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LEVERAGING AI AND MACHINE LEARNING FOR ENERGY-EFFICIENT SMART CITY OPERATIONS

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Abstract: The idea behind smart cities is to use advanced technologies for the administration and optimization of the city functionalities, which comprise the energy infrastructure as well. Optimizing energy infrastructure to reduce energy use, costs, and environmental impact is one of the largest challenges smart cities face. The study presents a machine-learning algorithm that accurately forecasts a building's energy efficiency, thereby enhancing the functionality of intelligent cities. The Kaggle Energy Efficiency Dataset is used as the source for the research. Before applying the two most popular regression techniques, Extra Tree and CatBoost, the research performs various data preprocessing steps, such as filling gaps, normalization, and outlier rejection. Evaluation criteria of the model performance include R^2, RMSE, MSE, MAE, and MAPE. The results show that the models have excellent predictive power, as demonstrated by 99.8% and 99.5% of the R 2 of the ExtraTree and CatBoost model respectively, and the error rate is very low based on all the measures. The findings demonstrate the superiority of ensemble techniques in handling complex energy consumption patterns; therefore, they are highly applicable to energy efficiency prediction, which would, in turn, streamline smart, data-driven decisions in contemporary cities.

Keywords: Smart Cities, Machine Learning, Energy Efficiency, Ensemble Methods, Regression Models, Energy Consumption.

1 INTRODUCTION

The unprecedented urbanization has led to numerous problems, such as the consumption of more energy and its effects to the environment, and the congesting traffic [1]security and privacy issues, and the general challenge of delivering effective services to an ever-expanding population. Governments are finding answers to these issues to create smart cities [2]. A smart city is the new vision becoming popular across the world to solve the problems of urbanization, ecological issues, and economic development [3]. As technology gains greater significance in life, the concept of a smart city becomes increasingly topical. The government and the private sector have dedicated significant funds in smart city projects in the past few years [2], [4]. With population growth in cities and advances in technology, smart cities are gaining relevance.

In the past 20 years, city smartness has increased, with cities employing information and communication technology (ICT) to assess the city's situation and operations. Some activities that can generate data in the city include traffic, transportation, power generation, utility provisioning, water supply, and waste management. Surveillance and decision support in a smart city platform involve using technological devices to collect and analyze data from various sensors and sources across the urban system. The information collected covers a range of aspects, including traffic dynamics, air quality indicators, noise levels, energy consumption, and similar factors.

Energy greatly influences the economic growth of a nation and the lives of the people especially in relation to the electricity demand [5]. Companies are adopting carbon-cutting solutions to reach a zero-carbon emissions target by 2050, and each of their supply chain processes must work toward using 100% renewable energy by then. There are three main directions in energy management: generating energy, storing energy, and conserving energy.

AI is valuable in terms of opening the full potential of smart cities, ranging from optimization of transportation systems to management of environmental resources, better governance, quality of life, economic development, and empowering citizens [6]. Artificial intelligence is not only driving drastic technological transformations but also influencing people's behavior and lifestyles on a massive scale. Artificial intelligence may be adopted in virtually any field of human activity. The collaboration between ML, blockchain, and IoT [6], [7] therefore introduces a landmark strategy for creating smart cities, with information management and decision-making processes becoming data-driven and guided by strong, reliable information. These issues can be overcome by incorporating ML into this framework. Their capacity to learn and act upon the data, extract and identify patterns, as well as make predictions, makes the ML algorithms [8]. The sole tool to extract actionable insights out of the enormous and heterogeneous data sets. In Deep learning algorithms, the system can make real-time decisions to maximize energy use and reduce costs. It not only overcomes the shortcomings of the past methods, including ILP, but also improves the overall efficiency and flexibility of the system [9]. Implementing deep learning technologies for home energy management provides a strong platform for incorporating renewable energy.

1.1 Motivation and Contributions of the Study

The high rate of urbanization has contributed significantly to the increased problems that comprise high rate of energy use, environmental degradation and poor city management. There is increasing demand for smart systems that not only improve quality of life but also use resources efficiently, as all urban areas are expected to become green and economically neutral by 2050. Energy management, renewable energy integration, and the development of environmentally friendly cities can all be improved through artificial intelligence and machine learning, which are the focus of the current study. What follows is a discussion of the study's most important contributions:

- Leveraged Energy Efficiency dataset sourced from Kaggle.
- Implemented a robust preprocessing pipeline, including checking and removing the null values, data standardization with min-max scaler and removal of the outliers.
- Applied the two efficient machine learning classifiers, namely ExtraTree Regressor and CatBoost Regressor.
- Assessed the models' effectiveness with detailed metrics including R2, RMSE, MSE, MAE, and MAPE.

