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# Efficient Usage of Energy Infrastructure in Smart City Using Machine Learning

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## Abstract

The concept of smart cities revolves around utilizing modern technologies to manage and optimize city operations, including energy infrastructure. One of the biggest problems that smart cities have to deal with is ensuring the efficient usage of energy infrastructure to reduce energy consumption, cost, and environmental impact. Machine learning is a powerful tool that can be utilized to optimize energy usage in smart cities. This paper proposes a framework for efficient usage of energy machine learning for city infrastructure in smart cities. The proposed framework includes three main components: data collection, machine learning model development, and energy infrastructure optimization. The data collection component involves collecting energy consumption data from various sources, such as smart meters, sensors, and other IoT devices. The collected data is then pre-processed and cleaned to remove any inconsistencies or errors. The machine learning model development component involves developing machine learning models to predict energy consumption and optimize energy usage. The models can be developed using various techniques such as regression, classification, clustering, and deep learning. These models can predict energy consumption patterns based on historical data, weather conditions, time of day, and other factors. The energy infrastructure optimization component involves utilizing the machine learning models to optimize energy usage. The optimization process involves adjusting energy supply and demand to reduce energy consumption and cost. The optimization process can be automated, and SVM based machine learning models can continuously enhance their precision over time by studying the data. The proposed framework has several benefits, including reducing energy consumption, cost, and environmental impact. It can also improve the reliability and stability of energy infrastructure, reduce the risk of blackouts, and improve the overall quality of life in highly developed urban areas. Last but not least, the projected framework for efficient usage of energy machine learning for city infrastructure in smart cities is a promising solution to optimize energy usage and reduce energy consumption and cost. The framework can be implemented in various smart city applications, including buildings, transportation, and industrial processes.

**Keywords:** Smart cities, Energy consumption, Cost efficient, Machine Learning

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## 1. Introduction:

Smart city infrastructure is important because it provides the backbone for modern city operations and improves the quality of life for citizens. Smart city infrastructure includes a wide range of technologies, such as IoT devices, sensors, cloud computing, AI, and machine learning, which are used to enhance the efficiency and effectiveness of city operations. Smart city infrastructure enables cities to collect and analyse real-time information on city operations such as traffic, air pollution, energy use, garbage disposal, and public safety. This data can be used to make informed decisions, optimize city operations, and improve the quality of life for citizens. For example, smart city infrastructure can be used to reduce traffic congestion by using real-time traffic data to optimize traffic flow. It can also be used to improve public safety by using sensors and AI to detect and respond to emergencies quickly. Smart city infrastructure can also help cities become more sustainable by reducing energy consumption, carbon emissions, and waste. This is achieved through the use of smart grids, energy-efficient buildings, and waste management systems that use real-time data to optimize operations and reduce resource consumption.

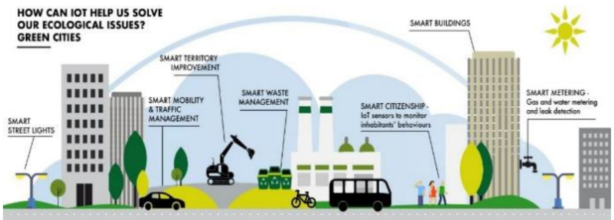


**Figure 1**. Smart city Infrastructure
Source: BBN Times

Overall, smart city infrastructure is critical for the sustainable and efficient operation of modern cities. It provides cities with the tools and technologies needed so that people might have a better standard of living, optimize operations, and create a more sustainable future. The implementation of energy consumption using smart city concepts involves the integration of various technologies and solutions to optimize energy usage and reduce energy consumption, cost, and environmental impact. Here are some examples of how smart city concepts can be implemented for energy consumption:

***Smart Meters:*** Smart meters can be installed in buildings to monitor energy usage and collect real-time data on energy consumption. This data can be used to identify areas where energy is being wasted and implement energy-saving measures.

***Energy-efficient Buildings:*** Smart city concepts can be used to design and construct energy-efficient buildings that use natural lighting, ventilation, and energy-efficient appliances. Smart building automation systems can be used to control energy usage and optimize energy consumption.

***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.

***Renewable Energy:*** Smart city concepts can be used to implement energy that can be replenished naturally, like sun, wind, and geothermal energy, as a means of cutting down on carbon emissions and decreasing dependency on fossil fuels.

***Energy Storage:*** Batteries and other energy storage devices and surplus energy from renewable sources may be stored and used later by using flywheels. it when needed. This can help reduce energy waste and improve the efficiency of energy usage.

