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Research Paper

DEEP ENERGY OPTIMIZER: CNN-BASED PREDICTION AND MANAGEMENT OF POWER CONSUMPTION IN SMART RESIDENTIAL ENVIRONMENTS

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ABSTRACT

Modern smart homes, integrated with various sensors and automated systems, offer significant potential for enhancing energy efficiency while maintaining occupant comfort. Studies reveal that smart homes contribute to around 40% of overall residential energy consumption, with intelligent optimization enabling up to 30% in potential energy savings. Despite this, over 60% of smart homes still rely on manual energy control methods, leading to inefficient energy usage. This underscores the need for automated, data-driven solutions for energy optimization. Traditional approaches such as manual scheduling, rule-based logic, and simple models like Decision Tree Regression (DTR) struggle to handle the complex, nonlinear nature of energy consumption patterns and often lack adaptability to real-time changes. To overcome these limitations, we propose a hybrid deep learning-based Smart Home Energy Optimizer that combines Convolutional Neural Networks (CNNs) for advanced feature extraction with a Random Forest Regressor for accurate energy usage prediction and optimization. The dataset undergoes thorough pre-processing, including normalization, outlier removal, and feature encoding, followed by a train-test split for performance evaluation. While CNNs are leveraged to capture temporal and spatial patterns in energy consumption, the Random Forest model provides strong generalization and robust regression capabilities. The proposed system is evaluated using standard performance metrics accuracy, precision, recall, and F1-score showing notable improvements compared to baseline methods. This intelligent solution ensures efficient power allocation, real-time responsiveness, and substantial energy savings in modern smart home environments.

Keywords: Smart Home Energy Optimization, Sensor Data, Energy Efficiency, Convolutional Neural Network.

1. INTRODUCTION

The global demand for energy is escalating rapidly, with residential buildings contributing to over 40% of the world's total energy consumption. According to the International Energy Agency (IEA), nearly 30% of this energy is wasted due to inefficient usage, lack of automation, and poor demand-side management. With increasing urbanization and the proliferation of smart devices, energy usage patterns are becoming more complex and harder to manage manually. As smart homes continue to evolve, the need for intelligent systems that can monitor and interpret energy data becomes more vital to minimize waste and improve sustainability.

Smart homes are equipped with a variety of Internet of Things (IoT) devices such as smart meters, HVAC systems, lighting, and kitchen appliances. These devices constantly generate large volumes of data, which, if analysed correctly, can reveal valuable insights into energy usage trends. For example, peak load times, idle energy consumption, and behavioural patterns of inhabitants can be detected through this data. However, most current energy management systems rely on rule-based or static configurations, making them incapable of adapting to real-time usage changes or learning from historical patterns.

As energy costs rise and environmental regulations become stricter, the need for smarter energy management within homes becomes more urgent. Governments and environmental agencies are increasingly promoting sustainable energy practices, offering incentives to consumers who adopt energy-efficient technologies. In this context, data-driven approaches can play a pivotal role by enabling predictive insights, automated control, and usage optimization, ultimately contributing to lower utility bills and reduced carbon footprints.

2. LITERATURE SURVEY

Severiche-Maury et. al. [1] presents a deep learning-based approach using Long Short-Term Memory (LSTM) recurrent neural networks to forecast residential energy consumption. Traditional methods, including linear regression and autoregressive models, often fail to capture complex temporal dependencies in energy usage. The proposed system employs two interconnected sub models—one predicting individual device consumption and usage time, while the other estimates total household energy consumption, allowing for a more precise forecast. The LSTM model demonstrates high accuracy, achieving mean squared error (MSE) values of 0.0163 for individual consumption and 0.0237 for overall household usage. By leveraging deep learning, this method improves energy consumption predictions, potentially enabling more efficient resource management in residential settings.

Khan et al. [2] explores heuristic-based optimization techniques (HOTs) to enhance smart home energy efficiency. Traditional energy management systems rely on predefined scheduling and rule-based automation, often failing to adapt dynamically to fluctuating energy demands. The proposed system integrates renewable and sustainable energy resources (RSERs) with energy storage systems (ESSs) while employing advanced heuristic algorithms such as Genetic Algorithm (GA), Binary Particle Swarm Optimization (BPSO), and Genetic Modified Particle Swarm Optimization (GmPSO) to optimize energy consumption. The research evaluates three real-world scenarios, demonstrating significant improvements in energy efficiency. For instance, the GmPSO algorithm reduced carbon emissions by 76.9%, electricity costs by 62.5%, and peak-to-average ratio (PAR) by 51.1%. These findings highlight the effectiveness of heuristic-based optimization in smart homes, paving the way for more adaptive and cost-efficient energy management solutions.