1.2 Significance of the Study

This research is critical because it could lead to more accurate energy-efficiency predictions, enabling smart cities to make more environmentally friendly choices. The study of highly accurate machine learning models for predicting heating and cooling loads has enabled energy management optimization, cost-effective operations, and environmentally friendly performance. Moreover, it provides a robust analytical foundation that can be very helpful to decision-makers, city planners, and architects during the transition to energy-efficient infrastructure.

1.3 Organization of the Study

The paper is structured as follows: Section II presents a literature review on energy efficiency in smart cities. Section III presents the research methodology, including the dataset, preprocessing, and model implementation. Section IV presents the experimental results, and Section V concludes the research and outlines possible future research.

2 LITERATURE REVIEW

The primary sources that contributed immensely to narrowing down the focus and identifying a general direction of the research were an exhaustive review and critical analysis of existing research on Energy-Efficiency in Smart City Operations.

Biswas and Tiwari (2025) report that performance is spectacular, with an expected latency of 5 milliseconds and a 98 percent packet delivery rate, which is significantly better than that of traditional protocols. Of special interest in this research is its contribution toward the design of adaptive communication systems that can support the burgeoning needs of smart urban environments, thus spurring new developments in the field of wireless communication technology [10].

De O. Rodrigues *et al.* (2025) present a modular architecture combining ML with SDN for real-time threat detection and mitigation in MQTT-based LoRaWAN networks. The system uses flow-level features to preserve privacy and enables dynamic policy enforcement via a REST API in the SDN control loop. They evaluate 13 ML models on the UNSW-NB15 dataset, with XGBoost achieving 0.8995 accuracy and 0.9927 AUC [11].

G N *et al.* (2024) propose using machine learning techniques as optimization methods for WSN-IoT nodes (sensor networks) used in Smart City initiatives. This is, to the best of their knowledge, the first review study that covers all machine learning methods in low-power WSN-IoT for urban smart cities. Here, the algorithms used varied in the context of type as shown by results suggesting supervised learning (61%) for smart city applications, unsupervised learning (12%), and reinforcement learning(27%) [12].

Ramasami and Maheswari (2024). The proposed approach comprises two key stages. Initially, each record in the dataset is labelled as normal or anomalous using an unsupervised Gaussian Mixture Model to identify aberrant patterns. The second stage involves different supervised classification algorithms, namely SVM, KNN, DT, NB and RF are used to classify the new instance. The results demonstrate that the RF achieves high accuracy in detecting insider threats with an accuracy of 99.97% [13].

Assayed, Alkhatib and Shaalan (2024) used the Seq2Seq model, which was trained on 2944 students' questions, a new deep learning chatbot is created to assist high school kids with college and career advice. For the decoder part of this model, there is a single dense layer with Softmax activation and a BiLSTM with 400 LSTM units in each direction. Testing the model with the Adam optimizer yielded significantly better results than testing it with the SGD optimizer. Results from the ROUGE-1 evaluation using ROUGE-N measures showed a very high level of accuracy, at 92% [14].

Sharma and Babbar (2023) present a design that detects DDoS attacks using various ML techniques. The primary objective of this research is to analyze the performance of DDoS attacks on the BoT-IoT dataset using several machine learning methods, including

RF, NB, and DT. The well-known BoT-IoT dataset was used to achieve the best accuracy of 91% with RF and 91% with DT, two machine learning methods [15].

Ajagunsegun *et al.* (2022) aim to enhance the state of the art in intelligent systems that use machine learning to control the energy efficiency of public buildings, an integral aspect of the smart city concept. The team used GBM techniques, such as LightGBM, Category Boosting (CatBoost), and Adaptive Boosting (AdaBoost), to develop energy consumption prediction models for individual public buildings. After comparing the key predictors retrieved by each approach, LightGBM created the best-performing model with a minimal root-mean-squared error of 1.119 [16].

The datasets, methodologies, measurements, results, and constraints utilized in the most recent research on Energy-Efficiency in Smart City Operations are summarized in Table 1.

