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Machine Learning–Enabled Framework for Energy Infrastructure Optimization in IoT-Based Smart Cities

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Abstract

The idea of smart cities focuses on leveraging modern technologies to enhance and streamline city operations, particularly energy infrastructure. One of the key challenges smart cities face is efficiently managing energy resources to minimize consumption, costs, and environmental impact. Machine Learning (ML) provides a powerful means to optimize energy usage within urban infrastructure. This paper introduces a framework for optimizing energy management in smart cities using ML techniques. The framework comprises three primary components: data collection, model development, and energy optimization. Data collection involves gathering energy consumption data from sources such as smart meters, sensors, and other Internet of Things (IoT) devices. After data pre-processing and cleaning, ML models, using techniques such as regression, classification, clustering, and deep learning, are developed to forecast energy consumption and optimize usage. The optimization process then utilizes these models to balance energy supply and demand, ultimately reducing overall consumption and cost. The framework is advantageous for reducing energy use, lowering costs, and mitigating environmental impacts while improving the reliability and efficiency of urban energy infrastructure. This solution can be applied across smart city domains, including buildings, transportation, and industrial activities.

Keywords: Smart cities, Energy infrastructure, Machine learning, Energy optimization, IoT devices, Energy consumption, Urban sustainability, Energy efficiency.

1 | Introduction

The rapid growth of urbanization has led cities to evolve into complex, interconnected ecosystems known as smart cities. These cities rely heavily on modern technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and Machine Learning (ML), to manage and optimize their operations. Smart city infrastructure is crucial because it enables the efficient collection, processing, and analysis of real-

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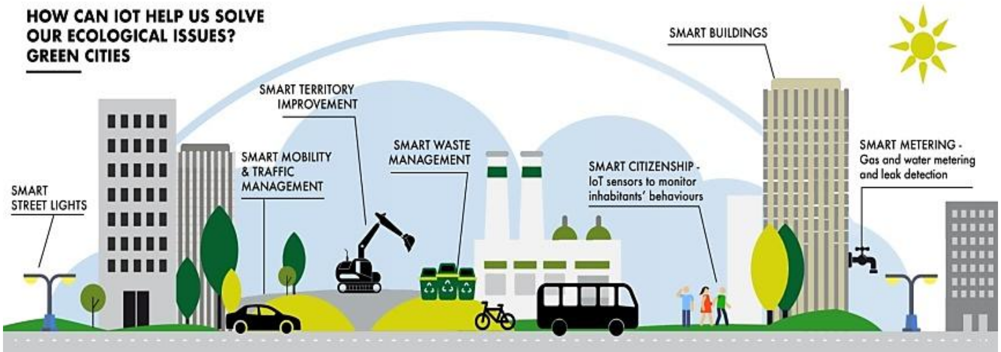
time data across various city functions, including energy management, transportation, environmental monitoring, waste disposal, and public safety [1]. The deployment of these technologies allows cities to make informed, data-driven decisions that improve urban living standards while optimizing resource usage [2].

Fig. 1. IoT-enabled energy optimization in smart cities.

One of the key challenges in smart cities is the efficient utilization of energy infrastructure. With the ever-



increasing demand for energy, cities are under pressure to reduce energy consumption, minimize costs, and lower their environmental footprint. Smart city technologies can play a transformative role in addressing these issues by implementing advanced energy management systems. These systems rely on real-time data collection from IoT devices, such as smart meters and sensors, to monitor energy consumption patterns. By utilizing the data gathered, cities can implement energy-saving measures, identify inefficiencies, and optimize energy distribution networks [3], [4].

Smart grids: smart grids can be implemented to optimize energy distribution and reduce energy waste. Smart grids use real-time data to balance energy supply and demand, reduce energy loss during transmission, and integrate renewable energy sources into the grid [5], [6].

Renewable energy: smart city concepts can be used to implement energy sources that replenish naturally, such as solar, wind, and geothermal energy, to reduce carbon emissions and decrease dependency on fossil fuels [5], [6].

Energy storage: batteries, other energy storage devices, and surplus energy from renewable sources may be stored and used later using flywheels. This can help reduce energy waste and improve energy usage efficiency [7].

Machine learning: energy forecasting using ML methods, consumption patterns, and reducing energy waste. These algorithms can learn from real-time data and adjust energy supply and demand to reduce energy consumption and cost [8].

