	0.0090

4.2 Machine learning approach

This section initially calculates efficiency scores using the Cross-efficiency DEA technique, which are subsequently employed to create an analytical model. A model for the comprehensive analysis and prediction of unit efficiency is developed and executed via machine learning techniques. This method facilitates the recognition of patterns and intricate correlations between input and output data. Table 4 shows a description of features.

Table 4 Description of 14 features for machine learning models

Features	Input/target for machine learning
Gas production (m^3)	input
Gas consumption (m^3)	input
Coal production (Ton)	input
Coal consumption (Ton)	Input
Oil production (m^3)	Input
Oil consumption (m^3)	Input
Gas production per capita (m^3)	Input
Gas consumption per capita (m^3)	Input
Coal production per capita (Ton)	Input
Coal consumption per capita (Ton)	Input
Oil production per capita (m^3)	Input
Oil consumption per capita (m^3)	Input
Population	Input
cross efficiency score	Target

4.2.1 Preparing Data

We executed the data preparation procedure before using machine learning models to ensure the quality and precision of the analysis. To accomplish this, procedures including data quality assessment, handling of missing values, and examination of outlier data were executed. The initial phase was the analysis of outliers and missing data. In the subsequent phase, we standardized all features using the min-max approach and formula number (3) to mitigate the disparity in scale among variables.

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$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

4.2.2 Training and validating models

The data was first partitioned into two sets: training and testing, for the purpose of training and validating machine learning models. In this split, 80% was allocated for training and 20% for testing, enabling the machine learning models to effectively examine the correlations between input and target features (performance scores). After training the models, their performance was evaluated using metrics such as MAE, MSE, and R^2. These metrics showed which model had better accuracy and generalizability for predicting performance scores. Table 5 compares the evaluation criteria for machine learning models with each other:

Table 5 Comparing the performance of machine learning models

Models	MAE	MSE	R^2
Xgboost	0.0155	0.0010	0.9784
LightGBM	0.0155	0.0008	0.9820
DT	0.0302	0.0026	0.9441
KNN	0.0164	0..0016	0.965
RF	0.0248	0.0025	0.9458
SVR	0.0648	0.0053	**0.8867**

Additionally, for each method, a graph depicting Actual vs Predicted Values is plotted, with the horizontal axis representing real values and the vertical axis representing values predicted by the model. These graphs graphically evaluate the models' accuracy, with points nearer to the diagonal line signifying superior model performance.