Table 1: Recent Studies on Energy-Efficiency in Smart City Operations

Reference	Dataset / Data Source	Methods / Techniques Used	Key Findings	Challenges / Limitations
Biswas & Tiwari (2025)	Not explicitly specified (focus on communication system evaluation)	Adaptive communication protocol design; latency and PDR evaluation in smart urban communication networks	Achieved 5 ms latency and 98% packet delivery ratio, outperforming traditional protocols; strong potential for adaptive systems in smart cities	Lack of details on scalability, generalization across diverse urban infrastructures, and real-world deployment constraints
De O. Rodrigues et al. (2025)	UNSW-NB15 intrusion detection dataset	Modular architecture combining ML + SDN; 13 ML models evaluated; flow-level features; SDN control loop with REST API	XGBoost: Accuracy 0.8995, AUC 0.9927; Supports privacy-preserving, real-time threat detection for MQTT-based LoRaWAN	Performance drop in non-flow–based scenarios; dependency on SDN infrastructure; latency concerns for large-scale deployments
G N et al. (2024)	Review paper—multiple WSN-IoT datasets across smart city applications	Survey of ML techniques for optimization in low-power WSN-IoT; supervised (61%), unsupervised (12%), RL (27%)	First comprehensive review of ML for low-power WSN-IoT nodes in smart cities; highlights ML dominance in optimization	Survey does not deeply evaluate model performance; lacks unified benchmarking; energy constraints remain unresolved
Ramasami & Maheswari (2024)	Insider threat dataset (not explicitly named)	Two-stage model: GMM (unsupervised anomaly detection) + supervised classification (SVM, KNN, DT, NB, RF)	Random Forest achieved 99.97% accuracy in detecting insider threats	Extremely high accuracy may indicate overfitting; dataset diversity not discussed; real-world insider threat variability hard to capture
Assayed, Alkhatib & Shaalan (2024)	2944 student inquiries for career guidance	Seq2Seq + BiLSTM (400 units each direction); Dense layer with Softmax; Adam vs. SGD comparison; ROUGE-N evaluation	Achieved 92% ROUGE-1 precision with Adam optimizer; improved chatbot response quality	Limited dataset size; domain-specific training reduces generalizability; lacks human evaluation benchmarks
Sharma & Babbar (2023)	BoT-IoT dataset	ML classification algorithms: RF, NB, DT for DDoS attack detection	RF and DT achieved 91% accuracy	Only traditional ML used—no deep learning comparison; BoT-IoT dataset imbalance may influence results
Ajagunsegun et al. (2022)	Energy consumption data from specific public buildings	Gradient Boosting models: LightGBM, CatBoost, AdaBoost	LightGBM achieved best performance with RMSE = 1.119; identified key predictors for energy consumption	Limited generalization to other building types; dataset may be context-specific; real-time integration not addressed

3 RESEARCH METHODOLOGY

The primary objective of this research is to create a reliable and accurate prediction model for smart city and building energy efficiency estimates. This project, using a well-prepared energy-efficiency dataset, seeks to identify the most effective regression model for calculating heating and cooling loads. The final purpose is to develop smart cities' energy management systems by getting very accurate predictions of energy efficiency. The flow of the methodology is depicted in Figure 1.

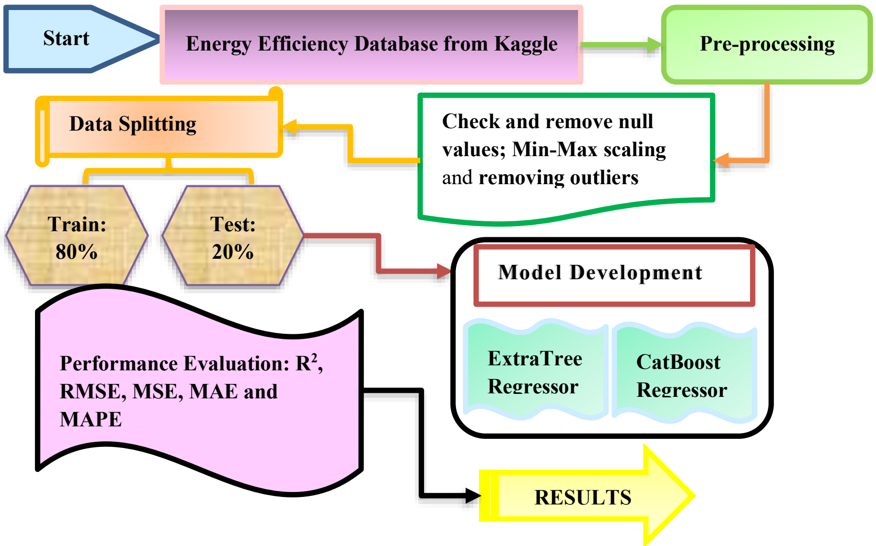


Figure 1: Proposed Methodology flowchart of Energy-Efficiency in Smart City Operations

The section below outlines the steps shown in the Energy-Efficiency in Smart City Operations flowchart.

3.1 Data Analysis

The energy efficiency database is one of the initial data sets of the research. The dataset consists of 768 building simulation specimens, each characterized by eight features (i.e., geometric and physical). This dataset provides a strong foundation for regression techniques in energy-efficiency modelling, as it includes heating and cooling loads as target variables. The data visualizations are given below:

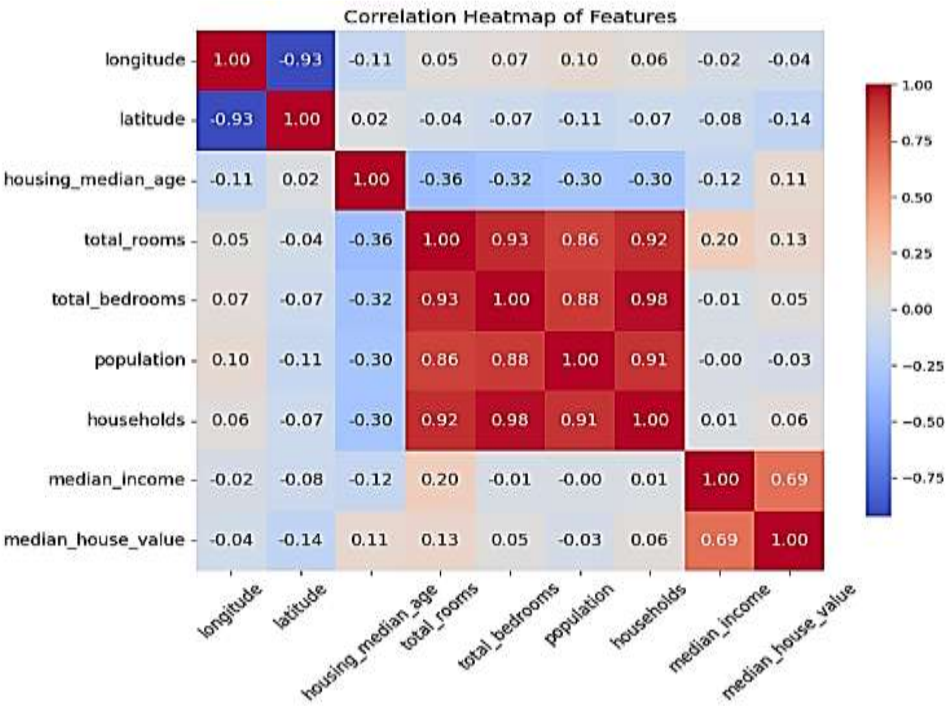


Figure 2: Correlation Heatmap

The most important connections between housing and demographic characteristics are depicted in the correlation heatmap in Figure 2. While the correlation between median income and housing value is moderate, the correlations between total rooms, bedrooms, population, and households are strong. Latitude and longitude have weak correlations with other features, but a strong negative correlation with each other.

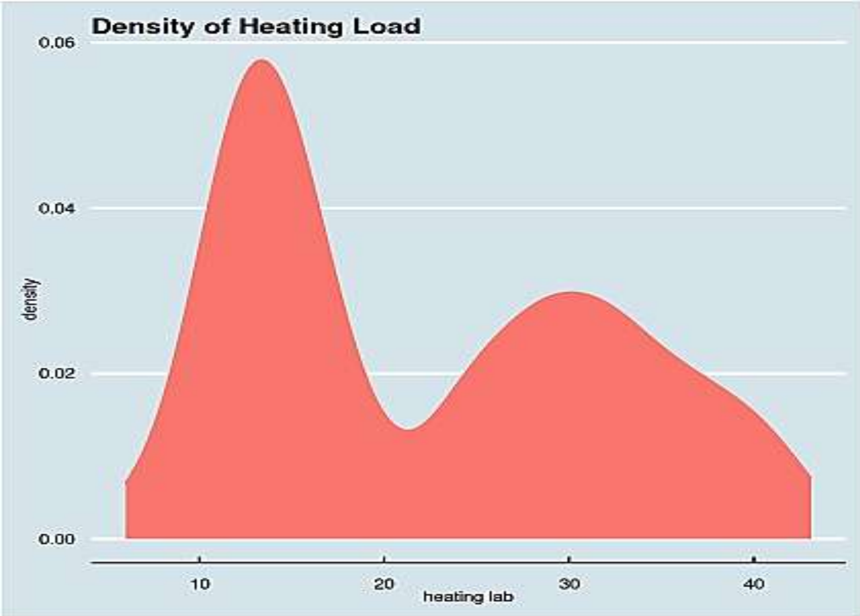


Figure 3: Density Plot of Heat Loading

Figure 3 shows the density distribution of heating load values, with two significant peaks. The peaks are signs of different user behaviors in the dataset. The first peak corresponds to low heating loads, while the broader second peak represents average loads. The continuous line shows the variation in heating demand across different buildings; thus, it helps understand typical energy consumption levels as well as fluctuations in heating performance.

