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Ensemble Machine Learning Approaches for Prediction of Türkiye's Energy Demand

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Abstract: Energy demand forecasting is a fundamental aspect of modern energy management. It impacts resource planning, economic stability, environmental sustainability, and energy security. This importance is making it critical for countries worldwide, particularly in cases like Türkiye, where the energy dependency ratio is notably high. The goal of this study is to propose ensemble machine learning methods such as boosting, bagging, blending, and stacking with hyperparameter tuning and k-fold cross-validation, and investigate the application of these methods for predicting Türkiye's energy demand. This study utilizes population, GDP per capita, imports, and exports as input parameters based on historical data from 1979 to 2021 in Türkiye. Eleven combinations of all predictor variables were analyzed, and the best one was selected. It was observed that a very high correlation exists among population, GDP, imports, exports, and energy demand. In the first phase, the preliminary performance was investigated of 19 different machine learning algorithms using 5-fold cross-validation, and their performance was measured using five different metrics: MSE, RMSE, MAE, R-squared, and MAPE. Secondly, ensemble models were constructed by utilizing individual machine learning algorithms, and the performance of these ensemble models was compared, both with each other and the best-performing individual machine learning algorithm. The analysis of the results revealed that placing Ridge as the meta-learner and using ET, RF, and Ridge as the base learners in the stacking ensemble model yielded the highest R-squared value, which was 0.9882, indicating its superior performance. It is anticipated that the findings of this research can be applied globally and prove valuable for energy policy planning in any country. The results obtained not only highlight the accuracy and effectiveness of the predictive model but also underscore the broader implications of this study within the framework of the United Nations' Sustainable Development Goals (SDGs).

Keywords: energy demand; ensemble machine learning; SDGs; Türkiye

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1. Introduction

Energy plays a vital role in supporting the social and economic development of a country from past to present. It drives economic growth, improves living standards, supports social services, enhances national security, and contributes to environmental sustainability. Ensuring reliable, affordable, and sustainable energy access is essential for a country's overall development and progress. Therefore, the development of energy policies and the estimation of energy demand are a most important priority for developed and developing countries. Türkiye is the 19th largest economy in the world, with a gross domestic product (GDP) of roughly USD 906 billion [1]. Therefore, as a fast-growing economy, Türkiye's energy consumption has undergone significant growth and diversification over the years. As a rapidly developing country, Türkiye has experienced a substantial increase in energy demand due to population growth, urbanization, industrialization, and economic expansion. In terms of energy sources, Türkiye has a mix of fossil fuels, renewable energy, and imports. Electricity consumption constitutes a significant portion of Türkiye's energy consumption. However, the energy production in Türkiye is rather low, in spite of the considerable increase in energy consumption.

In 2021, Türkiye produced approximately 41.3 MTOE (million tons of oil equivalent), mostly based on coal and lignite (57.5%). In contrast, the country's energy consumption reached approximately 109.8 MTOE in the same year. This substantial gap between energy production and consumption has led to Türkiye becoming one of the major energy-importing countries in Europe [2]. According to a report by the Ministry of Energy and Natural Resources in September 2021, Türkiye's energy dependency rate was reported to be around 74%. This means that Türkiye relied on imports to meet approximately 74% of its total energy consumption. The country heavily depended on imports of natural gas and oil to bridge the energy gap between domestic production and demand [3].

To provide energy either by importing or by producing it, forecasting energy consumption, and analyzing the relationship between energy demand and supply, are crucial issues in short- and long-term energy planning. Managing energy demand also involves identifying and prioritizing energy resources, optimizing energy utilization, improving energy efficiency, shaping policy decisions, and devising strategies to reduce emissions.

Furthermore, it is important to emphasize that the United Nations' SDGs provide a comprehensive blueprint for addressing global challenges and promoting sustainability by 2030 [4]. This study aligns closely with several of these goals, including Goal 7, Goal 8, and Goal 13, making a significant contribution to the broader aims of sustainable development. Accurate energy demand forecasting plays a central role in achieving 'Goal 7: Affordable and Clean Energy'. By optimizing energy production, distribution, and consumption, this study facilitates the provision of affordable, reliable, and clean energy. This, in turn, supports economic growth, enhances energy access, and reduces environmental impacts. Moreover, this study directly addresses 'Goal 13: Climate Action' by mitigating the effects of climate change. Through precise energy demand predictions, it empowers Türkiye to make informed decisions that reduce greenhouse gas emissions, promote renewable energy adoption, and foster a low-carbon, sustainable energy sector. Energy efficiency serves as a catalyst for economic growth and job creation, aligning with 'Goal 8: Decent Work and Economic Growth'. This study enables Türkiye to implement energy-efficient measures, leading to cost savings for industries and households.

Researchers have developed various statistical techniques, meta-heuristic algorithms, and artificial intelligence techniques in energy modeling. Artificial neural networks (ANNs) have garnered significant interest in energy planning due to their ability to handle complex nonlinear relationships between input and output data [5]. ANNs have been applied in various energy forecasting applications, including gas consumption [6], energy demand [7], electricity consumption [8], transportation energy demand [9–11], energy source analysis [12], and energy dependency [7]. Apart from ANNs, other prediction methods have emerged, such as fuzzy logic, adaptive network-based fuzzy inference systems (ANFIS), and general machine learning algorithms [13–15]. It is important to recognize that artificial neural networks (ANNs) are a subfield of machine learning (ML), which, in itself, is a subset of artificial intelligence (AI). Frequently, the terms AI, ML, and deep learning (DL) are used interchangeably to refer to intelligent systems or software. DL, specifically, extends the concept of ANNs by incorporating extra hidden layers and employing specialized activation functions that are not typically found in traditional ANN models.

AI-based prediction models have received considerable interest for solving a variety of problems in energy planning recently. These models leverage the power of artificial intelligence techniques to forecast future outcomes based on historical data patterns. These models use advanced algorithms and machine learning methods to analyze large datasets, identify patterns, and make predictions.

Research on predicting Türkiye's energy requirements began in the 1960s, with the State Planning Organization (SPO) employing basic regression techniques for energy forecasting. In the late 1970s, the Ministry of Energy and Natural Resources (MENR) and the Turkish Statistical Institute (TSK) started preparing energy demand projections [16], but the estimated values provided by MENR were found to be higher than the actual energy demand [17]. Numerous econometric modeling techniques were applied to forecasting energy consumption after 1984. The Model for Analysis of Energy Demand (MAED) is the most frequently used approach developed by MENR [18]. Nevertheless, the energy demand predictions generated by MAED continued to overstate actual demand, rendering them unreliable [19,20]. Utgikar and Scott [21] conducted an inquiry to understand the reasons behind unsuccessful energy predictions. They found that, although statistical models are favored by researchers due to their simplicity, they tend to deliver acceptable results only for short-term periods, while becoming increasingly unstable for longer-term forecasts. While statistical models have contributed valuable insights to energy forecasting studies, El-Telbany and El-Karmi [22] argue that these models, which rely on statistical methods, perform well under normal conditions but struggle to account for sudden changes in environmental or sociological variables. Due to the reasons discussed above, researchers have become interested in the field of energy demand modeling.

AI-based prediction methods utilize advanced algorithms and models that learn patterns, relationships, and trends from historical data to make accurate predictions about future events or outcomes. AI-based prediction methods have gained significant popularity due to their ability to handle complex, non-linear relationships and adapt to changing data patterns. Machine learning (ML) is an AI-based prediction method, which encompasses a range of algorithms that automatically learn and improve from data without being explicitly programmed. Deep learning (DL), a subset of ML, has emerged as a powerful AI-based prediction method.

AI-based prediction methods have demonstrated their effectiveness in various fields, including finance, healthcare, weather forecasting, sales forecasting, demand prediction, and fraud detection [23–26]. However, it is important to note that, when applying these methods to real-world scenarios, factors such as data quality, feature selection, model complexity, and interpretability should be carefully considered. Machine learning approaches can be broadly categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms include classification and regression tasks. Regression is used for energy demand in this work. In machine learning, ensemble learning and deep learning methods outperform traditional algorithms. Ensemble methods are learning algorithms that build a set of classifiers and then classify new data points by taking (weighted) votes of their predictions. The effectiveness of an ensemble method depends on several factors, including how the underlying models are trained and how they are combined. In the literature, there are common approaches to building ensemble models that have been successfully demonstrated in various domains [27–29].