***Machine Learning:*** Energy forecasting using machine learning methods consumption patterns and reduce energy waste. These algorithms can learn from real-time data and adjust energy supply and demand to reduce energy consumption and cost.

Overall, the implementation of energy consumption using smart city concepts requires the integration of various technologies and solutions to optimize energy usage and reduce energy consumption, cost, and environmental impact. Smart city concepts can be applied to buildings, transportation, industrial processes, and other areas of city operations to create a more sustainable and efficient city. Energy infrastructure is a critical component of smart cities, as it accounts for a significant portion of the city's carbon footprint and energy costs. Therefore, optimizing energy usage in smart cities is a major challenge to reduce energy consumption, cost, and environmental impact.

Machine learning is a powerful tool that can be used to optimize energy usage in smart cities. Machine learning models can predict energy consumption patterns based on historical data, weather conditions, time of day, and other factors. These models can then be used to optimize energy supply and demand to reduce energy consumption and cost. The proposed framework for efficient usage of energy machine learning for city infrastructure in smart cities includes three main components: data collection, machine learning model development, and energy infrastructure optimization. The data collection component involves collecting energy consumption data from various sources, such as smart meters, sensors, and other IoT devices. The collected data is then pre-processed and cleaned to remove any inconsistencies or errors.

The machine learning model development component involves developing machine learning models to predict energy consumption and optimize energy usage.

The models can be developed using various techniques such as regression, classification, clustering, and deep learning. These models can predict energy consumption patterns based on historical data, weather conditions, time of day, and other factors.

The energy infrastructure optimization component involves utilizing the machine learning models to optimize energy usage. The optimization process involves adjusting energy supply and demand to reduce energy consumption and cost. The optimization process can be automated, and the machine learning models can continuously enhance their precision over time by studying the data.

Overall, the proposed framework for efficient usage of energy machine learning for city infrastructure in smart cities is a promising solution to optimize energy usage and reduce energy consumption and cost. The framework can be implemented in various smart city applications, including buildings, transportation, and industrial processes. The benefits of the framework include reducing energy consumption, cost, and environmental impact, improving the reliability and stability of energy infrastructure, reducing the risk of blackouts, and improving the overall quality of life in smart cities.

## 2.Related Study:

As a result of the onset of the 4th Industrial Revolution and advances in Internet and telephone systems, the 21st century is undergoing profound and rapid transformations. Current city plans are transforming into "smart cities." as a result of this transition. Smart cities are sustainable communities that address pressing urban issues head-on by integrating information and communication convergence technology with eco-friendly technologies into everyday urban life. Energy is fundamental to urban life, and an IoT-based platform makes it possible to control energy systems effectively. The Internet of Things is a data-transfer system in which sensors are embedded in everyday items and communicate with one another across a network. As the Internet of Things grows and is used in more sectors, it is important that those resources be used wisely. In this work, we apply machine learning techniques to make predictions about how the smart city's energy infrastructure will be utilized. The suggested approach estimates the smart city's energy efficiency and enhances resource usage to construct the ideal smart city.[1]

Energy is a crucial urban resource, but it is also a major contributor to global warming. Energy management may be improved by incorporating the smart grid concept into the conventional method of distributing power through a power grid. The primary method for managing the power grid's collection, monitoring, and control is through the Internet of Energy (IoE). Machine learning (ML) is the method for maximizing productivity and minimizing waste in the realm of energy consumption. This paper summarizes the findings of previous research on the integration to ML in IoE the electrical smart grid as a stepping stone. The city of Batman is used as an example to illustrate the point.[2]

As the need for electricity in intelligent microgrids rises, the study of P2P electricity trading is expected to play an increasingly important role. However, it's difficult for households to save money because of their need for energy on demand. Supporting dispersed continuous monitoring of electricity resources in real time, producing timing is the focus of this paper, which introduces A Predictive Trading Algorithm Based on Machine Learning system. In addition, this article suggests the energy optimization technique for application in machine learning (EOA-ML). The platform's predictive analytical components were developed using machine learning, and it recommended two modules: fuel trading and intelligent contracts. The blockchain component enables decentralized energy monitoring in real time, peer-to-peer electricity trading, incentive modeling, and permanent transaction records. The intelligent contracts include a predictive analytic component that is meant to forecast short-term energy demand based on historical power usage data. Information about actual energy use was gathered from the electrical department of Jeju, a Korean province. The goal of this research is to identify the conditions under which power may most efficiently flow between consumers and prosumers through the use of crowdsourcing. To meet the needs of smart grids, the trading of power is dependent regular basis, realistic ecological management and the strategic positioning of power nodes. In addition, it makes use of data mining tools to collect and analyze historical power consumption time-series research. To ensure more effective and efficient planning and management of energy supply in the future, time series analytics encourage power control. The latency, throughput, and resource requirements of the proposed system utilization are demonstrated while employing a hyperleader calliper, and the efficacy of the suggested prediction model is evaluated using a variety of statistical methods. Finally, the proposed method is doing well implemented crowdsourcing to increase productivity consumer, Client, in order to achieve dependability of service in light of trial results. There is now a 95% confidence interval between the expected and actual costs. As a result of the increased efficiency, the delay rate is reduced to 40.3%. [3]