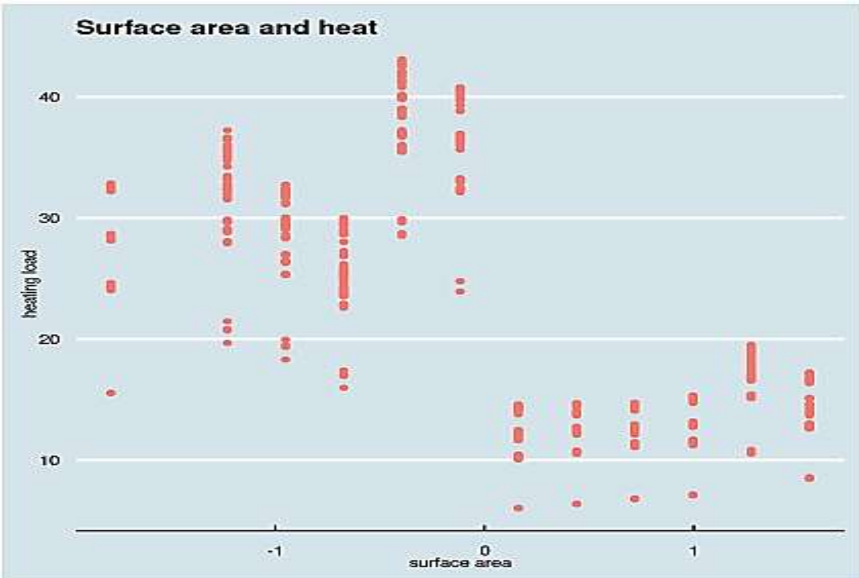


Figure 4: Scatter Plot of Surface Area and Heat

Figure 4 shows a scatter plot of the relationship between air surface area and heat load. The arrangement shows that when the surface dimension is smaller, the heating loads are larger. On the other hand, structures with lower heating loads tend to have larger surface areas. The increase in surface area usually results in a decrease in heating demand; this is demonstrated by the scatter plot, which shows a strong inverse correlation.

3.2 Data Pre-processing

The raw data must undergo preprocessing after data collection before it can be entered into a computer for prediction.

- **Checking and removing the null values:** The raw data contains several noisy and missing data points; therefore, this phase is essential. To normalize numerical discrepancies between data points, the data cleaning process is employed. To clean up the data, removed any missing values or blank observations.

- **Scaling the Dataset:** The normalization strategy speeds up the training process by improving the model's performance, which is necessary because there are noticeable variances among the target data. The normalization of min-max is given by Equation (1):

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

The original value x, the maximum value $\max(x)$ the minimum value $\min(x)$ and the normalized value z are all variables in this context.

- **Removing the outliers:** Two methods were used to identify the non-normal data points that were introduced into the series. Statistical approaches were mostly used to conduct a worldwide search on the power usage data. Their subsequent use was in the detection of anomalies stemming from forecasting mistakes.

3.3 Data Splitting

The data loaded into a training set before heading to a test set. Only 20% of the data used for testing, while 80% go into the training set.

3.4 Model Development

This section provides a detailed explanation of the proposed machine learning algorithms for measuring energy efficiency in smart city management.

ExtraTree Regressor: The RF method is the basis for several ensemble-based algorithms, one of which being the extra trees (ET) algorithm [17]. The following are two main distinctions between ET and RF: (1) the ET constructs trees using a randomly selected portion of data without replacing any of it, which aids in reducing bias, and (2) the ET's unpredictability is derived via randomly selected data splits instead of bootstrap aggregation. There are two steps to the ET algorithm's regression process, just as the RF algorithm: bootstrapping and bagging. Bootstrapping is the process of constructing decision trees using a randomly selected subset of the training dataset [18]. Decision nodes are partitioned using randomized subsets of training data during the bagging phase. Equation (2) expresses the ET regression process mathematically:

$$p = (x, \beta_1, \ldots, \beta_n) = \frac{1}{m} \sum_{i=1}^{m} p(x, \beta_n) \tag{2}$$

Where β is a distributed vector p is the p-th prediction tree.

CatBoost Regressor: CatBoost is the latest machine learning algorithm created in 2017 by Yandex, a Russian corporation. It is an improvement of the Gradient Boosting Decision Tree (GBDT). Standard forms of GBDT build individual decision trees on the basis of the residuals of the existing model ensemble, which causes the trees to highly depend on one another and lead to overfitting. CatBoost algorithm manages this problem by proposing the Ordered Boosting algorithm and a new weighting strategy. The process rearranges the training data and groups the similarity of the feature values in the same leaf node consequently increasing the precision and the stability of the gradients and also reducing the model variance which in effect eliminates the overfitting issues. The formula is given as below in equation (3):

$$\hat{x}_k^i = \frac{\sum_{j=1}^{N} I_{\{x_j^i = x_k^i\}} y_j}{\sum_{j=1}^{N} I_{\{x_j^i = x_k^i\}}} \tag{3}$$

With x_k^i indicating the i -th characteristic of the k-th training sample; $\hat{x}_k^i$ indicating the value in the mean; I an indicator variable indicating whether a particular condition is true; and y_j indicating the value of the label of the j-th sample.