Ensemble machine learning is a powerful technique in the field of machine learning that involves combining the predictions of multiple individual models (base models) to create a more accurate and robust predictive model. This approach, preferred over single methods, offers several key advantages. Firstly, ensembles enhance prediction accuracy by aggregating multiple models, reducing errors and biases. Secondly, they mitigate overfitting, a common issue in machine learning, by balancing out individual model weaknesses. Moreover, ensembles prove their robustness by effectively handling noisy data and outliers, making them suitable for real-world applications [30]. In automated decision-making applications, especially in engineering, ensemble methods have demonstrated superior performance compared to individual learners. This is attributed to their ability to capture diverse patterns, reduce bias and variance, and improve generalization. Ensemble methods are particularly effective when there is a large amount of data, complex relationships, and a need for high predictive accuracy.

Common ensemble method strategies comprise bagging, boosting, blending, and stacking. Bagging, exemplified by the Random Forest algorithm, enhances model robustness by reducing overfitting and improving prediction accuracy through the wisdom of the crowd [31]. Boosting is another ensemble technique that iteratively builds a strong predictive model by giving more weight to the data points that previous models misclassified [32]. Bagging reduces variance by averaging over multiple models; boosting focuses on reducing bias through weighted data points. Blending, sometimes referred to as model stacking or meta-ensembling, involves training multiple diverse base models on the same dataset and then combining their predictions using a separate model trained on the validation set. Stacking, similar to blending, combines multiple base models to form a meta-model but differs in its approach. In stacking, the predictions of the base models serve as input features for a meta-model, which learns to make the final predictions [33]. Blending combines diverse models with a separate meta-model, and stacking uses base models to create a meta-model for predictions. The choice among these ensemble methods depends on the specific problem, dataset, and the trade-off between bias and variance in the model [28].

The main objective of this study is to use ensemble machine learning methodologies, which have not received much attention in prior research on energy, to assess energy demand in Türkiye. In this paper, several significant contributions to the field of energy demand forecasting are presented. This study stands out for its exhaustive examination of 19 distinct ML algorithms, evaluated using five different performance metrics, offering a detailed understanding of their strengths and weaknesses. The study involves comprehensive hyperparameter tuning, ensuring that the models are finely tailored to Türkiye's energy demand data, enhancing their predictive accuracy. Additionally, the utilization of ensemble methods, which combine the predictions of multiple ML algorithms, leveraging their individual strengths, has led to an improved forecasting performance compared to relying on a single algorithm. This approach contributes to the understanding of how different ensemble strategies can be applied effectively in the domain of energy forecasting and provides valuable insights for future research and applications. To the best of my knowledge, this paper is the first to investigate Türkiye's energy demand using ensemble ML models. Collectively, these innovative elements contribute not only to the accuracy and efficacy of the predictive model but also have broader implications for energy policy planning, aligning with the United Nations' SDGs.

This paper is organized as follows: Section 2 will provide an overview of the scope and definition of energy demand studies. Section 3 will present the primary methods and approaches employed in energy demand study, along with the main data sources and challenges associated with energy. In Section 4, the principal findings and trends will be discussed using various ensemble learning algorithms. Section 5 will summarize the main implications and recommendations from the results of energy demand study. Finally, this paper will conclude with a discussion of limitations and directions for future research.

2. Literature Review

Energy demand forecasting is an important task for planning and managing energy systems. It involves predicting the future energy consumption of different sectors, regions, or appliances based on various factors such as weather, economic activity, population, lifestyle, etc. This literature review aims to summarize some of the key findings and trends from recent articles on this topic.

2.1. Review of Energy Demand Forecasting in the World

Global energy demand has been affected by the COVID-19 pandemic and the economic recovery in 2021. According to the Global Energy Review 2021 by the International Energy Agency (IEA), global energy demand is expected to grow by 4.6% in 2021. The IEA projects that global energy demand will grow by 0.8% per year on average between 2021 and 2030 in its Stated Policies Scenario (STEPS), which reflects current and announced policies and targets [34].

This literature review provides a brief overview of some of the main findings and trends from recent articles on energy demand in the world. There are many methods of energy demand forecasting, spanning from conventional approaches like econometric and time series models [35–38] to contemporary soft computing techniques, including artificial intelligence methods and evolutionary algorithms [39–44]. A systematic literature review encompassing 419 articles on energy demand modeling, covering the period between 2015 and 2020, was conducted by Verwiebe et al. [45]. They analyzed the methodologies, prediction accuracy, input variables, energy sources, sectors, temporal scopes, and spatial resolutions employed in these models. They found that machine learning techniques were the most used, followed by engineering-based models, metaheuristic and uncertainty techniques, and statistical techniques. They also discussed the drawbacks and countermeasures of each technique. Another systematic literature review of energy demand forecasting methods published in 2005–2015 was conducted by Ghalehkhondabi et al. [46]. They focused on the methods that are used to predict energy consumption and compared their performance and applicability. They reported that neural networks were the most cited technique and had notable performance but also high computation time. They suggested that hybrid methods could be a promising field for future research.

2.2. Energy Demand Forecasting in Türkiye

A summary of studies for Türkiye's energy demand forecasting is tabulated in Table 1. However, to the best of my knowledge, there is no research paper that employs ensemble machine learning methods and compares them with each other to forecast Türkiye's energy demand.

Table 1. A summary of the literature on Türkiye's energy demand.

Author(s)	Year	Method Used	Dataset	Input Parameters	Performance Metric	Forecasting for
Aslan [47]	2023	Archimedes Optimization Algorithm	1979–2005 1979–2011	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Korkmaz [48]	2022	Bezier Search Differential Evolution Black Widow Optimization (BWO)	2000–2017	Passenger-km, Freight-km, Carbon dioxide emissions, GDP, Infrastructure Investment	AE, APE, Std_AE, Std_APE, R^2, Adj R^2, MAE, MAPE, and RMSE	Transportation Energy
Aslan and Beşkirli [49]	2022	Improved Arithmetic Optimization Algorithm	1979–2011	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Ağbulut [50]	2022	Deep Learning (DL) Support Vector Machine (SVM) Artificial Neural Network (ANN)	1970–2016	GDP, Population, Vehicle-km, Year	R^2, RMSE, MAPE, MBE, rRMSE, and MABE	Transportation Energy
Özdemir et al. [51]	2022	Modified Artificial Bee Colony Algorithm	1979–2005	GDP, Population, Import, Export	AE, APE, Std_AE, Std_APE, R^2, MAE, MAPE, and RMSE	Energy
Özkış [52]	2020	Vortex Search Algorithm (VS)	1979–2005 1979–2011	GDP, Population, Import, Export	The Amount of Error	Energy
Tefek et al. [53]	2019	Hybrid Gravitational Search, Teaching, Learning-Based Optimization Method	1980–2014	Population, Gross Generation, Net Consumption, GDP, Installed Power	R^2, RMSE, MAPE	Energy
Beskirli et al. [54]	2018	Artificial Algae Algorithm (AAA)	1979–2005	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Cayir Ervural and Ervural [55]	2018	Grey Prediction Model Based on GA Grey Prediction Model Based on PSO	1996–2016	Previous Annual Electricity Consumption Data	RMSE, MAPE	Electricity Energy consumption
Koç et al. [56]	2018	Gravity Search Algorithm (GSA), Invasive Weed Optimization Algorithm (IWO)	1979–2011	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Öztürk and Öztürk [57]	2018	ARIMA	1970–2015	Previous Energy Consumption Data	AIC	Energy
Beskirli et al. [58]	2017	Differential Evolution Algorithm (DE)	1979–2011	GDP, Population, Import, Export	Mean Absolute Relative Error, Relative Error (%), Magnitude of Error	Energy
Daş [59]	2017	Neural Network Based on Particle Swarm Optimization	1979–2005	GDP, Population, Import, Export	Absolute Relative Error, Relative Error (%), R^2, RMSE, MAPE, and MAD	Energy