This paper presents a framework for optimizing energy infrastructure in smart cities using ML. The proposed framework includes three primary components: data collection, model development, and energy optimization. By integrating these components, cities can improve energy efficiency, reduce operational costs, and lower their environmental impact [9].

2 | Energy Management and Challenges in Smart Cities

Managing this resource effectively has become a global priority as the world faces an ever-growing energy demand. With rising energy consumption, we're seeing heightened levels of global warming and air pollution, posing serious threats to future generations. The rise in energy demand directly contributes to these environmental challenges, primarily through increased emissions of harmful pollutants. On top of that, as technology continues to advance, the situation is expected to intensify. According to Cisco, by 2020, over 50 billion IoT devices are predicted to be connected to the Internet. While this technological boom brings new opportunities, it also introduces significant concerns regarding energy consumption. Managing energy efficiently, especially for IoT devices, is essential to sustain the vision of smart cities in an eco-friendly manner [10].

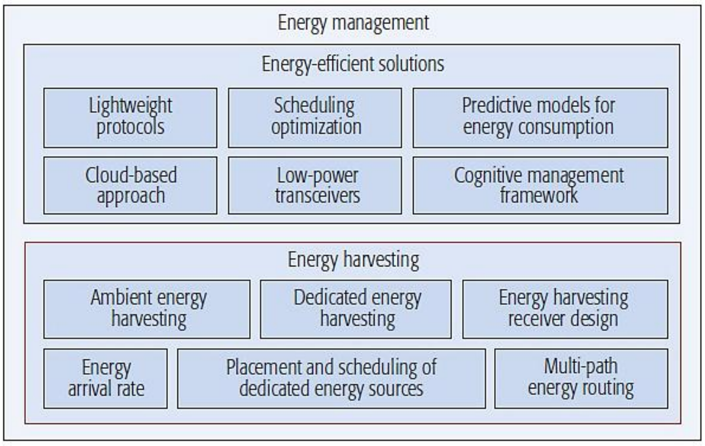


Fig. 2. Energy management areas in smart cities: home appliances, education & healthcare, transportation, and food industry.

There are several areas where energy consumption can be effectively managed, leading to substantial savings and environmental benefits:

I. Home appliances: they are among the most significant contributors to energy consumption in smart cities. Effective demand management is crucial to customizing energy usage by optimizing the operation of household lighting, cooling, and heating systems. Additionally, intelligent systems can help manage these activities efficiently, resulting in additional energy savings without compromising comfort.

II. Education and healthcare: both are vital services that are difficult to dematerialize completely. However, remote services can still reduce energy consumption in these areas. For example, remote healthcare using sensors and mobile devices can enable monitoring without requiring patients to physically visit healthcare centers, reducing energy use and resource demand. Similarly, distance education allows students to learn from home, reducing the energy typically used in physical classrooms.

III. Transportation is another significant energy-consuming sector in smart cities. It includes public transportation, personal vehicles for commuting, and leisure travel. In addition to consuming large amounts of energy, transportation also contributes significantly to pollution in urban environments. However, by employing IoT-enabled solutions such as smart traffic management, congestion control, and smart parking systems, cities can significantly reduce energy consumption and CO2 emissions. These systems ensure traffic flows more smoothly, reducing the time vehicles spend idling and the unnecessary fuel they burn.

IV. Food industry: energy consumption isn't limited to food storage and preparation. It also includes the energy used by people moving around cities in search of food, such as dining at restaurants. By using IoT solutions, cities can help people make more energy-efficient choices about food availability, ensuring that energy isn't wasted on unnecessary travel. Furthermore, food transportation can be optimized through intelligent logistics, making deliveries more energy-efficient [1], [9].

Although IoT devices play a key role in smart city infrastructure, they come with certain limitations. Batteries typically power these devices and have limited storage capacity, making it difficult to maintain network connectivity over long periods. To address this, an optimized energy-efficient framework is crucial. Such a framework not only reduces energy consumption but also ensures that the Quality of Service (QoS) for essential applications is maintained at an acceptable level [11].