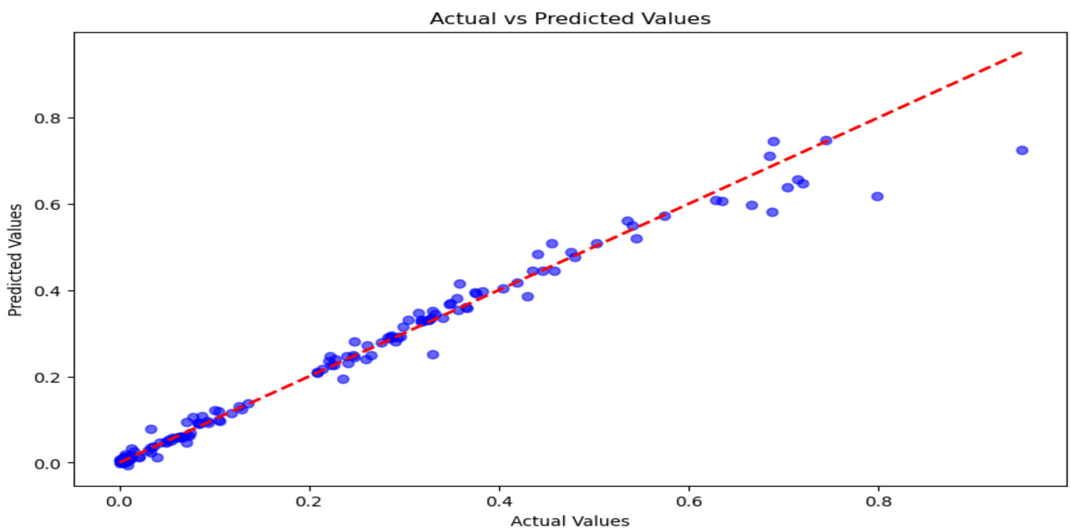

Fig. 2 Actual vs. predicted by XGBoost model

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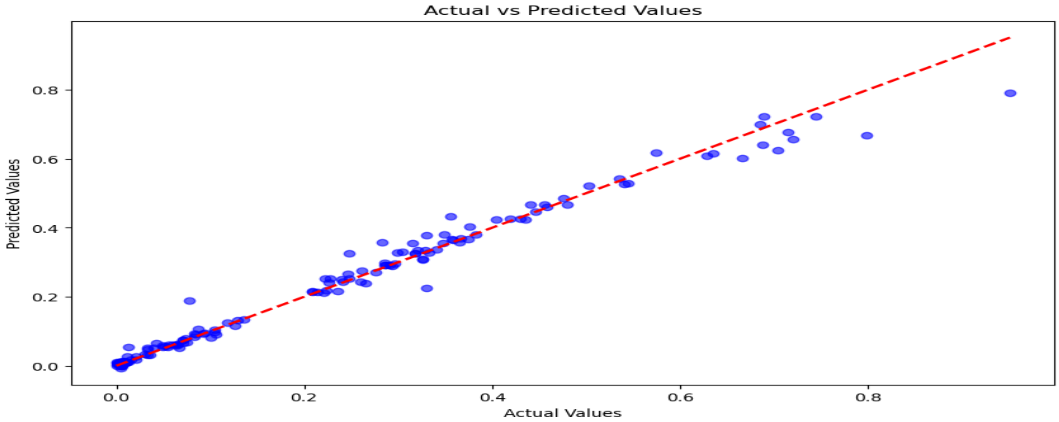