Table 1. *Cont.*

Author(s)	Year	Method Used	Dataset	Input Parameters	Performance Metric	Forecasting for
Kankal and Uzlu [60]	2017	ANN	1980–2012	GDP, Population, Import, Export	Average Relative Error, RMSE, and MAE	Electricity Energy
Uguz et al. [61]	2015	Artificial Bee Colony with Variable Search Strategies (ABCVSS)	1979–2005	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Tutun et al. [62]	2015	Regression and ANN	1975–2010	Import, Export, Gross generation, Transmitted energy	R^2, RMSE, MAPE, MSE, MA, and SSE	Electricity Energy consumption
Kıran et al. [63]	2012	Hybrid Meta-Heuristic (Particle Swarm Optimization, Ant Colony Optimization)	1979–2005	GDP, Population, Import, Export	Relative Error (%), R^2	Electricity Energy consumption
Kankal et al. [64]	2011	Regression Analysis/ANN	1980–2007	GDP, Population, Import, Export, Employment	Relative Error (%), R^2 and RMSE	Energy
Ünler [17]	2008	Particle Swarm Optimization	1979–2005	GDP, Population, Import, Export	The Amount of Error, Relative Error (%)	Energy
Ediger and Akar [65]	2007	Autoregressive Integrated Moving Average (ARIMA) and seasonal ARIMA (SARIMA)	1950–2005	Previous Energy Consumption Data	MSE and MAED	Energy
Toksarı [66]	2007	Ant Colony Optimization	1970–2005	Population, GDP, Import, Export	R^2	Energy
Sözen et al. [67]	2005	ANN	1975–2003	Population, Gross Generation, Installed Capacity, Import, Export	R^2, RMSE, and MAPE	Energy
Canyurt et al. [68]	2004	Genetic Algorithm	1970–2001	GDP, Population, Import, Export	Relative Error (%)	Energy
Ceylan and Öztürk [69]	2004	Genetic Algorithm	1970–2001	GDP, Population, Import, Export	Relative Error (%), MSE, and R^2	Energy
Ceylan et al. [70]	2004	Genetic Algorithm	1990–2001	GDP, Population, Import, Export	Average Relative Error	Energy and exergy production and consumption

3. Materials and Methods

In this section, the proposed methodology is introduced in detail. Ensemble methods refer to algorithms that combine multiple machine learning models into a unified framework. These methods have gained significant attention and recognition in the machine learning community due to their ability to enhance prediction accuracy and robustness [40,41]. By combining the predictions of multiple models, ensemble methods can mitigate the limitations of individual models and provide more accurate and reliable results. Several types of ensemble methods commonly used in machine learning are bagging, boosting, blending, Random Forest, and stacking [28,31–33]. This paper proposes and analyzes different ensemble combination models that can be achieved by using diverse base models, varying model architectures, or training on different subsets of the data.

3.1. ML Algorithms

In the context of forecasting Türkiye's energy demand, a selection of 19 ML algorithms was automatically generated through the use of AutoML's capabilities. The choice of these 19 ML algorithms was guided by the necessity to thoroughly explore, compare, and evaluate various modeling approaches for energy demand forecasting, all while considering the specific requirements and characteristics of the Türkiye dataset.

Given the complex and dynamic patterns inherent in energy demand data, the objective was to identify models that are robust and effective in capturing intricate patterns under varying conditions. AutoML streamlined this process, providing a systematic and efficient means to evaluate multiple algorithms without manual intervention. The resulting set of 19 ML algorithms encompasses a diverse range of machine learning techniques, including linear and non-linear models, tree-based methods, neural networks, and ensemble methods.

These algorithms are briefly described below.

- Light Gradient Boosting Machine (LightGBM) [71]

LightGBM is a popular machine learning algorithm used for both regression and classification tasks. It is designed to efficiently handle large-scale datasets with high-dimensional features. LightGBM is known for its speed, accuracy, and ability to handle complex problems. LightGBM is based on the gradient boosting framework, similar to other boosting algorithms.

- XGBoost [72]

XGBoost Regressor is a powerful machine learning algorithm used for regression tasks. XGBoost Regressor is known for its efficiency, accuracy, and ability to handle complex datasets. The algorithm minimizes a loss function by iteratively adding decision trees to the ensemble. Each tree is trained to predict the residuals (the differences between the actual and predicted values) of the previous ensemble. The process continues until a specified number of trees is reached or the desired level of performance is achieved.

- Extra Trees Regression [73]

Extra Trees Regression is a machine learning algorithm used for regression tasks. It belongs to the ensemble learning family and is an extension of the popular Random Forest algorithm. Extra Trees Regression combines multiple decision trees to make predictions by aggregating their outputs. The algorithm builds a user-defined number of decision trees using random subsets of the training data and random subsets of features.

- Passive Aggressive Regressor (PAR) [74]

PAR is a machine learning algorithm used for regression tasks. In PAR, the algorithm updates the regression model incrementally, making predictions on new instances as they arrive. It adapts to new data points by adjusting the model's parameters without revisiting the entire training set. This property makes it suitable for handling large-scale datasets or scenarios where data arrives in a streaming fashion.

- Elastic Net [75]

Elastic Net is a regression method that combines the Lasso and Ridge regression techniques. It is used for feature selection and regularization in linear models, providing a balance between the two methods. In Elastic Net, the algorithm aims to minimize the sum of squared residuals between the predicted and actual values, similar to ordinary least-squares (OLS) regression.

- Least Angle Regression (LARS) [76]

LARS is a regression method used for feature selection and model building. LARS starts with an empty set of selected features and gradually adds features in a way that balances their correlations and coefficients. The algorithm continues this process until it reaches the desired number of selected features or the maximum number of available features.

- Lasso Least Angle Regression [76]

Lasso Least Angle Regression is a regression method that combines the features of the Lasso regularization and the Least Angle Regression algorithm. It is used for feature selection and regularization in linear regression tasks. Lasso Least Angle Regression aims to estimate the coefficients of a linear regression model while simultaneously performing feature selection by encouraging sparsity in the solution.

- Orthogonal Matching Pursuit (OMP) [77]

OMP is an algorithm used for sparse signal recovery and feature selection tasks. It aims to find the most relevant features or components of a signal by iteratively selecting and reconstructing the signal based on a small subset of measurements or features. OMP leverages the orthogonality property to efficiently select features and estimate the signal. At each iteration, the algorithm ensures that the selected features are orthogonal or nearly orthogonal to each other, which helps in accurate signal reconstruction and efficient convergence.

- Random Forest Regressor [78]

Random Forest Regressor is a popular machine learning algorithm used for regression tasks. It belongs to the ensemble learning family and is built upon the concept of decision trees. In Random Forest Regressor, a user-defined number of decision trees are constructed. Each tree is built using a random subset of the training data and a random subset of features. The process of constructing each tree involves recursively splitting the data based on different features and their respective splitting points. The splitting is done in a way that minimizes the variance of the target variable within each resulting subset.

- Gradient Boosting Regressor [32]

Gradient Boosting Regressor is a powerful machine learning algorithm used for regression tasks. It belongs to the boosting family of algorithms and is designed to create a strong learner by iteratively combining weak learners. Gradient Boosting Regressor works by minimizing a loss function through an additive approach, where each new model is built to correct the errors made by the previous models.

- AdaBoost Regressor [79]

AdaBoost Regressor, short for Adaptive Boosting Regressor, is a machine learning algorithm used for regression tasks. The algorithm iteratively trains a series of weak regressors, each focusing on the instances that were wrongly predicted by the previous regressors, to improve the overall prediction accuracy. In AdaBoost Regressor, each weak regressor is trained on a subset of the training data. During training, the algorithm assigns weights to each instance, with initially equal weights for all instances.

