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Predictive machine learning for smart grid demand response and efficiency optimization

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ABSTRACT

This paper explores the evolution of smart grids (SGs) and how they enable consumers to schedule household appliances based on demand response programs (DRs) provided by distribution system operators (DSOs). This study looks at and compares four distinct regression models: linear regression, random forest regressor, gradient boosting regressor, and support vector regressor. This is being done because more and more people are using machine learning (ML) methods to make this process better. The models are trained and tested using a dataset that includes a variety of parameters, such as humidity, temperature, and the amount of power used by appliances. Mean squared error (MSE) and R-squared values are two important performance measures that are used to judge these models and see how well they can make predictions. These results reveal that the gradient boosting regressor was the most accurate model for figuring out how much energy smart homes use. This algorithm could be a great tool for better managing energy use because it can figure out the complicated connections between the things that are input and the amount of energy that appliances use. This study makes a big difference in the creation of strong regression models by emphasizing how important it is to be accurate when making predictions. This, in turn, helps to enhance energy sustainability and economic stability in smart home environments.

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1. INTRODUCTION

Smart grids (SGs) consist of sophisticated and intricate technological components, encompassing both physical and logical elements. Their adoption and advancement are rapidly expanding worldwide [1], driven by the numerous advantages they offer over traditional electricity distribution networks. These varied benefits make energy distribution networks more flexible, reliable, and efficient. To set up an SG, you need to build a sophisticated communication network that can keep an eye on and control the grid by watching how power is generated and distributed. This is important to help set up an SG. To handle and analyze the huge amounts of data that come in through such a thick communication network, you need to use complicated procedures. This is crucial to get the most out of the data that would be obtained otherwise. The rise in computing power has enabled the development of diverse and increasingly potent AI-based techniques, coupled with the generation and analysis of big data. This convergence has brought forth a wide array of innovative capabilities to address longstanding challenges that previously lacked straightforward solutions [2]-[5]. AI-driven techniques applied to analyze the extensive data collected by smart grids offer a suite of tools for performing reasoning, efficient planning, knowledge acquisition, and rapid and effective management of various issues. These capabilities include outage management, fraud detection, optimization of power distribution, and handling potential security breaches, among others. The literature surrounding energy consumption and its ramifications on climate change is extensive, highlighting the urgent need for comprehensive interventions [6]. Recent reports underscore that nearly 80% of carbon emissions are linked to excessive energy consumption, positioning it as a primary driver of environmental instability [7]-[11]. All of this is in accordance with the United Nations' goal of achieving the Sustainable Development Goals (SDGs) around the world. These targets stress how important it is to cut emissions by 2030 and make it easier for people to get to renewable energy sources.

The literature also underscores the profound influence of weather conditions on residential sectors, particularly in association with smart household appliances. Carbon emissions from devices like lighting, heating, cooling, and various plug devices contribute substantially to national-level emissions [12]-[15]. This highlights the potential for mitigating climate impact by strategically reducing the consumption of such devices [16]-[20]. The Office for National Statistics in the UK just issued a study that looked at how climate change has affected people's homes and living conditions. The study found that dwellings and other residential buildings are responsible for 26% of the greenhouse gas emissions in the UK [21]. The report highlights that, in 2020, Northern Ireland exhibited the highest domestic emissions per capita, surpassing even London in emissions per square kilometer. Notably, approximately 34% of adults made no explicit lifestyle changes aimed at mitigating emissions [21]-[23]. A survey conducted on lifestyle and energy consumption underscores the potential for positive changes in household energy efficiency [24]. The study suggests that alterations in lifestyle choices can contribute significantly to energy conservation in residential settings. A small social experiment involving 77% of adults demonstrated that lifestyle modifications not only lead to reduced energy consumption but also play a crucial role in mitigating emissions [25]-[26]. In our research, we utilized a smart house dataset to investigate how contextual factors such as weather conditions and appliance usage influence overall household energy consumption. The goal of this study was to employ six different machine learning models to try to predict how much energy would be used over the next two days. The models were a support vector regressor, a gradient boosting regressor, a random forest regressor, and a linear regression. Additionally, we evaluated the performance of these models using metrics such as mean squared error (MSE) and R-squared values.