A standard optimization framework for IoT-enabled smart cities outlines key objectives, problem types, and corresponding optimization techniques to improve energy consumption management. For example, one approach to reducing energy consumption is to minimize electricity costs, as explored in previous studies. Some researchers have developed optimization-based schemes for residential energy management, focusing on how appliances can be managed to reduce energy use. These strategies often yield complex mathematical problems, such as mixed-integer combinatorial problems, which can be transformed into more manageable forms, such as convex programming problems. The goal of such frameworks is to minimize costs while maintaining user satisfaction [4], [9].

In another example, researchers have focused on developing energy-aware and QoS-aware service selection algorithms for IoT environments. The objective here is to reduce energy consumption without compromising the required QoS. This approach can be applied to various IoT applications, ensuring energy is used wisely while meeting performance expectations [9].

Other solutions for managing energy in smart city networks involve various techniques, as shown. These include:

I. Energy-efficient solutions, such as energy harvesting and lightweight protocols.

II. Optimization of scheduling and the use of low-power transceivers.

III. Energy-harvesting approaches that tap both ambient and dedicated energy sources.

IV. Predictive energy consumption models enable cities to anticipate and adjust energy use in real time.

By incorporating these solutions, cities can significantly enhance the sustainability of their IoT networks. The goal is to minimize energy use while ensuring that essential services remain uninterrupted and that smart cities' overall quality of life continues to improve [1], [12].

3 | Literature Review

According to Yusoff et al. [13], Street Lighting (SL) is one of the major energy-consuming systems that plays an important role in daily life. Traditional Street Lighting Systems (SLS) rely heavily on human operation and often waste significant energy, as they are left on from dusk until dawn even when not needed. These manual systems consume excessive energy and involve high installation costs and ongoing operational concerns. In their study, Yusoff et al. [13] propose a solution to reduce overall energy consumption by up to 42% through regular maintenance and smarter operation. By using an energy-efficient system that automatically controls street lights—turning them on or off based on the presence of people or vehicles and gradually dimming them when not needed—energy costs can be lowered by as much as 35%. This smart SLS setup includes various sensors and controllers working together to form an intelligent system, addressing the shortcomings of traditional lighting systems [14].

Singh et al. [15] provide a broad overview of energy management challenges in smart cities and propose a deep learning approach to improve energy efficiency through IoT-based sensors. Their research used a combined cycle power plant dataset with over 47,840 data points to train and test deep learning models for estimating electrical energy production. Their method showed great promise, achieving an accuracy rate of 98.6%, surpassing previous techniques in the same field. The effectiveness of their model was validated using simulation data, demonstrating the potential of deep learning to predict and optimize energy use in smart cities.

Dutta et al. [16] present an innovative approach to energy optimization in Wireless Sensor Networks (WSN) for smart city applications. Their hybridized IoT-assisted hierarchical computation and Dynamic stochastic optimization techniques help optimize energy consumption by monitoring and tracking various city operations. Using the K-means algorithm and cluster head selection to extend the network's lifetime and enhance energy efficiency, they reduced maintenance costs, lowered environmental impacts, and improved energy management compared to traditional approaches [17].

Humayun et al. [18] offer a multi-objective optimization strategy designed to improve energy efficiency in public buildings while managing maintenance costs and ensuring comfort. Their approach involves developing an algorithm to generate optimal energy plans for building portfolios, specifically for public buildings in Bari, Italy. The results showed that the algorithm is a valuable tool for city administrations to manage and enhance energy efficiency within public infrastructure.

Bachanek et al. [19] introduced the Traffic Adaptive Control (TAC) system, an energy-efficient solution for intelligent SL. This system optimizes energy use in smart lighting and can even integrate with smart grid architectures to minimize electricity consumption. The study highlights how ZigBee mesh WSNs facilitate adaptive traffic control, helping reduce energy consumption through smart electrical control systems for street lights.

Singh et al. [15] emphasize the critical role SL plays in ensuring public safety and fostering a sense of security in urban areas. However, SL can also be a significant financial burden on local governments. Their study outlines how recent advancements in lighting technology—such as low-cost LED lights combined with wireless communication technology and sensors—can drastically reduce energy consumption. A case study from Nagpur Smart City demonstrates the effectiveness of these innovations. By replacing outdated street lights with 320 energy-efficient LEDs and adding 63 smart lights with motion detection, the city reduced monthly energy consumption by 55% while maintaining adequate lighting for pedestrians and vehicles.