- Linear Regression [80]

Linear regression is a statistical method that models the relationship between a dependent variable (y) and one or more independent variables (x). It can be used to estimate how the dependent variable changes as the independent variables change, and to test hypotheses about the strength and direction of the relationship. There are different types of linear regression, such as simple linear regression, multiple linear regression, and multivariate linear regression.

- Lasso Regression [81]

Lasso Regression (LASSO) is a method of regression analysis that performs both variable selection and regularization. It aims to improve the prediction accuracy and interpretability of the regression model by shrinking the coefficients of some predictor variables to zero and reducing the magnitude of others.

- K-Neighbors Regressor [82]

K-Neighbors Regressor is a machine learning algorithm used for regression tasks. It is a non-parametric method that predicts the target value of an instance by considering the average or weighted average of the target values of its k nearest neighbors in the training data. In K-Neighbors Regressor, the algorithm identifies the k nearest neighbors of a given instance based on a distance metric, such as Euclidean distance. The target values of these neighbors are then used to calculate the predicted value for the instance.

- Bayesian Ridge Regression [83]

Bayesian Ridge Regression is a regression method that incorporates Bayesian principles into the linear regression framework. In Bayesian Ridge Regression, the algorithm places a prior distribution on the regression coefficients, typically assuming a Gaussian distribution. This prior distribution represents the initial belief about the likely values of the coefficients before observing the data.

- Decision Tree Regressor [84]

Decision Tree Regressor is a machine learning algorithm used for regression tasks. It is based on the concept of a decision tree, which partitions the input space into regions and predicts the target value based on the average or majority value of the training instances within each region. In Decision Tree Regressor, the algorithm recursively splits the data based on different features and their respective splitting points to create a tree-like structure.

- Ridge Regression [85]

Ridge Regression is a linear regression method used for modeling and prediction tasks. It is an extension of ordinary least-squares (OLS) regression that introduces a regularization term to handle multicollinearity and prevent overfitting. In Ridge Regression, the algorithm seeks to minimize the sum of squared residuals between the predicted and actual values, similar to OLS regression. However, Ridge Regression adds a penalty term, known as the Ridge or L2 penalty, to the cost function.

- Huber Regressor [86]

Huber Regressor is a robust regression method that combines the benefits of both the least-squares regression and robust regression techniques. Huber Regressor addresses these issues by introducing a hybrid loss function that behaves like least squares for small residuals and like a scaled absolute loss for large residuals.

- Dummy Regressor

Dummy Regressor is a simple baseline model used for regression tasks. It provides a straightforward way to establish a baseline performance against which other regression models can be compared. Dummy Regressor makes predictions based on simple rules or heuristics rather than learning patterns from the data.

3.2. Structure of the Proposed Methods

This section presents the structure and abstract overview of the study, with a basic conceptual flow shown in Figure 1. The methodology consists of several key steps to improve the accuracy of the models. The first step entails data preparation, encompassing data preprocessing, normalization, and transformation to ensure the dataset is primed for analysis. Following this, the performance of 19 different ML algorithms has been assessed. This evaluation forms the basis for creating various ensemble combinations that leverage the strengths of individual models. In the third step, four different ensemble techniques like bagging, boosting, blending, and stacking models have been used to create powerful ensemble models that can capture complex patterns and relationships in the data. Finally, this study concludes with the fourth step, where it has carefully evaluated and compared these ensemble models, gaining insights into their strengths and weaknesses. This comprehensive evaluation process has informed my final prediction, guiding us towards data-driven decisions that hold the potential to advance the field of artificial intelligence and machine learning.

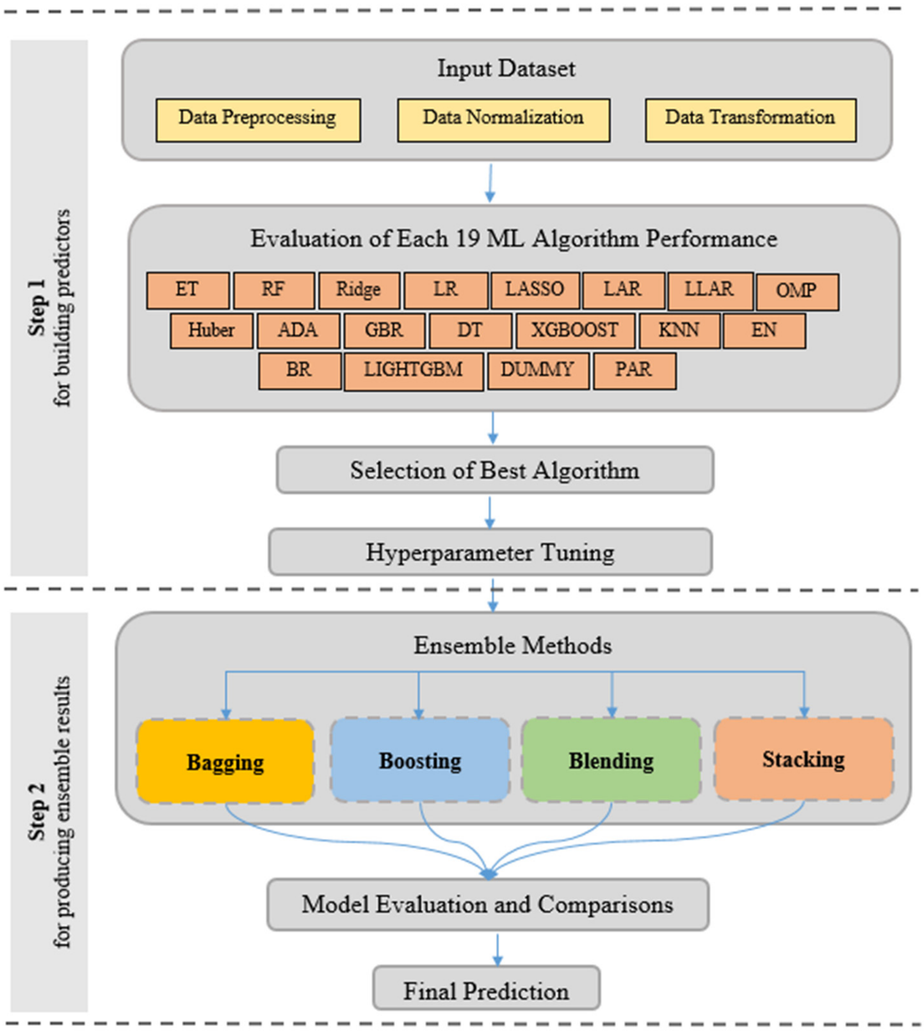

Figure 1. A basic conceptual flow of this study.

3.2.1. k-Fold Cross-Validation

The next step in the processing block involves selecting machine learning algorithms that exhibit superior performance and diverse learning capabilities when applied to the energy dataset. k-fold cross-validation is a technique used in machine learning algorithms to evaluate the performance of a model by dividing the available data into k equally sized subsets or "folds". The process entails iteratively training the model on $k-1$ folds and then evaluating it on the remaining fold. This cycle is repeated k times, with each fold being used as the test set exactly once. The final evaluation is obtained by averaging the performance results from each iteration. The value of k is usually chosen as k = 5 or k = 10. A 5-fold cross-validation was used to obtain groups of performance measures in this study.

3.2.2. Model Hyperparameters Tuning

Hyperparameter tuning is the process of finding the optimal values for the hyperparameters of a machine learning algorithm. Hyperparameters are parameters that are set before the learning process begins and determine how the algorithm learns and generalizes from the training data [87].

In this study, hyperparameter tuning was employed to improve model performance and prevent overfitting before proceeding to the next stage of the framework. The commonly used approaches for hyperparameter tuning are Grid Search, Random Search, and Bayesian Optimization. The choice of the technique ultimately depends on the specific problem, available computational resources, and the characteristics of the hyperparameter search space. In this work, the Grid Search approach has been used.