2. UTILIZATION OF MACHINE LEARNING TO ASSESS ENERGY CONSUMPTION

The dataset encompasses meter readings for total electricity consumption, as well as electricity consumption readings specific to household appliances, along with weather behavior data Figure 1 (see Appendix). We categorized these properties into two distinct groups: the first group focused on monitoring weather impacts, while the second group centered on monitoring the electricity consumption of household appliances Table 1.

Table 1. Data set description

Sl. No	The categories of features	Characteristics before the pre-processing
1	Total power consumption	Overall, home
2	Home appliances	Dishwasher
		Microwave
		Living room
3	Weather information	Temperature
		Humidity

3. TYPES OF REGRESSION MODELS

3.1. Linear regression

Linear regression is a statistical modeling method that tries to figure out the relationship between a dependent variable and as many independent variables as possible. The first stage in the regression model that is used to make predictions about outcomes is to find a link between an independent variable and a dependent variable. When there are a lot of independent and dependent variables, the model tries to figure out how a set of explanatory variables and a response variable are related to each other. It is customary to use measurements like R-squared and mean squared error (MSE) to find out how well this linear regression model worked. These metrics convey information about how well the model fits the data and how well it can explain events by giving the goodness of fit a number.

3.2. The random forest regressor

The random forest regressor uses an ensemble learning method that mixes a lot of decision trees to make its predictions more accurate. Combining the predictions of individual trees is one of the most significant parts of the random forest regressor's algorithm for addressing problems. Using a weighted average of the predictions made by each decision tree in an ensemble makes the forecast more reliable and accurate. The random forest regressor is a handy tool for a lot of regression problems since it uses an ensemble strategy that helps prevent overfitting and encourages generalization. This is because an ensemble method makes things more general.

3.3. The gradient boosting regressor

The gradient boosting regressor is an ensemble learning method that uses a stage-wise procedure. This method makes a predictive model by combining the predictions of weak learners, which are generally decision trees. Gradient boosting is a way to solve problems that require fitting new models one after the other to fix the mistakes made by the current ensemble. The contributions of each model are based on how well they do, and the final forecast is the weighted sum of all the contributions from the preceding models. By using this method on a regular basis, the remaining mistakes are eliminated, which leads to a prediction model that is accurate and very dependable.

3.4. The support vector regressor (SVR)

The support vector machine (SVM) model is a flexible tool that can be used for both classification and regression. It has a number of varied uses. Support vector machines (SVMs) can handle data that can be separated into two or more groups, whether they are linear or not. They are great at working with complicated datasets that have groups that are not connected to each other. Support vector machines use a number of kernels, such as sigmoid, radial basis function, linear, and polynomial, to transform input into spaces with additional dimensions. Support vector machines, or SVMs, are very good at generalizing, avoiding overfitting, and working well in high-dimensional spaces.

4. PERFORMANCE EVALUATION METRICS

For regression models, key measures such as MSE and R-squared were utilized to gauge the accuracy and predictive capability of the models.

4.1. Mean squared error

In regression analysis, the MSE is a statistic that is often used. It is the average of the squared differences between the expected values and the values that were actually seen. The MSE looks at the most important mistakes in forecasts to give a full picture of how accurate they are. To find the MSE, you divide the sum of the squared errors by the total number of observations.

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{k}(yi - \hat{y}i)^2 \quad (1)$$

4.2. R-squared error

R-squared (R^2), known as the coefficient of determination, is a statistical measure used in regression models to show how much the independent variables explain the changes in the dependent variable. In particular, it shows how well the model fits the dataset and checks how well the model matches the dataset. To find the R^2, divide the variance that can be explained by the total variance.

$$R^2 = 1 - \frac{\sum_{i=1}^{k}(yi - \hat{y}i)^2}{\sum_{i=1}^{k}(yi - \bar{y}i)^2} \quad (2)$$

$\bar{y}i$ -Actual values

The following measures assess the effectiveness of regression models. The following metrics were utilized for performance evaluation.