3.5 Performance Parameters

The machine learning models used in this research were created by combining the two methods of algorithm development. half of the dataset was used to train the model, while another half was used to assess how well the model could generalize to new, unknown data. Coefficient of determination (R2), mean absolute error (MAE), root mean square error (RMSE), mean squared error (MSE), and mean absolute percentage error (MAPE) are some of the commonly used metrics for evaluating models. A comprehensive analytical evaluation was then carried out. The degree to which the model's projected results match the actual values can be quantified using the aforementioned performance metrics. Below, in equations (4)-(8), Show the formulae for these measures:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y_i})^2}{\sum_{i=1}^{N} (y_i - \bar{y_i})^2} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\widehat{y_i} - y_i)^2}{N}} \tag{5}$$

$$MAE = \sum_{i=1}^{N} \frac{|y_i - \overline{y_i}|}{N} \tag{6}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{7}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \widehat{y_i}}{y_i} \right| \tag{8}$$

4 RESULTS AND DISCUSSION

The system came with 16 GB of RAM, an NVIDIA GeForce GTX 1650 GPU with 4 GB of VRAM, 16 virtual CPUs, and an ASUSTek AMD Ryzen 7 5800H (R) CPU running at 2.20 GHz.

4.1 Experimental Findings

In Table II, the performance of the Extra Trees and CatBoost models is compared for predicting the energy efficiency of smart city operations using different evaluation metrics. The Extra Trees model not only outperforms but also demonstrates the highest R^2 (99.8%) and the least error values using (0.4277) for RMSE, (0.1964) for MSE, (0.2745) for MAE, and (0.0125) for MAPE, all of these percentages by a huge gap. Conversely, CatBoost manages lower accuracy, resulting in an R^2 of 99.5% and higher error measures that are well noticeable. To sum up, the results indicate that Extra Trees provide the most accurate and reliable predictions, making them the most suitable model for energy-efficiency forecasting in smart city settings.

Table 2: Performance of Energy-Efficiency in Smart City Operations

Metrics	Extra Tree	Catboost
R2	99.8	99.5
RMSE	0.4277	0.9468
MSE	0.1964	0.9601
MAE	0.2745	0.6081
MAPE	0.0125	0.0226

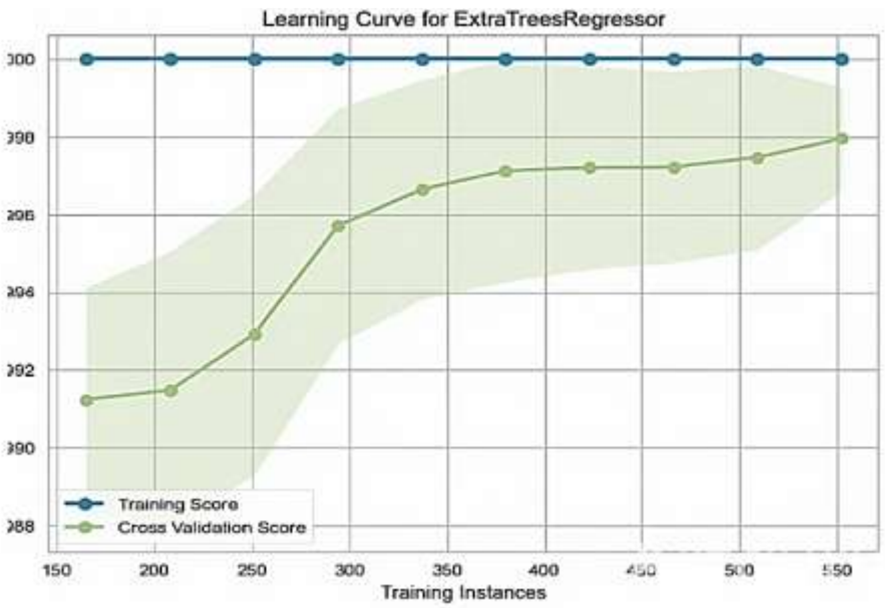
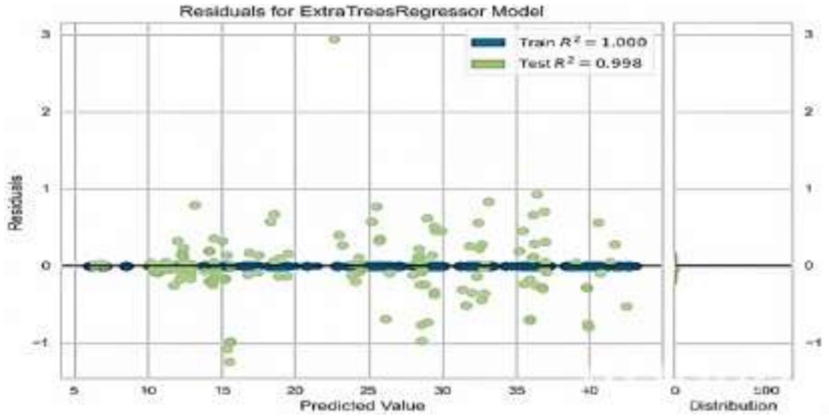


Figure 5: Learning Curve of the ExtraTree Regressor

Figure 5 illustrates the learning curve of the ExtraTreesRegressor, in which the training score is still very high for all sample sizes, but the cross-validation score slowly increases when more data is used. Also, the shrinking shaded area indicates less variation across the validation folds. In fact, the figure is almost a point-by-point graphical confirmation that additional data leads to better generalization, but the small, consistent difference between the training and validation curves indicates a slight overfitting.