3.2.3. Performance Metrics

The performance of ML algorithms in the energy demand problem was estimated using powerful validation techniques. Five validation methods, Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2), were employed to evaluate the models [10].

The standard predictive performance metrics are represented by Equations (1)–(5):

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{(\check{y}_i - O_i)^2}{n} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\check{y}_i - O_i)^2}{n}} \tag{2}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |\check{y}_i - O_i|}{n} \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{m} \sum_{i=1}^{m} \left| \frac{\check{y}_i - O_i}{\check{y}_i} \right| \tag{4}$$

$$R^2 = 1 - \frac{\sum_i (\check{y}_i - O_i)^2}{\sum_i (O_i - \overline{O}_i)} \tag{5}$$

Here, $(\overline{O}_i)$ represents the magnitude of the actual values, $(\check{y}_i)$ is the model's predicted value, (O_i) stands for the real data, and (n) indicates the number of observed data points.

3.3. Data Collection

The dataset used in this paper includes independent variables such as population (in millions), gross domestic product (GDP), import, and export, which were selected based on a comprehensive literature review. This dataset spans the years 1979–2021 and was sourced from various government agencies, including the Turkish Statistical Institute [88], the Turkish Ministry of Energy and Natural Resources (MENR) [89], the World Bank [1] and European Commission [2]. Additionally, the energy consumption data (measured in million tons of oil equivalents, MTOE) was obtained from the MENR. The details of the variables are given in Table 2.

Table 2. Input parameter-use rationales.

Variable	The Influencing Factors for Using This Variable
GDP	There exists a strong correlation between GDP and energy consumption, as the level of economic activity directly impacts the demand for energy. When the GDP of a country increases, it generally indicates a growth in industrial and commercial activities, leading to higher energy consumption. Considering the substantial impact of GDP on energy demand, GDP is often chosen as an independent variable in studies analyzing energy consumption patterns.
Population	Population growth directly affects the demand for energy in a country or region. As the population increases, there is a greater need for energy to meet the demands of the growing population, including residential, commercial, industrial, and transportation sectors. Understanding and considering population values as an independent variable is crucial for analyzing and planning energy resources.
Import	The relationship between imports and energy consumption is significant, as the availability and reliance on imported energy resources can directly impact a country's energy demand. The import values of energy resources are chosen as independent variables in this study due to their influence on the overall energy consumption patterns.
Export	The relationship between exports and energy consumption is an important aspect of understanding a country's energy demand. The export values of energy resources are chosen as independent variables in this study due to their potential impact on a country's overall energy consumption patterns.

The predictors mentioned above have been commonly utilized in numerous energy forecasting studies, as seen in Table 1. Considering the data collection period from 1979 to 2021, the population grew from 43.19 million to 84.78 million, while GDP increased from USD 82 billion to USD 819.04 billion, indicating a roughly 2 times and 10 times increase, respectively, by 2021. Import and export volumes also saw significant growth, rising from 5.07 and 2.26 to 271.42 and 225.29, respectively, marking approximately a 55 times and 100 times increases by 2021. Furthermore, the demand for transportation energy surged nearly fivefold, from 26.37 Mtoe in 1979 to 123.86 Mtoe in 2021. Detailed historical data for these parameters from 1979 to 2021 can be found in Table 3.

Table 3. Observed historical data related to the energy demand in Türkiye.

Years	Population (10^6)	GDP (USD 10^9)	Import (USD 10^9)	Export (USD 10^9)	Energy (Mtoe)
1979	43.19	82.00	5.07	2.26	26.37
1980	44.09	68.82	7.91	2.91	27.51
1981	44.98	71.04	8.93	4.70	27.60
1982	45.95	64.55	8.84	5.75	29.59
1983	47.03	61.68	9.24	5.73	30.25
1984	48.11	59.99	10.76	7.13	31.75
1985	49.18	67.23	11.34	7.96	32.73
1986	50.22	75.73	11.10	7.46	34.59
1987	51.25	87.17	14.16	10.20	38.70
1988	52.28	90.85	14.34	11.66	39.73
1989	53.31	107.14	15.80	11.62	40.40
1990	54.32	150.68	22.30	12.96	42.24

Table 3. *Cont.*

Years	Population (10^6)	GDP (USD 10^9)	Import (USD 10^9)	Export (USD 10^9)	Energy (Mtoe)
1991	55.32	150.03	21.05	13.59	43.09
1992	56.30	158.46	22.87	14.71	44.70
1993	57.30	180.17	29.43	15.35	48.26
1994	58.31	130.69	23.27	18.11	45.77
1995	59.31	169.49	35.71	21.64	50.53
1996	60.29	181.48	43.63	23.22	54.85
1997	61.28	189.83	48.56	26.26	57.99
1998	62.24	275.97	45.92	26.97	57.12
1999	63.19	256.39	40.67	26.59	55.22
2000	64.11	274.30	54.50	27.77	61.60
2001	65.07	201.75	41.40	31.33	55.60
2002	65.99	240.25	51.55	36.06	59.49
2003	66.87	314.59	69.34	47.25	64.59
2004	67.79	408.88	97.54	63.17	68.24
2005	68.70	506.31	116.77	73.48	70.33
2006	69.60	557.06	139.58	85.53	74.82
2007	70.47	681.34	170.06	107.27	79.79
2008	71.32	770.46	201.96	132.03	77.76
2009	72.23	649.27	140.93	102.14	78.36
2010	73.20	776.99	185.54	113.88	79.84
2011	74.17	838.76	240.84	134.91	84.91
2012	75.28	880.56	236.55	152.46	88.84
2013	76.58	957.78	260.82	161.48	88.07
2014	78.11	938.95	251.14	166.50	89.25
2015	79.65	864.32	213.62	150.98	99.47
2016	81.02	869.69	202.19	149.25	104.57
2017	82.09	859.00	238.72	164.50	111.65
2018	82.81	778.47	231.15	177.17	109.44
2019	83.48	759.94	210.35	180.83	110.65
2020	84.14	720.30	219.52	169.64	113.70
2021	84.78	819.04	271.42	225.29	123.86

The dataset used for the predicting of energy is divided into training and test subsets, comprising approximately 75% and 25% of the total observations, respectively. The training set consists of 32 observations, while the test set has 11 samples.

4. Results and Discussion

4.1. Implementation Setup

A detailed overview of the implementation setup is given in this section. Python, a popular and general-purpose programming language that allows users to work quickly and integrate systems more effectively, was used. Python has become a popular choice for data science and ML. Its high-level, specially developed ML libraries allow users to quickly start building models and experiment with different configurations. PyCaret, a

Python-based open-source machine learning library, provides automated machine learning capabilities. Its default behavior involves automating several steps of the ML process, including data preprocessing, feature engineering, and model selection. In this study, PyCaret was utilized to automate machine learning workflows, streamlining the process and enhancing efficiency. PyCaret's robust automation tools played a significant role in quickly initiating the construction of the models mentioned in Section 3.1 and experimenting with various setups after the dataset was provided. This exhaustive approach enabled us to conduct a comprehensive evaluation of various models across different categories (linear, non-linear, tree-based, etc.) to identify algorithms most suitable for capturing potential hidden patterns that might be missed by a smaller set of models. Python version 3.11.0 and PyCaret version 3.0.4 were used, which were the latest versions as of October 2022 and July 2023, respectively. All codes were implemented in Google Colab, a cloud-based platform that provides free access to GPUs and TPUs for running machine learning experiments. All experiments were conducted on a system equipped with an Intel i7 3.40 GHz processor and 8 GB of memory.

4.2. Feature Selection

In machine learning, a correlation matrix is a table that shows how different features in a dataset are related to each other and how they affect the outcome of a model. Figure 2 presents the correlation matrix of the dataset, which includes the target variable as one of the features.