5. RESULTS AND DISCUSSION

The MSE is a number that tells you how far off the predicted values were from the actual values in a linear regression study. The MSE for the specific linear regression model that is being looked at is 5138.61. A lower MSE number means that the model is better at making predictions and is a measure of how accurate the model is overall. The R-squared value is another statistic that may be used to see how well the linear regression model can explain the changes in the dependent variable. This R-squared score is 0.681, or 68.1%. So, this means that the linear regression model in Figure 2 explains around 68.1% of the changes in the dependent variable.

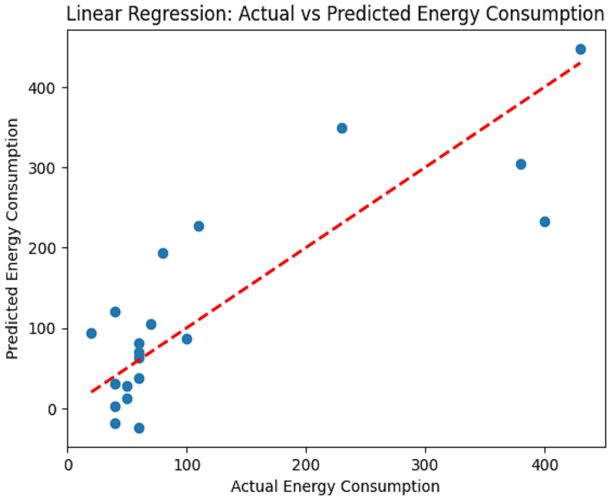

Figure 2. Regression plot for linear regression

Figure 3 shows the random forest regressor with an MSE value of 7884.39. This number is the average of the squared differences between the values that were actually seen and those that were expected. The R-squared score, which is 0.5105 (51.1%), shows how well the model can explain changes in the dependent variable. Even though the MSE is greater, the model can explain 51.1% of the variation. Figure 4 shows that the gradient boosting regressor has a high level of predictive power because its MSE value is 4694.95. Its R-squared score of 0.711 (71.1%) shows that it can explain a considerable part of the variation in the dependent variable. This means that it is good at finding patterns in the data in Table 2. This is shown by the fact that it can explain 72.1% of the difference. Figure 5 shows that the support vector regressor doesn't do a good job of predicting since its MSE value is too high at 19321.68. There is a big difference between the values that were predicted and the ones that really happened. A low R-squared score (-.2.0) means that the model doesn't explain the data very well and doesn't fit it very well.