Figrue 6: Residuals of the ExtraTree Regressor

In Figure 6, show the residual plot for the ExtraTreesRegressor, which indicates that both the training and test residuals are very close to zero. Thus, the predictions are highly accurate. The model achieves an R^2 of 1.000 on the training data and 0.998 on the test data, indicating an outstanding fit with minimal error. The absence of substantial patterns or trends in the residuals indicates that the model has learned the underlying relationships and, therefore, there is no significant systematic error.

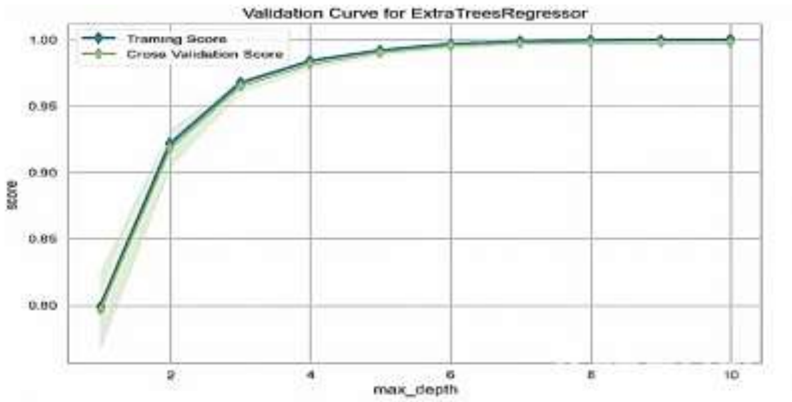


Figure 7: Validation Curve of the ExtraTree Regressor

Figure 7 displays the ExtraTreesRegressor's validation curve, which shows that testing and cross-validation scores began to decline around 4 for the max_depth parameter. There is no overfitting to the depth levels evaluated since the two curves are so close together, which means the model can handle fresh data.

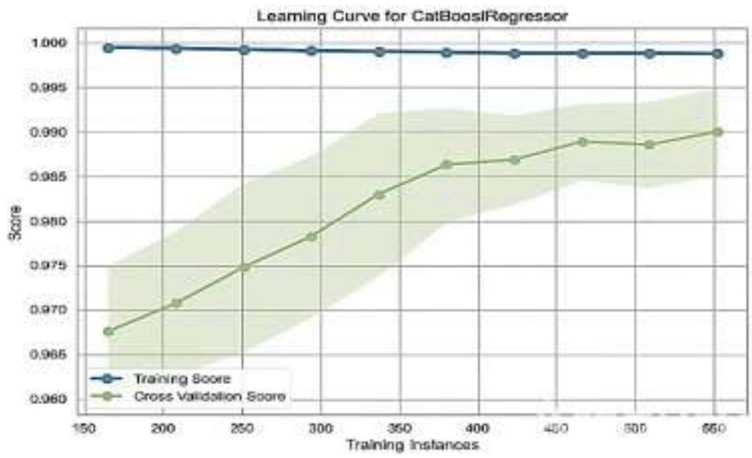


Figure 8: Learning Curve of the CatBoost Regressor

Figure 8 depicts the learning curve of a CatBoostRegressor, with the training score remaining very high and almost constant across all training sizes, indicating that the model fits well. The shaded region indicates that the cross-validation score steadily increases as the number of training examples increases.

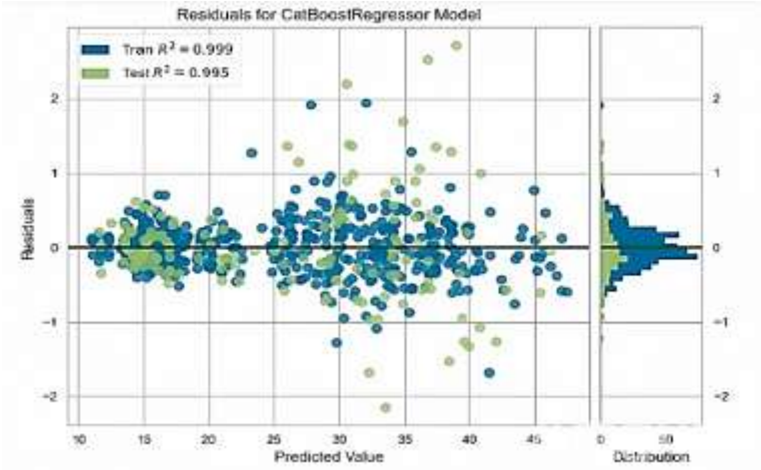


Figure 9: Residuals of the CatBoost Regressor

Figure 9 provides the residual plot for the CatBoost Regressor, where it can be seen that the residuals for both the training and test sets are very closely grouped around zero, thus the predictions can be believed to be precise and stable. The model demonstrates very good fit, with R^2 values of 0.999 for training and 0.995 for testing. The residual distribution on the right side of the figure is a good indication that the majority of the errors are small and close to the center, thus implying that there is no significant bias or systematic pattern.