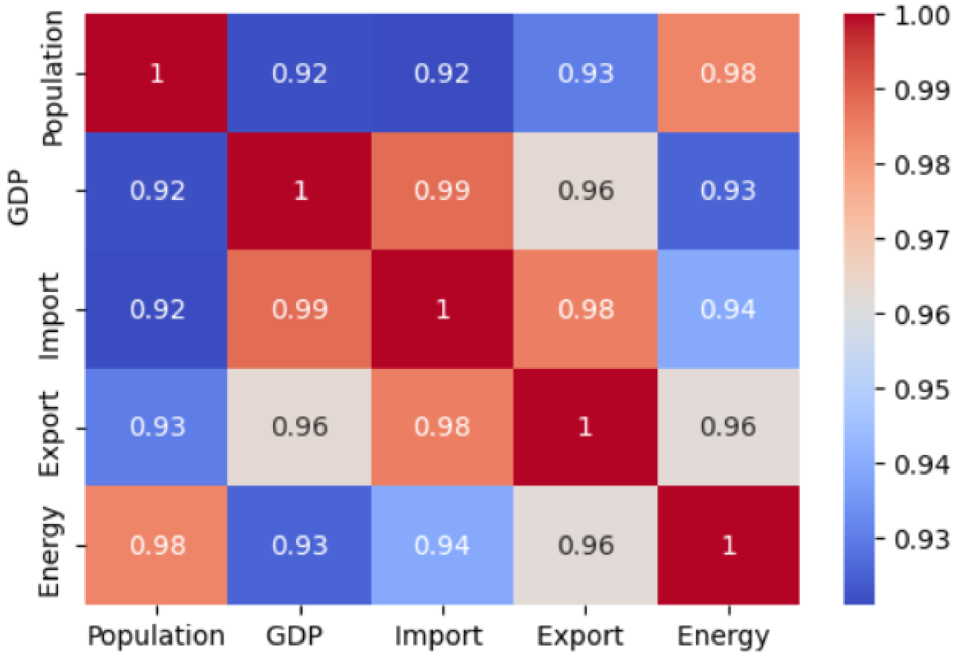

Figure 2. Correlation matrix of all variables including the target variable.

The values within the matrix describe both the intensity and direction of the correlation between pairs of features. Each element represents the correlation between two specific features. In Figure 2, the maximum correlation value is 1, while the minimum is 0.92, observed between the 'import-population' and 'population-GDP' features. A positive correlation between two features implies that, as one property's value increases, the other feature's value also tends to increase. It is worth noting that all features exhibit correlations with each other. Additionally, population exhibits the strongest correlation with the target variable 'Energy', while GDP shows the weakest correlation.

The selection and combination of features is important in machine learning because it can affect the performance and complexity of the model. Different features may have different levels of relevance, redundancy, and noise for a given problem and a given algorithm. By selecting and combining the most appropriate features, the dimensionality of the data, the computational cost, and the risk of overfitting can reduce. All combinations of predictor variables (i.e., population, GDP, import, and export) are outlined within Table 4. For instance, Model 1 (M_1) comprises two independent variables, i.e., GDP and Population, while Model 7 (M_7) comprises GDP, Population, and Import. The ML performance results with 5-fold cross-validation on the training set, using the created models that include different combinations of features, are given in Table 4. To test the models, 19 ML algorithms were run, and the best three results, sorted by the highest R-square, are provided in Table 5. The Extra Tree Regressor performed well based on the provided metrics using Model 11 (M_{11}). The lowest MAE (2296.86), MSE (8,756,864.57), and RMSE (2932.96) values indicate that the model is making accurate predictions. Additionally, the highest R-squared value of 0.9788 suggests a good fit to the data. The low MAPE of 0.0464 indicates that the model's percentage errors are relatively small.

Table 4. The combinations of features.

Model	Input
M_1	GDP, Population
M_2	GDP, Import
M_3	GDP, Export
M_4	Population, Import
M_5	Population, Export
M_6	Import, Export
M_7	GDP, Population, Import
M_8	GDP, Population, Export
M_9	Population, Import, Export
M_{10}	GDP, Import, Export
M_{11}	* GDP, Population, Import, Export

* All features.

Table 5. Top three results of ML algorithms based on the training set using models' combinations.

Models	ML Algorithm	MAE	MSE	RMSE	R^2	MAPE
M_1	Extra Trees Regressor	2743.27	14,435,527.00	3622.18	0.9751	0.0546
	Huber Regressor	3419.46	20,734,897.00	4395.82	0.9642	0.0749
	Extreme Gradient Boosting	3725.91	22,807,495.50	4551.60	0.9625	0.0655
M_2	K-Neighbors Regressor	6881.86	84,149,616.80	8596.44	0.8710	0.1104
	Random Forest Regressor	6809.08	114,145,888.80	9963.98	0.8252	0.1167
	Extra Trees Regressor	6452.43	123,658,755.00	9929.56	0.8117	0.1178
M_3	Extra Trees Regressor	3977.99	44,054,367.30	5730.78	0.9299	0.0695
	Random Forest Regressor	4631.80	55,354,193.10	6583.28	0.9162	0.0797
	Gradient Boosting Regressor	5351.58	64,199,913.90	7220.71	0.9031	0.0901
M_4	Extra Trees Regressor	3042.48	17,937,995.55	3844.90	0.9733	0.0591
	Random Forest Regressor	3666.07	22,957,290.18	4448.29	0.9716	0.0685
	Gradient Boosting Regressor	4156.41	26,308,872.75	4930.11	0.9652	0.0742
M_5	Huber Regressor	3864.21	36,775,418.87	5527.85	0.9541	0.0601
	Lasso Regression	4003.55	36,200,997.00	5456.62	0.9530	0.0678
	Least Angle Regression	4003.72	36,196,280.60	5456.35	0.9530	0.0678

Table 5. *Cont.*

Models	ML Algorithm	MAE	MSE	RMSE	R^2	MAPE
M_6	K-Neighbors Regressor	5707.22	80,792,845.60	7992.88	0.8962	0.1035
	Random Forest Regressor	5455.21	77,021,388.80	8193.73	0.8644	0.0930
	Extra Trees Regressor	5511.29	82,472,925.80	8300.80	0.8540	0.0950
M_7	Extra Trees Regressor	2308.94	12,339,053.90	3277.79	0.9754	0.0488
	Random Forest Regressor	2972.75	17,408,515.60	3854.32	0.9608	0.0576
	AdaBoost Regressor	3400.27	18,546,026.70	4014.45	0.9538	0.0640
M_8	Extra Trees Regressor	3189.81	17,110,325.38	3874.79	0.9716	0.0537
	AdaBoost Regressor	4293.89	29,715,232.81	5282.08	0.9475	0.0728
	Random Forest Regressor	4287.09	35,730,037.10	5185.02	0.9460	0.0700
M_9	Extra Trees Regressor	3018.13	30,503,239.40	4394.13	0.9477	0.0407
	Random Forest Regressor	3583.32	45,575,422.90	5273.91	0.9304	0.0473
	AdaBoost Regressor	4069.59	37,580,683.81	5358.08	0.9285	0.0609
M_{10}	K-Neighbors Regressor	5670.51	74,121,506.00	7652.91	0.9017	0.1003
	Random Forest Regressor	5372.22	75,187,291.90	7930.92	0.8896	0.0942
	Ridge Regression	7009.35	69,191,604.80	8277.45	0.8621	0.1643
M_{11}	Extra Trees Regressor	**2296.86**	**8,756,864.57**	**2932.96**	**0.9788**	**0.0464**
	Random Forest Regressor	3186.05	14,777,499.11	3817.37	0.9684	0.0658
	Ridge Regression	3676.12	21,641,675.00	4466.13	0.9655	0.0736

During the model-building process, all possible combinations were explored, and finally, the configuration with four inputs, displaying the highest R-squared and lowest error terms, was chosen for application in the next part of the study.

4.3. Performance Evaluation

Firstly, the performance of 19 ML individual algorithms were compared using five different metrics with all features (GDP, Population, Import, Export). Table 6 presents the performance results achieved by training 19 ML algorithms using 5-fold cross-validation. The first column in Table 6 lists the base ML algorithms. The subsequent columns, numbered second through to sixth, display the best values for various training-phase metrics, including MAE, MSE, RMSE, R2, and MAPE. The ML algorithms' results are organized in descending order of R-squared values, from the highest to the lowest. The Extra Tree Regressor yields the best results among the others during the training phase, as demonstrated in Table 6. The prediction performance of the selected Extra Tree model in the test set is presented in Table 7. The R-squared value in Table 7 is slightly higher than the value from the training set and indicates the absence of overfitting.