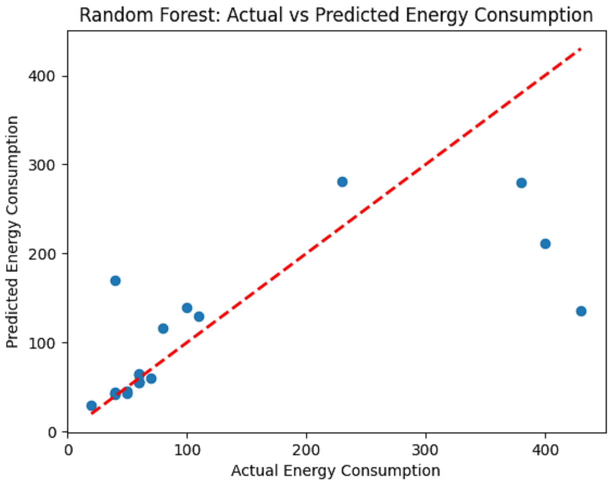

Figure 3. Regression plot for random forest

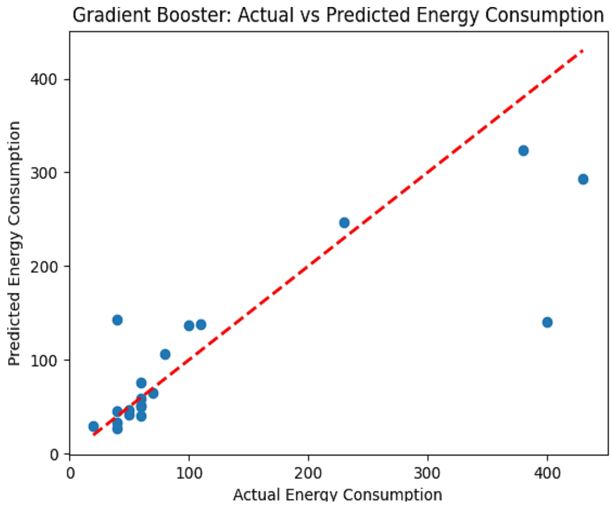

Figure 4. Regression plot for gradient booster

Table 2. Performance evaluation

Types of regression models	Mean squared error	R-squared
Linear regression	5138.61	0.681
Random forest regressor	7884.39	0.5105
Gradient boosting regressor	4694.95	0.711
Support vector regressor	19321.68	-2.0

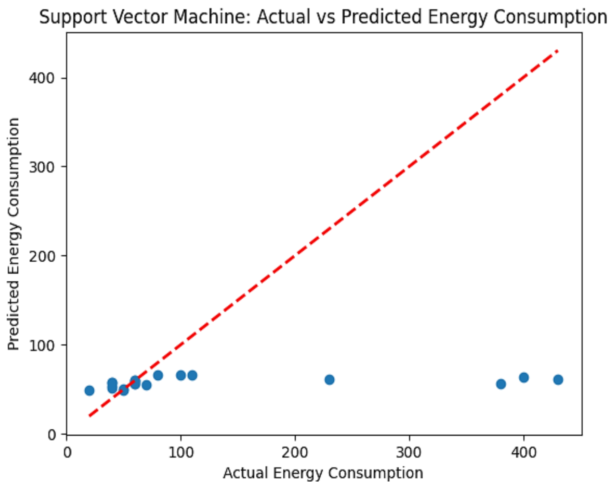

Figure 5. Regression plot for SVM

5.1. Comparison of the R-squared regression model

The provided code creates a bar plot using the Matplotlib library to compare the R-squared values of different regression models. Figure 6 shows a bar chart with the R-squared value of each regression model. The x-axis shows the several regression models, while the y-axis shows the R-squared values for each one. It gives a short summary of what the graphic is for. R-squared shows how well the regression model can explain the differences in the dependent variable. The model fit has been better since the R-squared value has gone up. As a result, this number is a good representation of the whole. can see how well each regression model works by looking at how well it can explain the data's variability in a way that is both rapid and easy to comprehend.

5.2. Comparison of mean squared error for regression models

The application uses the Matplotlib library to make a bar chart that shows the mean squared error (MSE) values of several regression models. On one side, we have the different regression models, and on the other side, we have the MSE values that go with each of those models. Figure 7 shows a picture that makes it easy and quick to examine how well each regression model does in terms of the mean squared error.