Fig. 3 Actual vs. predicted by LightGBM model

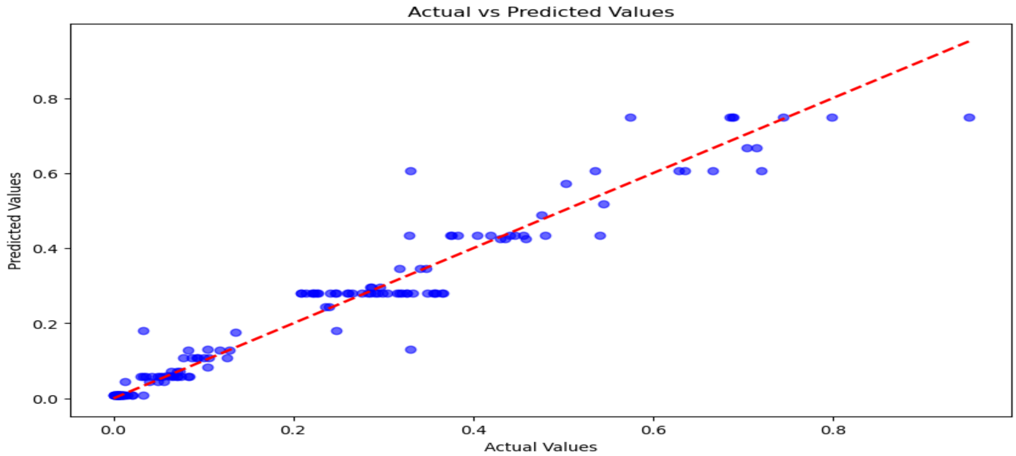

Fig. 4 Actual vs. predicted by DT model

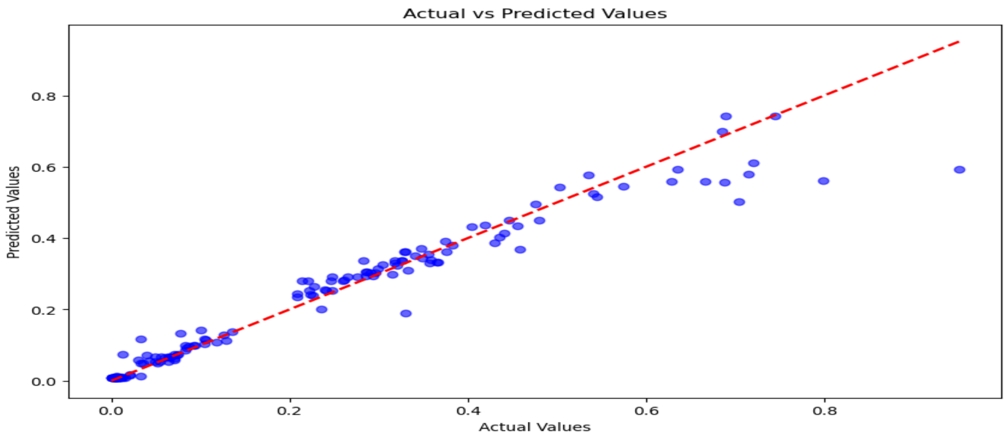

Fig. 5 Actual vs. predicted by RF model

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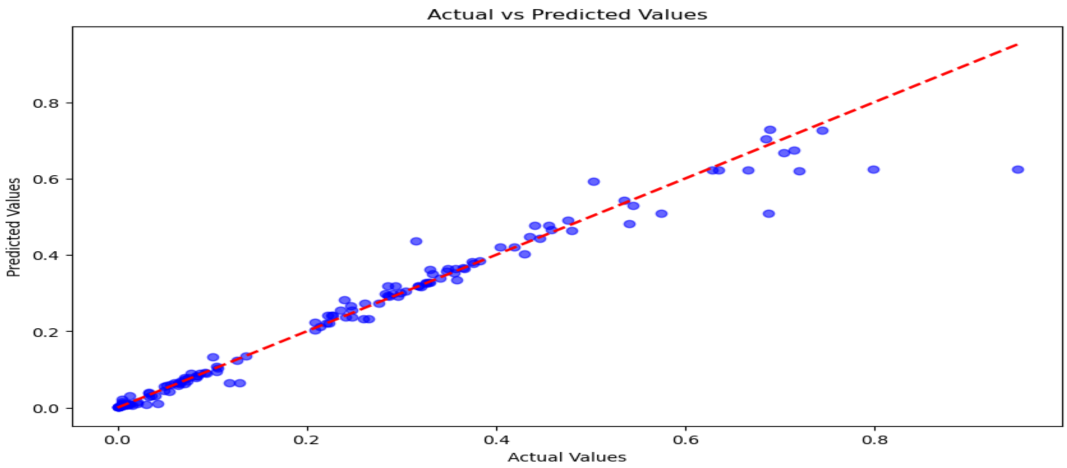

Fig. 6 Actual vs. predicted by KNN model

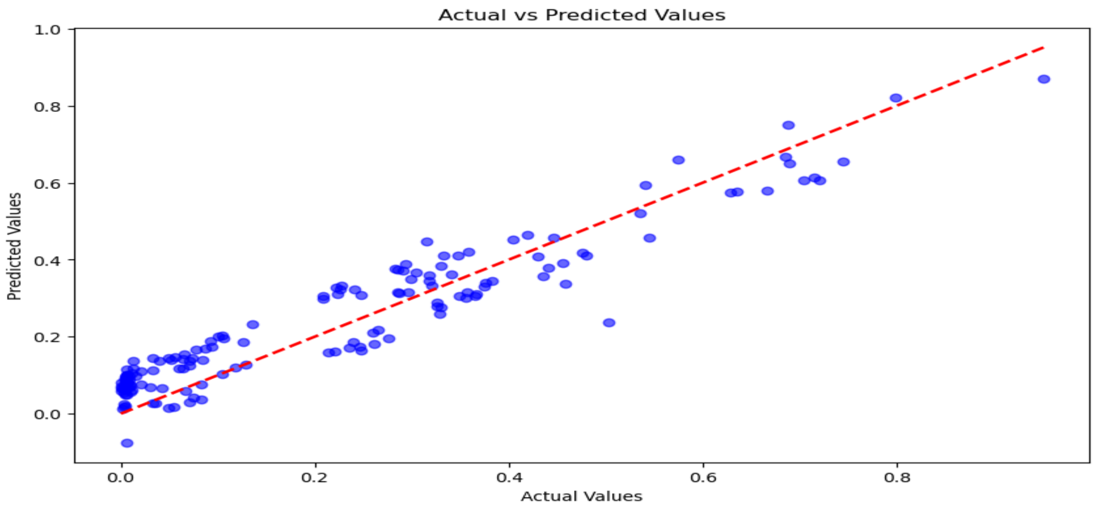

Fig. 7 Actual vs. predicted by SVR model

This study identified the LightGBM algorithm as the top-performing model among all evaluated techniques. It achieved the highest R^2 score of 0.9820, along with the lowest Mean Squared Error (MSE) of 0.0008 and Mean Absolute Error (MAE) of 0.0155. The exceptional performance of LightGBM can be attributed to its utilization of advanced techniques, such as leaf-wise tree growth and memory optimization.