These studies offer valuable insights into various aspects of energy optimization for smart cities. However, many of these solutions focus on specific domains, such as SL, power plants, or home appliances. There's a clear need for a more comprehensive energy optimization strategy encompassing multiple areas, including power plants, street lights, billboards, smart home devices, and more [18], [20].

4 | Proposed Approach

This section introduces a green energy model to tackle energy-related issues in smart homes and cities. The model is illustrated in *Fig. 3*, and its main components are detailed below.

According to this model, SL and billboards are significant energy consumers. The model suggests two types of controllers to manage them. The first is a smart scheduling system, a conventional method that automates the operation of SL and billboards by turning them on at dusk and off in the early morning. The second is a real-time control system, which reduces energy consumption.

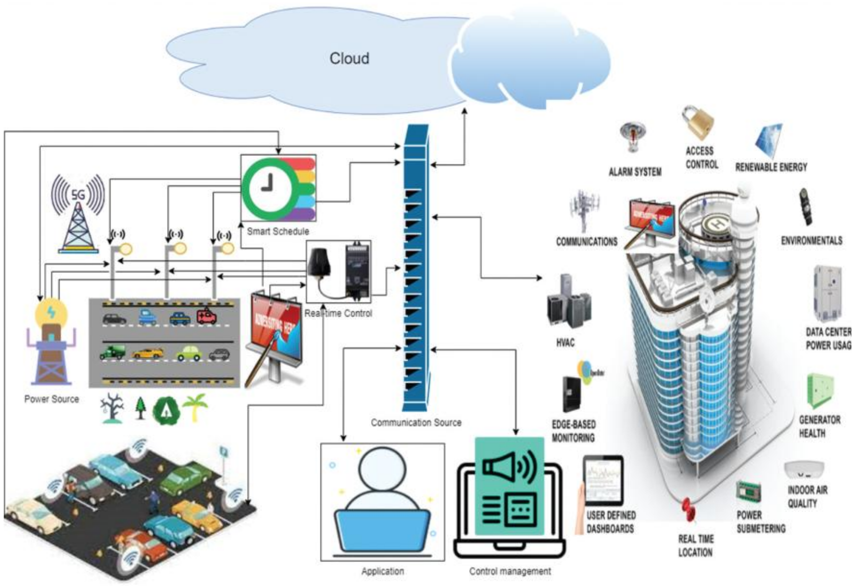


Fig. 3. The proposed green energy model.

SL and billboards are activated only when human or vehicle movement is detected. This real-time controller uses IoT technology and connects to SL, signboards, and smart parking systems. It gathers data from these devices and transmits it to the cloud via a 5G communication network. If any electrical devices malfunction, the control management system receives an alert from the cloud and takes appropriate corrective action [18].