Figure 6. Comparison of the R-squared regression model

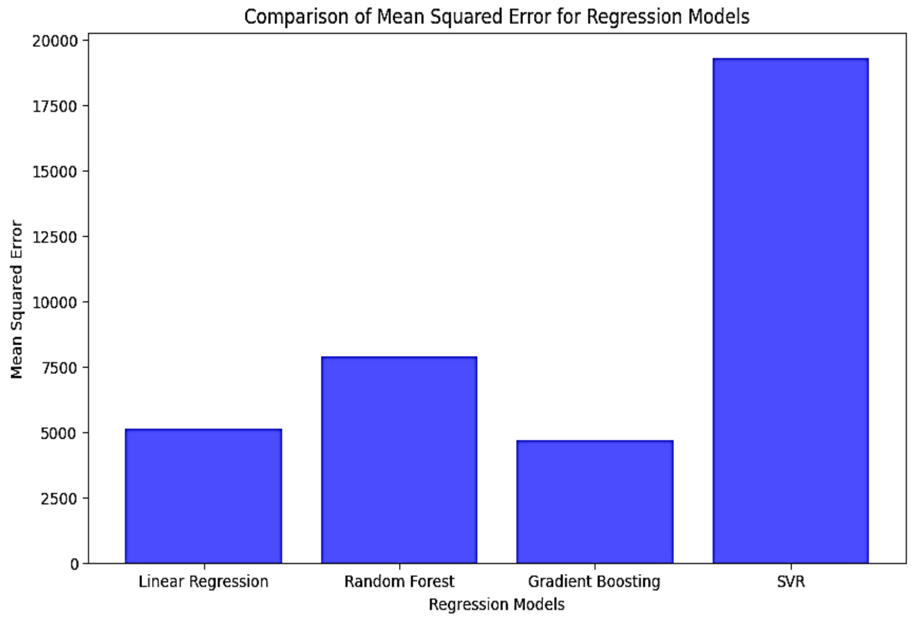

Figure 7. Comparison means mean-squared error regression models

6. CONCLUSION

Four different machine learning methods were used in this study to predict how much energy smart home equipment would use. The techniques used were linear regression, random forest regressor, support vector regressor, and gradient boosting regressor. The dataset utilized for this investigation had information about how much energy households used and about the weather. The Gradient Boosting Regressor did better than the other models in the evaluation since it had the lowest mean squared error (MSE: 4694.95) and the greatest R-Squared value (R2: 0.711). The support vector regressor, on the other hand, was the least accurate, with a far higher error (MSE: 19321.68) than the other two classification techniques. These results show how well ensemble-based models work for applications like predicting energy use. To make predictions even more accurate, future research should focus on improving the quality of the data by adding more accurate weather data and indicators of energy use. More study into deep learning methods and hybrid models could lead to the creation of energy consumption prediction systems that are more accurate. As a result of the findings of the study, improved energy management systems for smart homes are currently in the process of being developed. These systems will assist with the conservation of energy and the appropriate utilization of resources.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
J. C. Vinitha	✓	✓	✓	✓	✓	✓			✓	✓			✓	✓
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors have reviewed and agreed to this conflict of interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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APPENDIX

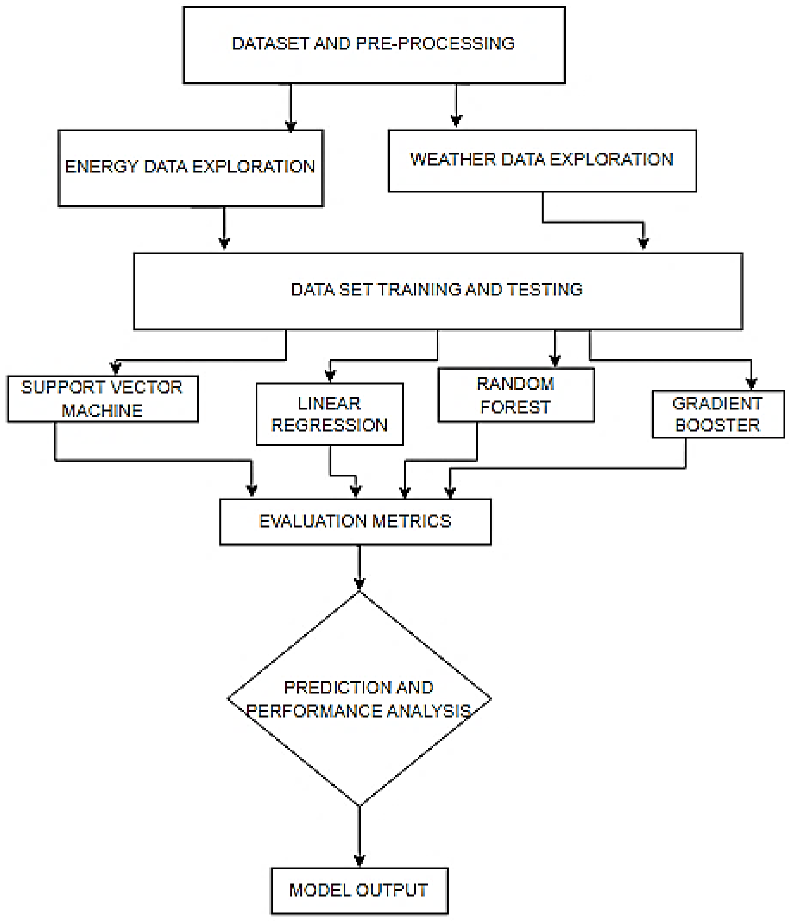

Figure 1. Flowchart for the proposed model

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