Arabasy et al. [3] examines the integration of machine learning (ML) in smart housing to enhance sustainable urban planning, interior design, and development. Traditional urban planning methods often struggle with optimizing resource management, waste disposal, and public safety due to static decision-making models. The proposed system leverages ML algorithms to analyze energy consumption, waste management, and environmental sustainability, enabling dynamic and adaptive solutions. The research demonstrates a 20% reduction in total energy consumption, a 15% increase in renewable energy usage, and a 25% improvement in waste management efficiency. Additionally, ML models significantly enhance public safety by reducing response times by 30%, while achieving an average accuracy of 92% in predicting power usage, traffic patterns, and air quality. These findings highlight the transformative potential of ML in smart housing, paving the way for more efficient and sustainable urban environments.

Mahendran et al. [4] explores the integration of IoT and blockchain with BiLSTM-RNN models to enhance smart home automation. Traditional systems rely on centralized architectures, which pose security risks and inefficiencies in managing energy consumption and device control. The proposed system leverages blockchain for decentralized security and BiLSTM-RNN for predictive automation, ensuring real-time optimization of smart home operations. By incorporating deep learning-based forecasting, the model improves energy efficiency and device scheduling. Experimental results demonstrate a 30% reduction in energy wastage, a 40% improvement in security authentication, and an accuracy rate of 94% in predicting user behavior and energy consumption patterns. These findings highlight the potential of combining IoT, blockchain, and deep learning to create more secure and efficient smart home environments.

Rojek et al. [5] explores the role of advanced deep learning algorithms in optimizing energy usage within smart cities. Traditional energy management systems rely on predefined models and historical data, often struggling to adapt to real-time fluctuations in energy demand. The proposed system integrates reinforcement learning, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) to analyze real-time data from IoT sensors, enabling dynamic load balancing and reducing energy waste. Additionally, generative adversarial networks (GANs) simulate energy usage scenarios for strategic planning, while federated learning ensures privacy-preserving data sharing across distributed energy systems. The study demonstrates significant improvements, with deep learning models achieving high accuracy in predicting energy demand and optimizing power distribution. These findings highlight the transformative potential of AI-driven energy management in creating more sustainable and efficient urban environments.

Chahardoli et al. [6] proposed an advanced approach to predicting energy consumption in smart cities using a CNN-LSTM network enhanced with game theory and the Namib Beetle Optimization (NBO) algorithm. Traditional energy forecasting models often struggle with imbalanced datasets and inaccurate predictions, limiting their effectiveness in real-world applications. The proposed system addresses these challenges by first balancing the dataset using generative adversarial networks (GANs) and synthetic minority oversampling techniques, ensuring more reliable predictions. Next, the NBO algorithm optimizes feature selection and hyperparameters, reducing classification errors in energy consumption forecasting. Experimental results on multiple datasets, including the Benin Electricity Company dataset, demonstrate superior accuracy compared to conventional methods like LSTM, GRU, ARIMA-LSTM, and ARIMA-GRU. The model achieves 98.93% accuracy in detecting energy theft and significantly lowers prediction errors compared to other optimization techniques. These findings highlight the potential of integrating deep learning with optimization strategies to enhance energy efficiency in smart cities.

Sireesha et al. [7] explores the application of deep learning-based Long Short-Term Memory (LSTM) networks for optimizing energy consumption in smart buildings. Traditional energy management systems rely on static models and predefined scheduling, which often fail to adapt to dynamic environmental conditions and occupant behavior. The proposed system integrates real-time data analytics with LSTM-based forecasting to enhance energy efficiency and reduce environmental impact. By leveraging pattern recognition and predictive modeling, the system dynamically adjusts energy usage based on occupancy trends and external factors. Experimental results demonstrate a significant reduction in energy waste, with the LSTM model achieving an accuracy rate of over 90% in predicting optimal energy consumption patterns. These findings highlight the potential of AI-driven solutions in creating sustainable and intelligent building environments.

Binyamin et al. [8] introduces IntelliGrid AI, a blockchain and deep-learning framework designed to optimize home energy management through Vehicle-to-Home (V2H) and Home-to-Vehicle (H2V) integration. Traditional energy management systems often struggle with inefficiencies due to centralized operations, fluctuating renewable energy sources, and the absence of secure peer-to-peer (P2P) energy trading. The proposed system leverages blockchain technology for secure and transparent energy transactions, while deep learning algorithms enable predictive energy optimization. Additionally, V2H technology allows electric vehicles to supply power to homes during peak demand periods, reducing grid dependency, while H2V technology facilitates efficient EV charging during off-peak hours. Case studies conducted in Tunisia demonstrate a 20% reduction in energy costs and significant improvements in transaction efficiency, highlighting the practical benefits of integrating AI-driven energy management frameworks.