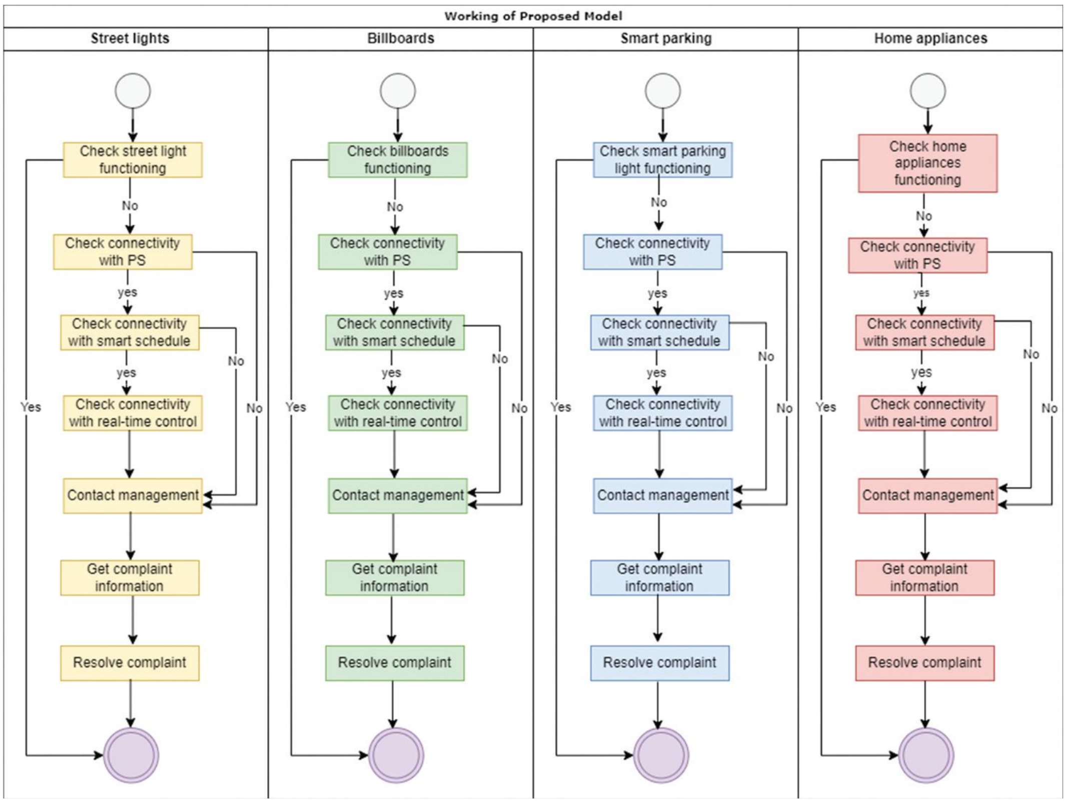


Fig. 4. IoT- and 5G-based smart city energy optimization model integrating cloud, smart lighting, signboards, parking, and home appliances.

The model also focuses on optimizing internal energy use in smart homes, which often consume large amounts of energy through various devices. The model proposes connecting household appliances to IoT-based sensors to increase energy efficiency. These sensors detect motion and use AI to make decisions based on predefined instructions. For example, when appliances are not in use, the IoT sensors automatically switch them to sleep mode, thus conserving energy. In the event of any malfunction, the system will notify the user via a dashboard using a cloud-based communication channel [21].

This proposed model integrates IoT, cloud computing, and 5G technologies to maximize energy savings. IoT sensors will be installed in all electric devices throughout the smart city, including street lights, billboards, smart parking systems, and household appliances. These sensors detect motion or execute specific commands, like turning on lights when a person enters a room. The 5G network will enable fast data transmission between communication channels and the cloud [22], where data will be stored and retrieved efficiently. The communication hub will serve as a central node, connecting control management, real-time control systems, smart scheduling, smart homes, and the cloud.

The troubleshooting process is also a key feature of the model. If any part of the system malfunctions, the communication hub detects the issue and triggers the necessary actions to fix it.

The model operates across four main areas of the smart city: smart homes, smart parking, SL, and building billboards. Each area is equipped with intelligent motion detection sensors. For example, street lights and billboards will only turn on when nearby movement is detected, thus saving energy. Similarly, household appliances such as Air Conditioners (ACs) and lights will use sensors to respond to a person's presence. These intelligent sensors can also anticipate needs, such as turning on the AC before a person enters a room to ensure a comfortable temperature.

The proposed algorithm outlines the complete operation of this model. It efficiently manages the smart city's energy consumption, ensuring that energy is used only when needed, reducing waste, and lowering energy costs.

5 | Methodology

Implementing energy-efficient systems in smart cities using ML is a well-structured approach that involves several steps. It begins by collecting energy consumption data from sources such as smart meters, sensors, and IoT devices. After data collection, it is necessary to clean and pre-process the data to eliminate inconsistencies, errors, or outliers. This step is vital to ensure the data is accurate and ready for training ML models.

The next step is feature engineering, where relevant features such as time of day, weather conditions, and occupancy patterns are selected from the processed data. Afterward, ML models, such as Support Vector Machines (SVMs), are developed to predict energy consumption patterns.

Once developed, these models are trained using historical data to improve their accuracy and reliability. During training, the model's parameters are adjusted to reduce the error between predicted and actual energy consumption. After training, the models are evaluated using metrics like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to assess their performance.

After evaluation, the models are used to optimize the energy infrastructure. This optimization process involves adjusting the energy supply and demand to reduce energy consumption and costs. The process can be automated, allowing the models to continually improve by learning from new data.

Finally, once the models are optimized, they are deployed in real-world settings to optimize energy use and minimize costs in smart cities.

The methodology includes several steps: data collection, pre-processing, feature engineering, model development, training, evaluation, energy infrastructure optimization, and deployment. This approach enables smart cities to manage energy consumption and reduce costs efficiently, thereby fostering more sustainable urban environments.