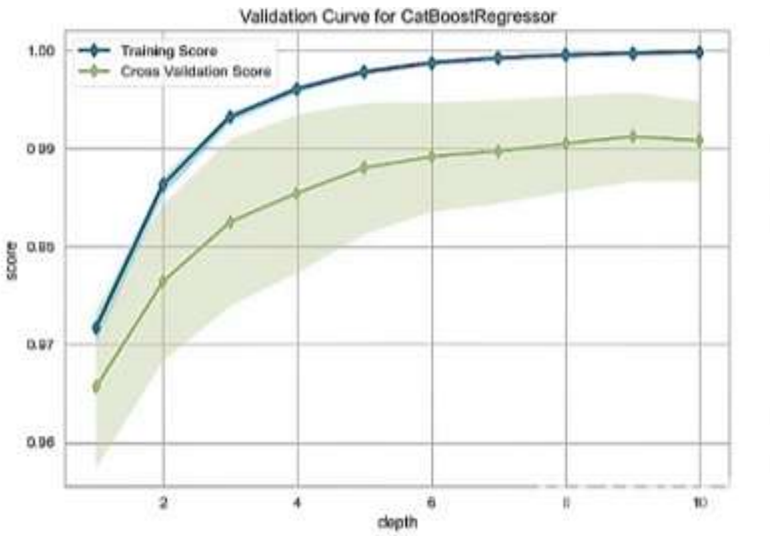


Figure 10: Validation Curve of the CatBoost Regressor

Training and cross-validation scores both increase with tree depth (Figure 10), with the greatest improvement occurring up to tree level 4, as indicated by the CatBoost Regressor validation curve. Beyond that point, the curves plateau at quite high values, suggesting that deeper depths yield very little additional return. Given the relatively small distance between the two curves, it can be considered a good generalization, with only slight overfitting detected at deeper levels.

4.2 Comparitive Evaluation

Table III compares model performance for energy-efficiency evaluation in smart cities using R^2. LSTM and GRU-NN outputs are 74.0 and 93.0, and GPT-4O and QDA are 97.3 and 87.0, respectively. The performance of the newly proposed ExtraTree and CatBoost models is phenomenal, with R^2 values of 99.8 and 99.5, respectively, indicating their superlative predictive accuracy and reliability.

Table 2: Performance Comparison for Energy-Efficiency in Smart City Operations

Ref.	Model	R2
[19]	LSTM	74.0
[20]	gpt-4o	97.3
[21]	Quadratic Discriminant Analysis (QDA)	87.0

[22]	GRU-NN	93.0
Prop.	**ExtraTree**	**99.8**
Prop.	**CatBoost**	**99.5**

According to the proposal, the ExtraTree and CatBoost algorithms have outperformed previous approaches in predicting energy efficiency for the operation of the smart city. On the other hand, compared to other deep-learning and statistical techniques, they are far more accurate, generalize better, and are less sensitive to underlying assumptions. The findings reveal that the proposed models performed higher than the evaluation metrics, meaning that they were more robust and reliable and hence the most appropriate to use in the forecasting exercise.

5 CONCLUSION AND FUTURE SCOPE

The fundamental requirement of sustainable, efficient, and quality-enhancing urban operations is Smart city infrastructure. The current research demonstrates that both the ExtraTree and CatBoost models achieve excellent prediction of building energy efficiency, with R 2 values of 99.8 and 99.5, respectively. Their potent learning capability enables them to ultrasonic the heating and cooling load patterns and perform it with less than no error. The findings of this work demonstrate how effective the advanced machine learning methods are to solve energy-related concerns in smart cities. These models which make correct and predictable predictions are of significant assistance in such fields as operational planning, resource distribution, and energy management; therefore, they are indirectly helpful at any time. The study once again shows that data-driven solutions are the fundamental factor in the formation of sustainable city zones, the reduction of energy waste, and the renovation of smart city infrastructure.

The use of larger and more diverse sets of data, the integration of real-time IoT-based energy measurements, evaluation of more advanced models or hybrid approaches can be explored in the future research. Perhaps, the shift towards including the environmental factors and multi-building conditions could not only enhance the precision of predictions but also make the implementation of the energy management in smart cities more comprehensive.

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