Electric vehicles (EVs) are rapidly gaining popularity as a fundamental component of smart mobility in smart city applications due to their ability to help lower greenhouse gas emissions. However, the strain on power grid infrastructure from widespread EV deployment is one of the biggest obstacles. Using intelligent scheduling algorithms is the answer to keeping up with the rising public charging demand. Scheduling algorithms can be improved by analysing EV charging habits with data-driven tools and ML approaches. Predicting behavior, such as departure time and energy demands, has been a major focus of research on the use of past charging data. Weather, traffic, and surrounding events are all factors that have been mostly ignored but that might potentially improve representations and forecasts. This study proposes a method for predicting Time spent using an EV and energy expended utilising common Learning Machines techniques, with the likes of XGBoost, deep neural networks, and random forests, by combining such data with weather, traffic, and event records. Average SMAPE scores for sessions 9.9 and 11.6 time & power use Interchangeable, are attained via an ensemble learning model, which outperforms previous efforts in the literature. We show substantial improvement over prior interact with the same data collection in both predictions and emphasize the significance information about traffic and the weather in making predictions about pricing behavior [4].

"Smart cities" aim to alleviate the stresses of increasing urbanization by reducing energy consumption, preserving natural resources, stimulating regional commerce, and inhabitants' standard of living, and increasing access to and use of innovative forms of communication and computing. Policymaking, decisionmaking, plan implementation, and the provision of beneficial services are all made possible by ICT in "smart" cities. The fundamental purpose of this research is to examine the functions played by AI and ML. AI technologies like supervised and unsupervised deep reinforcement learning are two types of education technology. All of these techniques can be applied to the challenge of creating optimal rules for a smart city. This article goes into depth on the topics of "smart" transportation, "cyber-security," "energy-efficient usage of smart grids (SG)," and "efficient use of unmanned aerial vehicles (UAVs) to guarantee the best 5G and beyond 5G (B5G) communications," additionally "smart" health monitoring. Finally, we talk about the remaining research obstacles and possible future research routes that might bring the "smart city" concept closer to reality [5].

Ghosh et al.'s 2023 study focuses on "Water Quality Assessment Through Predictive Machine [6] Learning", highlighting the use of machine learning for analyzing and predicting water quality parameters. In "Unraveling the Heterogeneity of Lower-Grade Gliomas," Rahat, Ghosh, and colleagues (2023) delve [7] into deep learning-assisted segmentation and genomic analysis of brain MR images, offering new insights into this medical condition. Potato Leaf Disease Recognition and Prediction [8] using Convolutional Neural Networks," by Ghosh, Rahat, and team (2023), showcases the application of convolutional neural networks in accurately identifying diseases in potato leaves. Mandava, Vinta, Ghosh,[9] and Rahat's 2023 research presents "An All-Inclusive Machine Learning and Deep Learning Method for Forecasting Cardiovascular Disease in Bangladeshi Population", integrating advanced AI techniques for health predictions. The 2023 study by Mandava [10] et al., titled "Identification and Categorization of Yellow Rust Infection in Wheat through Deep Learning Techniques", applies deep learning methods to detect and categorize wheat infections effectively. Khasim, Rahat, Ghosh,[11] and colleagues' 2023 article, "Using Deep Learning and Machine Learning: Real-Time Discernment and Diagnostics of Rice-Leaf Diseases in Bangladesh", explores AI-based solutions for diagnosing rice-leaf diseases. Deciphering Microorganisms through Intelligent Image Recognition", authored by Khasim, Ghosh, Rahat, and others in 2023, discusses [12] the use of machine learning and deep learning in identifying microorganisms through advanced image recognition techniques. The 2023 study by Mohanty, Ghosh, Rahat, and Reddy,[13] "Advanced Deep Learning Models for Corn Leaf Disease Classification", focuses on the application of deep learning in classifying diseases in corn leaves based on a field study. Alenezi and team's 2021 research, "Block-Greedy and CNN Based Underwater [14] Image Dehazing for Novel Depth Estimation and Optimal Ambient Light", investigates novel CNN-based methods for enhancing underwater image clarity and depth estimation.