Table 6. Results of ML algorithms based on train set.

ML Algorithm	MAE	MSE	RMSE	R^2	MAPE
Extra Trees Regressor	**2296.86**	**8,756,864.57**	**2932.96**	**0.9788**	**0.0464**
Random Forest Regressor	3186.05	14,777,499.11	3817.37	0.9684	0.0658
Ridge Regression	3676.12	21,641,675.00	4466.14	0.9655	0.0736
Linear Regression	3780.00	23,739,669.80	4668.86	0.9635	0.0825
Lasso Regression	3779.85	23,736,214.80	4668.54	0.9635	0.0825

Table 6. *Cont.*

ML Algorithm	MAE	MSE	RMSE	R^2	MAPE
Least Angle Regression	3780.00	23,739,655.90	4668.86	0.9635	0.0825
Lasso Least Angle Regression	3779.85	23,736,205.30	4668.54	0.9635	0.0825
Orthogonal Matching Pursuit	3780.00	23,739,655.90	4668.86	0.9635	0.0825
Huber Regressor	3828.58	22,823,167.86	4595.40	0.9634	0.0785
AdaBoost Regressor	3575.50	15,583,915.43	3934.88	0.9611	0.0691
Gradient Boosting Regressor	3772.78	16,872,570.61	4096.12	0.9556	0.0707
Decision Tree Regressor	3768.74	16,856,622.84	4094.38	0.9554	0.0707
Extreme Gradient Boosting	3768.71	16,856,282.40	4094.34	0.9554	0.0706
K-Neighbors Regressor	3987.62	29,417,635.00	5274.57	0.9493	0.0848
Elastic Net	7402.15	81,150,325.20	8721.88	0.8666	0.1248
Bayesian Ridge	22,303.79	705,872,003.20	25,684.29	−0.0970	0.4306
Light Gradient Boosting Machine	22,303.79	705,872,041.79	25,684.29	−0.0970	0.4306
Dummy Regressor	22,303.79	705,872,041.60	25,684.29	−0.0970	0.4306
Passive Aggressive Regressor	40,863.75	2,361,836,689.9	48,178.33	−3.9041	0.5635

Table 7. Results of the Extra Trees Regressor algorithm based on the test set.

ML Algorithm	MAE	MSE	RMSE	R2	MAPE
Extra Trees Regressor	2989.27	17,145,375.48	4140.6975	0.9811	0.0406

The hyperparameters were tuned via grid searches because it is a critical step in the machine learning model development process. When ML performance degraded, this step was skipped, and the model was applied to the successive stages without tuning the hyperparameters. After this stage, ensemble methods were suggested and applied for predicting Türkiye's energy demand. The prediction performance of the ensemble methods (bagging, boosting, blending, and stacking) in both training and test sets are shown in Table 8. Compared to the preliminary results of data from the training of 19 ML algorithms shown in Table 6, the mean R-squared values are as follows: 0.9801 with bagging, 0.9809 with boosting, 0.9874 with blending, and 0.9882 with stacking methods. Among these, the stacking ensemble model yielded the highest R-squared value, indicating its superior performance. Additionally, when considering other evaluation metrics such as MAE, MSE, RMSE, and MAPE, the stacking ensemble model consistently outperforms the others, further confirming its superiority in predictive accuracy.

Bagging and boosting techniques were used to improve the accuracy and robustness of the individual machine learning model. The Extra Tree Regressor (ET) algorithm was trained on different subsets (which were created through a process called bootstrapping) of the training data by the bagging ensemble method. In boosting, the focus is on correcting the errors made by previous models. The base model ET was trained until a certain level of accuracy was achieved.

In the blending approach, I harnessed the predictive power of three distinct machine learning algorithms: Extra Trees Regressor (ET), Random Forest Regressor (RF), and Ridge Regression (Ridge). To execute blending, each of these algorithms was initially trained separately on a portion of thetraining dataset, generating individual predictions for the target variable. Subsequently, I combined the predictions from ET, RF, and Ridge using a straightforward averaging technique. By averaging these predictions, I effectively created an ensemble prediction that capitalizes on the strengths of each algorithm.

Table 8. Performance of the ensemble models in both the training and test dataset.

				Training					Test				
Ensemble Methods	**Fold**	**Base Learners**	**Meta Learner**	**MAE**	**MSE**	**RMSE**	**R^2**	**MAPE**	**MAE**	**MSE**	**RMSE**	**R^2**	**MAPE**
Bagging	0	ET		2384.30	10,532,299.28	3245.35	0.9855	0.0425	3247.76	20,526,807.39	4530.65	0.9773	0.0476
	1			2428.40	10,139,704.39	3184.29	0.9870	0.0583					
	2			1320.12	4,588,805.18	2142.15	0.9606	0.0211					
	3			2943.76	18,949,550.99	4353.11	0.9814	0.0811					
	4			2833.04	10,421,373.56	3228.22	0.9859	0.0642					
	Mean			2381.92	10,926,346.68	3230.62	**0.9801**	0.0534					
	Std			574.24	4,594,895.36	699.59	**0.0099**	0.0204					
Boosting	0	ET		2324.68	10,142,168.21	3184.68	0.9861	0.0401	2791.95	16,986,253.22	4121.44	0.9811	0.0367
	1			2292.10	7,616,694.33	2759.84	0.9902	0.0526					
	2			1591.23	6,141,944.75	2478.29	0.9473	0.0249					
	3			2450.57	10,639,983.49	3261.90	0.9895	0.0582					
	4			2256.76	6,211,550.01	2492.30	0.9916	0.0484					
	Mean			2183.07	8,150,468.16	2835.41	**0.9809**	0.0448					
	Std			303.05	1,910,132.98	333.12	**0.0169**	0.0116					
Blending	0	ET RF Ridge		2621.68	13,996,026.78	3741.13	0.9808	0.0456	3138.73	20,627,053.08	4541.70	0.9772	0.0430
	1			2115.51	6,368,872.54	2523.66	0.9918	0.0388					
	2			1227.95	2,599,808.47	1612.39	0.9777	0.0213					
	3			2266.80	7,245,254.56	2691.70	0.9929	0.0348					
	4			1783.21	4,566,049.47	2136.83	0.9938	0.0311					
	Mean			2003.03	6,955,202.36	2541.14	**0.9874**	0.0343					
	Std			472.02	3,864,676.67	705.55	**0.0068**	0.0081					
Stacking	0	ET RF Ridge	Ridge	2332.41	10,667,480.27	3266.11	0.9853	0.0383	2704.34	15,710,000.99	3963.58	**0.9826**	0.0359
	1			2359.09	6,559,821.14	2561.21	0.9916	0.0470					
	2			1133.61	2,887,446.54	1699.25	0.9752	0.0187					
	3			2110.38	6,221,784.33	2494.35	0.9939	0.0343					
	4			1520.56	3,762,509.98	1939.72	0.9949	0.0294					
	Mean			1891.21	6,019,808.45	2392.13	**0.9882**	0.0335					
	Std			484.35	2,714,418.86	545.46	**0.0073**	0.0094					

Unlike traditional ensemble methods like bagging and boosting, stacking takes a more sophisticated approach by using the predictions of base models as input features to train a higher-level model that makes the final predictions. The 14 ML algorithms with R-squared values higher than 0.90 in Table 6 were separately combined to select a set of diverse base models. After trying many combined base models and conducting trial-and-error experiments, I leveraged the capabilities of three diverse base machine learning algorithms: ET, RF, and Ridge. To implement stacking, each of these base models was initially trained separately on a portion of the training dataset, obtaining individual predictions for the target variable. Next, a new dataset was created where each data point consisted of these base model predictions. This dataset served as the input for the meta-learner. Based on the empirical investigation, it was determined that employing a linear regression algorithm as the meta-learner for the second level of the stacking regressor was optimal, as it consistently demonstrated superior performance in terms of R-squared compared to alternative machine learning algorithms. Ridge Regression, as the meta-learner on the second level of the stacking ensemble, was selected and trained to learn how to best combine the predictions from ET, RF, and Ridge. To prevent overfitting during the training phase, 5-fold cross-validation is employed. The utilization of the Ridge model within the stacking ensemble model demonstrated notable advantages within the context of energy-related problems. Ridge Regression, known for its ability to mitigate multicollinearity and overfitting, proved effective in enhancing the robustness of my model when dealing with energy demand forecasting.