These features not only reduce the model's training time but also significantly enhance its predictive accuracy. Consequently, LightGBM demonstrated a clear advantage over the other models, delivering superior performance and efficiency in this study. XGBoost algorithm exhibited performance comparable to that of LightGBM. This gradient boosting-based method effectively identifies intricate patterns in data. A significant feature of XGBoost is its capacity to manage huge datasets and outliers, rendering it one of the most prevalent models in machine learning. Despite its performance being somewhat inferior to LightGBM in this research, it was nevertheless recognized as one of the premier models. KNN algorithm obtained the third position in this study. While its reliance on sample similarity contributed to its notable performance, certain limitations, such as susceptibility to noise, resulted in

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outcomes that were less accurate compared to those of LightGBM and XGBoost. The Random Forest algorithm ranked fourth, followed by the Decision Tree in fifth position.

Both models demonstrated commendable performance, primarily due to their ability to handle nonlinear relationships and effectively partition data using tree-based structures. However, challenges such as data imbalance limited their accuracy, preventing them from achieving performance levels comparable to those of LightGBM and XGBoost in this study. In order to identify key factors affecting energy efficiency, Feature Importance in the LightGBM model has been analyzed. This analysis is based on the best evaluated model and can help policymakers in management decisions.

Table 6 Feature Importance in LightGBM Model

Feature	Importance
Gas production per capita (m³)	15.0528
Coal production per capita (Ton)	10.1142
Gas consumption per capita (m³)	9.14384
Gas consumption (m³)	8.34591
Gas production (m³)	7.3538
Oil production per capita (m³)	7.2460
Coal consumption (Ton)	7.2029
Coal production (Ton)	6.6422
Oil consumption (m³)	6.6422
Population	6.1893
Oil consumption per capita (m³)	5.9521
Coal consumption per capita (Ton)	5.4345
Oil production (m³)	4.6797

5 Discussion and conclusion

This study evaluated the energy efficiency of 28 countries from 1995 to 2021 with a hybrid methodology combining DEA and machine learning approaches. Cross-efficiency DEA approach was employed to compute efficiency scores, further examined using six machine learning methods. Among the assessed models, the LightGBM method demonstrated superior performance, exhibiting a notable advantage over other methods with a high accuracy (R^2 = 0.9820) and low errors (MSE = 0.0008 and MAE = 0.0155). XGBoost demonstrated performance comparable to LightGBM and was acknowledged as one of the preeminent approaches among the assessed models. KNN, Random Forest and Decision Tree models exhibited middling accuracy and had more restricted applicability compared to gradient boosting models, whilst SVR had the poorest performance owing to data complexity and processing limits. The results demonstrate the significant potential of gradient boosting models, particularly LightGBM, in the investigation and prediction of energy efficiency.

This study emphasizes the efficacy of machine learning approaches, particularly gradient boosting methods like LightGBM, in the analysis and prediction of energy efficiency. The examination of feature significance revealed that variables such as gas production per capita (m³) and coal output per capita (ton) are among the most impactful in assessing energy efficiency. These findings underscore the necessity for governments to prioritize the optimization of these resources to enhance energy efficiency. Moreover, recognizing essential characteristics aids policymakers in formulating resource allocation methods grounded in empirical facts, thus advancing the management of energy resources.

A review of actual and anticipated productivity values consistently identifies Australia and Canada as the countries with the highest productivity. For instance, Australia had a projected score of 0.7908 in 2018 (actual score: 0.9514), whereas Canada had a projected score of 0.7236 in 2005 (actual score: 0.7446). This high standard demonstrates the effective management of energy resources, sophisticated infrastructure, and prudent policymaking in these countries. On the other hand, nations such as Tajikistan and Georgia exhibited reduced effects. Tajikistan's projected score in 2010 was 0.0266 (actual score: 0.0215), whereas Georgia's forecasted value in 2017 was 0.0035 (actual score: 0.0011). The poor scores are likely due to inadequate infrastructure, inefficient resource management, and a considerable dependence on non-renewable energy sources. The yearly trend in productivity exhibits considerable variability. Productivity reached the heights between 1999 and 2018, perhaps due to technology advancements and effective regulations implemented during those times. Conversely, 1997 and 2014 had the lowest productivity scores, which may be attributable to factors such as economic downturns, escalating energy expenses, or policy inefficiencies. These variations indicate that a nation's energy efficiency performance relies not just on resources and technology, but also on the sustainability of policies and the capacity to manage external shocks.

6 Suggestions for future researchers

It is recommended that future researchers investigate the incorporation of additional sophisticated machine learning methodologies, including deep learning or ensemble hybrid models, to further improve the precision of energy efficiency forecasts. Deeper insights might also be obtained by including a wider range of inputs, such as policy indicators or the use of renewable energy. Broader application may also result from extending the investigation to more nations or areas over longer time periods. Lastly, it is advised to use time-series models to examine the dynamic effects of policy changes on efficiency.

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