## 3. Methodology:

The methodology for implementing efficient energy usage in smart cities using machine learning is a structured approach that outlines the steps involved in developing and deploying machine learning models to optimize energy consumption in smart cities. The methodology involves collecting energy consumption data from various sources, pre-processing the data to remove inconsistencies and errors, developing machine learning models to predict energy consumption patterns, training and evaluating the models, optimizing energy infrastructure, and deploying the models in real-world applications.

The methodology for implementing efficient energy usage in smart cities using machine learning involves several steps. Here is a detailed overview of the methodology:

***Data Collection:*** The first order of business is to amass energy consumption information gathered from a number of sources, such as smart metres, sensors, and other IoT devices. The data should be collected over a period of time to get a comprehensive view of energy consumption patterns.

***Data Pre-processing:*** The collected data needs to be cleaned, normalised, and pre-processed to remove any inconsistencies, errors, or outliers. This step is critical to ensuring that the data is accurate and can be used to train machine learning models.

***Feature Engineering:*** Feature engineering involves selecting and extracting relevant features from the pre-processed data. Relevant features may include time of day, weather conditions, and occupancy patterns.

***Model Development:*** Once the data is pre-processed and features are selected, SVM machine learning models can be developed to predict energy consumption patterns.

***Model Training:*** The developed machine learning models need to be trained using historical data to improve their accuracy and reliability. As part of the training process, the models using past information and a little tweaking of the model parameters minimise the error between predicted and actual energy consumption.

***Model Evaluation:*** After training, the models need to be evaluated to determine their accuracy and reliability. The models can be evaluated using a number of measures include RMSE and MAE (mean absolute error).

***Energy Infrastructure Optimisation:*** Once the machine learning models are trained and evaluated, they can be used to optimise energy usage in smart cities. The optimisation process involves adjusting energy supply and demand to reduce energy consumption and costs. The optimisation process can be automated, and the machine learning models can continuously enhance their precision over time by studying the data.

***Deployment:*** Once the models are trained, evaluated, and optimised, they can be deployed in real-world applications to optimise energy usage and reduce energy consumption and costs in smart cities.

Overall, the methodology for implementing efficient energy usage in smart cities using machine learning involves several steps, Feature engineering, model building, data collecting, and preprocessing development, model Instruction and Model Assessment, energy infrastructure optimisation, and deployment. By following this methodology, smart cities can optimise energy usage and reduce energy consumption and costs, resulting in a more sustainable and efficient city.

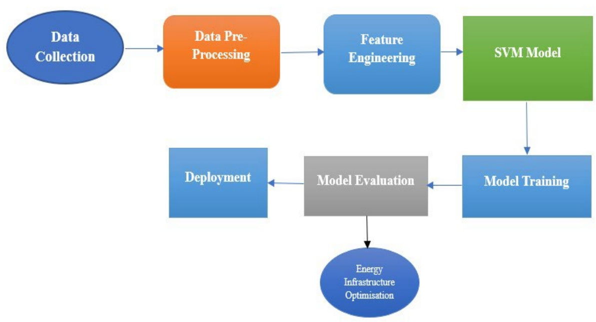


**Figure 2.** Proposed System Architecture

The widely used machine learning method known as a support vector machine (SVM) may be put to work in a variety of energy infrastructure optimisation in smart cities. SVM uses a non-linear approach to classify data by mapping input data into a high-dimensional feature space. The following equations are used for SVM-based energy infrastructure optimisation in smart cities:

$$f(x) = sign(w^T x + b) \text{ –(1)}$$

Where,

- x is the input data vector.
- w is the weight vector.
- b is the bias term.
- sign is the sign function that returns the sign of the output.

$$min\ 0.5||w||^2 + C\, \Sigma\, \xi$$

$$s.t. y\_i(w^T x\_i + b) \geq 1 - \xi\_i, \xi\_i \geq 0 \text{ -(2)}$$

Where,

- ||w||2 is the regularisation term.
- C is the penalty parameter that controls the trade-off between maximising the margin and minimising the classification error.
- _i is the slack variable that allows some misclassification errors.
- y_i is the class label (+1 or -1).
- x_i is the input data vector.