Stacking's flexibility in utilizing both weak and strong learners makes it a powerful technique for enhancing predictive performance in various machine learning tasks. In practice, researchers often employ a mixture of weak and strong learners to construct a versatile ensemble that performs effectively across diverse datasets and problem domains. The choice of whether the base models are weak or strong is flexible and depends on the problem and the effectiveness of the ensemble. In recent years, it can also be seen that researchers have started to utilize AutoML approaches, which automatically select the best-performing models for ensembles [90–92]. In this study, different combinations of both weak and strong base models to create a diverse ensemble were experimented with. The aim was to enhance interpretability and transparency by the manual creation of ensemble models. It was observed that the combinations composed of strong base learners consistently delivered superior results in forecasting Türkiye's energy demand.

The results also show that the stacking ensemble model yielded the best accuracy rates when applied to a small dataset. The robustness of the evaluation is emphasized through metrics such as R-squared, which reached an impressive accuracy rate of 0.9882 with the stacking model. This rigorous evaluation process provides confidence in the reliability of the results despite the dataset's size. This aligns with Dietterich's [28] assertion that, when the available data is limited, ensemble learning can assist in finding a good approximation and enhancing prediction accuracy by averaging the outputs of individual models.

In order to evaluate the efficacy of the developed ensemble methods, the prediction performance on the test set is presented in Table 8. Notably, the stacking model achieved a remarkable R-squared value of 0.9826. When compared with the findings in Table 7 and other ensemble models, the stacking model's metrics consistently reveal a significant enhancement. These observations lead us to assert, in accordance with the scientific paper, that my proposed stacking ensemble model does not exhibit signs of either overfitting or underfitting. The utilization of features (Population, GDP, Import, Export) enhances the model's accessibility and interpretability, facilitating its utility for generating accurate and reliable forecasts of Türkiye's energy demand, as detailed in the paper.

Table 9 provides detailed descriptions of the model's predicted outcomes in the 'Prediction' column, alongside the corresponding ground truth values for 'Energy'. It presents the prediction performance of the stacking ensemble model for each of the five folds, utilizing all dataset features and evaluating it using five different metrics.

Table 9. Comparison of the actual values 'Energy' and predicted values using the proposed stacking ensemble model.

Years	Observed Energy Demand (Mtoe)	Predicted Energy Demand (Mtoe)	Amount of Errors	Relative Errors (%)
1980	27.51	26.96	0.55	1.99
1983	30.25	28.97	1.28	4.23
1984	31.75	30.42	1.33	4.18
1988	39.73	38.69	1.04	2.62
1989	40.40	40.53	−0.13	−0.32
2002	59.49	62.74	−3.25	−5.46
2007	79.79	76.95	2.84	3.56
2010	79.84	81.93	−2.09	−2.62
2013	88.07	91.51	−3.44	−3.91
2014	89.25	96.05	−6.80	−7.62
2021	123.86	113.73	10.13	8.18

Three scenarios have been used to predict Türkiye's energy demand between 2024, 2025, and 2030:

Scenario 1: It is assumed that the average growth rate of GDP is 4%, population growth rate is 0.5%, and the average imports and exports growth rate is 2%.

Scenario 2: It is assumed that the average growth rate of GDP is 5%, population growth rate is 0.6%, the average import growth is 3.5%, and export growth rate is 2%.

Scenario 3: It is assumed that the average growth rate of GDP is 6%, population growth rate is 1.5%, and the average imports and exports growth rate is 5%.

The comparison of the results from these three different scenarios is illustrated in Figure 3. Considering economic advancements and the rising number of electric vehicles, all scenarios indicate higher values than in previous years. Scenario 1 estimates a lower energy consumption compared to the other scenarios, while Scenario 3 predicts a higher energy consumption. Ultimately, the three scenarios demonstrate that Türkiye's predicted energy consumption in 2030 would range between 144.56, 147.25, and 154.93 Mtoe.

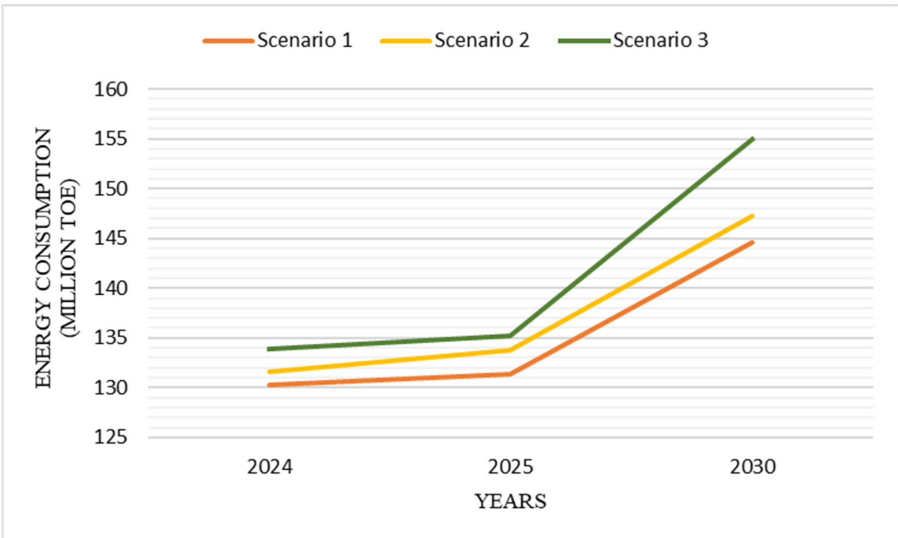

Figure 3. Estimation of total energy demand according to Scenarios 1–3.

5. Conclusions

This paper has presented a comprehensive methodology for applying ensemble techniques and machine learning algorithms to the crucial task of forecasting Türkiye's energy demand. The primary objectives of this methodology were threefold: Firstly, to enhance the accuracy of energy demand predictions in Türkiye. Secondly, to provide authorities and institutions with an interpretable model that facilitates informed decision-making and policy development. Lastly, this study aligns closely with the United Nations' SDGs, contributing to the broader aims of sustainable development by addressing global challenges.

Accordingly, the following key findings can be derived based on the current research.

- The GDP, population, import, export, and energy data taken between 1979 and 2021 were used and it is observed that there is a strong correlation among them.
- Five statistical metrics are discussed to evaluate the performance of the algorithms in the forecast.
- A total of 19 machine learning algorithms were constructed and analyzed to select models for diverse ensemble combinations.
- Considering all metrics collectively, the stacking ensemble model utilizing Ridge Regressor as a meta-learner outperforms single ML algorithms as well as other bagging, boosting, and blending models.
- The predicted values reveal that the stacking ensemble model has delivered highly satisfactory outcomes in comparison to the actual energy demand outputs.
- These ensemble models can readily be adapted and recommended for future energy demand forecasts in other countries. Notably, the stacking ensemble model demonstrates statistically superior results compared to other models, making it a more suitable choice for accurate forecasting.

It is anticipated that the outcomes of this study will make a significant contribution to the field of energy forecasting, laying the groundwork for Türkiye's sustainable energy future. Furthermore, this research represents a meaningful step toward a more equitable, prosperous, and sustainable world for all. As future research, further improvements can be explored through the use of different hybrid techniques for optimizing hyperparameter tuning, feature selection, and more.

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