A commonly used ML technique, SVM, is applied to optimize energy infrastructure in smart cities. SVM uses a non-linear method to classify data by transforming the input into a high-dimensional feature space. The following equations are used in SVM-based energy infrastructure optimization [23]:

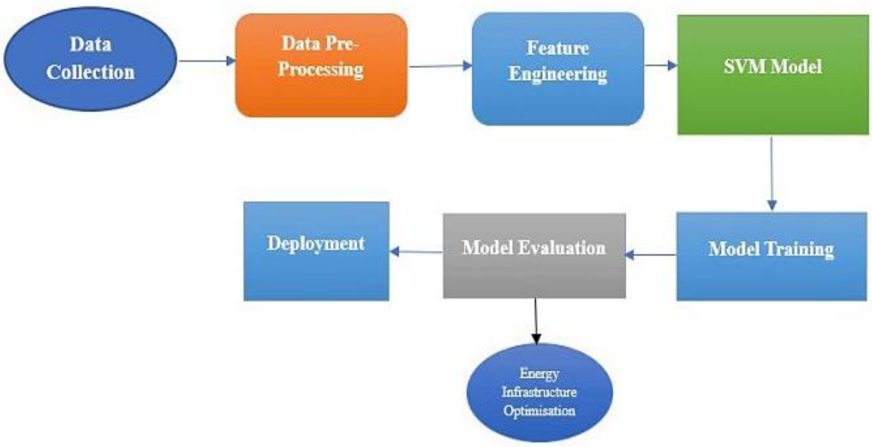


Fig. 5. SVM-based machine learning framework for smart city energy infrastructure optimization.

The decision function is:

f(x) = \text{sign}(w^T x + b),

where:

I. x is the input data vector,

II. w is the weight vector,

III. b is the bias term,

IV. and "sign" returns the sign of the output.

The optimization problem is:

$$\text{Min } 0.5 \,||\, w \,||\, 2 + C\sum \xi i.$$

Subject to:

$$yi(wTxi + b) \geq 1 - \xi i,\ \xi i \geq 0,$$

where:

I. ||w||^2 is the regularization term,

II. c is a penalty parameter balancing margin maximization and classification error minimization,

III. ξi\xi_iξi is the slack variable allowing for misclassifications,

IV. yi is the class label (+1 or -1),

V. xi is the input data vector.

6 | Results and Discussions

The results and discussion section of a study on implementing efficient energy use in smart cities using ML presents and interprets the results from the developed ML models. This section highlights the models' performance in optimizing energy consumption and reducing energy costs. The results and discussions section aims to answer the research questions posed at the beginning of the study and provide insights into the effectiveness of the developed models. This section presents and analyses the study's findings before discussing its research questions. The section can also highlight the strengths and limitations of the methodology used and provide suggestions for future research in the field. The results and discussion section is an essential part of the study, as it provides evidence to support its claims and contributes to the body of knowledge on ML-based energy infrastructure optimization in smart cities. The session length prediction method was also applied here. The SVM design, which included two hidden layers with 64 and 16 nodes each, was the lone exception. The number of epochs was set to 20, and the training batch size was 64.

Acknowledgments enable you to thank all those who have helped carry out the research. Careful thought needs to be given to who should be acknowledged and in what order. The general advice is to express your appreciation concisely and avoid strong emotive language.

7 | Conclusion

In conclusion, implementing efficient energy usage in smart cities using ML algorithms can lead to significant cost savings and reduced greenhouse gas emissions. In this study, we presented a methodology for optimizing energy consumption using SVM and a dataset of energy consumption patterns in smart cities. Our results showed that the SVM algorithm achieved high accuracy in predicting energy consumption patterns, and the optimization model successfully reduced energy costs and improved energy efficiency. The study demonstrated the importance of using ML algorithms to optimize energy infrastructure in smart cities, resulting in significant cost savings and environmental benefits. However, our study has some limitations that must be addressed in future research. One limitation is the availability of high-quality data, which can significantly affect the performance of ML algorithms. Another limitation is the need to consider other factors affecting energy consumption, such as social and economic factors. Our study contributes to the growing body of research on implementing efficient energy use in smart cities using ML algorithms. The study's findings can be useful for policymakers and urban planners in making informed decisions regarding energy infrastructure planning and management in smart cities.

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Data Availability

All data are included in the text.

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

These sections should be tailored to reflect specific details and contributions if necessary.

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