## 4. Results and Discussions:

The results and discussions section of a study on implementing efficient energy usage in smart cities using machine learning involves presenting and interpreting the results obtained from the developed machine learning models. This section highlights the performance of the models in optimising 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 them in relation to the study's 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 discussions section is an essential part of the study as it provides evidence to support the study's claims and contributes to the body of knowledge on energy infrastructure optimisation in smart cities using machine learning.

The session length prediction method was also applied here. The SVM design, which in this case 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. The training phase's loss curve is shown in Appendix 2. The 10-fold cross-validation results on the training set are listed in Table 1.

**Table 1:** Scores obtained during Training for Energy Consumptions

| Models | RMSE (kWh) | MAE (kWh) | $R^2$ | SMAPE |
|---|---|---|---|---|
| Random Forest | 6.54 | 4.74 | 0.79 | 12.3 |
| XG Boost | 6.65 | 4.85 | 0.72 | 12.4 |
| ANN | 6.57 | 4.73 | 0.78 | 12.7 |
| LSTM | 6.85 | 4.77 | 0.74 | 12.9 |
| Support Vector Machine | 6.49 | 4.69 | 0.68 | 11.6 |

In contrast to the other three models, RF gets the highest cross-validation results. To create the two ensemble models, we chose the top two models, RF and XGBoost. In this instance, the ensemble models produced identical training outcomes rather than outperforming the top RF model.

Table:1, shows the scores obtained during the training of Energy consumptions. Here the RMSE refers to the Root mean square Error and MAE refers to the Mean Absolute Error. Random Forest method gives 6.54kWh, XG Boost gives 6.65kWh, Artificial Neural Network based training gives 6.57 kWh, LSTM based training receives 6.85 and finally our proposed method Support Vector Machine gives 6.49kWh. With respect to the Mean Absolute Error Random Forest gives 4.74 kWh, XG Boost gives 4.85 kWh, ANN based training gives 4.73 kWh, LSTM based training gives 4.77 kWh and finally our proposed Method SVM based training receives 4.69 kWh. The $R^2$ based score for Random Forest is .79, where XG Boost is 0.72, ANN gives 0.78, LSTM gives 0.74 and finally our proposed Method Support Vector Machine is 0.68. Finally, the SAMPE is shown in (%), where Random Forest gives 12.3%, XG Boost gives 12.4%, ANN gives 12.7%, LSTM gives 12.9% and finally SVM gives 11.6%.

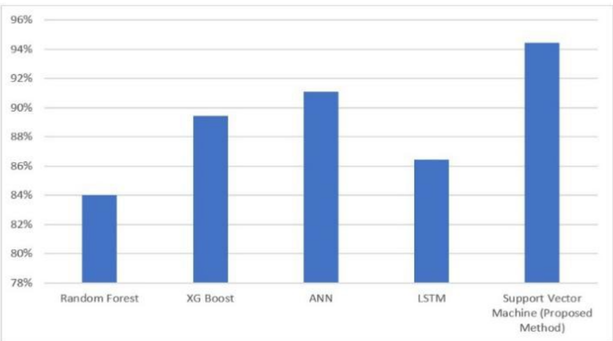


**Figure 3**. Accuracy Comparison Graph

Figure 4.1 shows the accuracy compression between the Proposed method with the existing. Here the Random Forest give the 84% of accuracy, XG Boost gives 89.5% of accuracy, ANN based approach gives 91.4% of accuracy and LSTM gives 87.1% of accuracy and Finally our Support Vector Machine gives the 95.1% of accuracy. These accuracy rate helps to implement for efficient energy consumption.

## 5. Conclusion:

In conclusion, the implementation of efficient energy usage in smart cities using machine learning algorithms can lead to significant cost savings and a reduction in greenhouse gas emissions. In this study, we presented a methodology for optimising energy consumption using support vector machines (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 optimisation model was successful in reducing energy costs and improving energy efficiency. The study demonstrated the importance of using machine learning algorithms for energy infrastructure optimisation in smart cities, as it can lead to significant cost savings and environmental benefits.

However, there are some limitations to our study that need to be addressed in future research. One limitation is the availability of high-quality data, as this can significantly affect the performance of machine learning algorithms. Another limitation is the need to consider other factors that may affect energy consumption, such as social and economic factors. In summary, our study contributes to the growing body of research on implementing efficient energy usage in smart cities using machine learning algorithms. The findings of the study 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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