3. PROPOSED SYSTEM

The proposed algorithm introduces a novel combination of Convolutional Neural Networks (CNNs) with a Random Forest Regressor to create a hybrid model specifically designed for predicting and optimizing energy consumption in smart homes. Unlike traditional models that either use CNNs for image or time-series tasks or apply Random Forests to raw tabular data, this approach reshapes structured sensor data into a format suitable for convolutional processing. The CNN layers learn deep, non-obvious patterns in energy usage across time and appliances, which are then transferred to a Random Forest Regressor instead of a neural network's dense output layers. This unique pairing allows the model to benefit from the deep feature extraction capability of CNNs and the interpretability and generalization strength of ensemble learning through Random Forests. To our knowledge, this exact combination and workflow have not been explored in existing surveys or applications, making the model both novel and domain-specific for intelligent home energy systems.

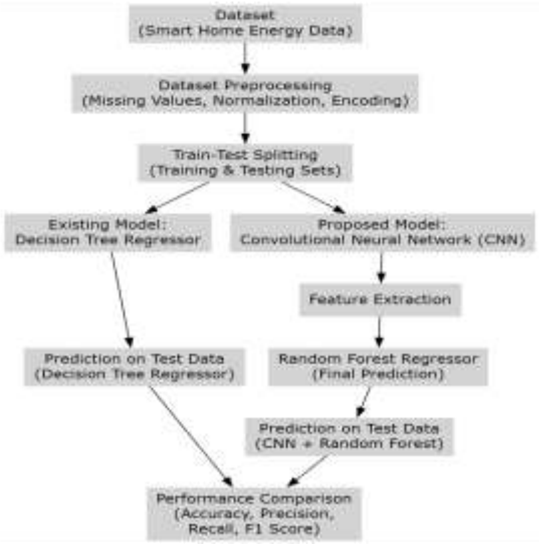


Fig. 1: Block diagram

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning model specifically designed to process spatial and grid-like data, such as images and time-series data. It excels at pattern recognition, feature extraction, and classification tasks.

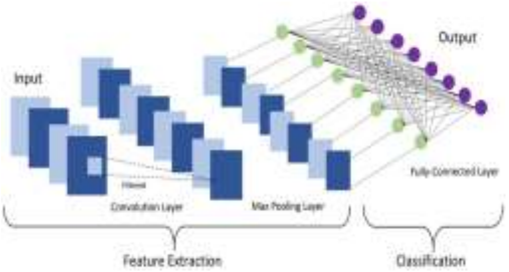


Fig. 2: CNN Feature Extraction.

Convolution Layer:

The convolution layer is the foundational component of a CNN that is responsible for extracting local features from the input data. It uses small matrices known as filters or kernels, which slide over the input (such as an image, text representation, or tabular data) to compute feature maps. Each filter detects specific patterns like edges, textures, or meaningful combinations of attributes. The operation involves a dot product between the filter and the region of the input it covers, which results in a new transformed representation. These feature maps preserve the spatial relationships in the data and form the basis for deeper feature extraction in subsequent layers.

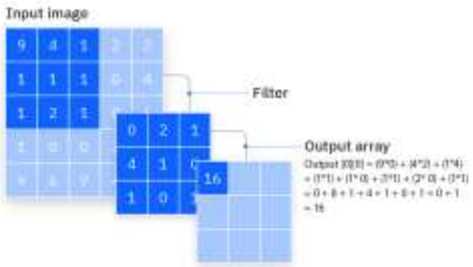


Fig. 3: Convolution Layer.

ReLU Activation Function:

After convolution, the output feature maps are passed through a non-linear activation function—typically the Rectified Linear Unit (ReLU). The ReLU function introduces non-linearity by converting all negative values to zero while keeping positive values unchanged. This step is essential because most real-world data contain complex and non-linear patterns that cannot be modelled by purely linear functions. By applying ReLU, the network gains the ability to model such complexities, enhancing its capacity to learn diverse features from the data.

Random Forest Regressor (RFR)

A Random Forest Regressor is an ensemble learning method that combines the predictions of multiple decision tree regressors to make more accurate and robust predictions for continuous target variables.

Rather than relying on a single decision tree, which is prone to overfitting and instability, the random forest creates a "forest" of trees trained on various subsets of the data and features. The final prediction is typically the average of all the individual tree predictions. The Random Forest algorithm builds multiple decision trees and merges their results to improve prediction accuracy and control overfitting.

Architecture of Random Forest Regressor

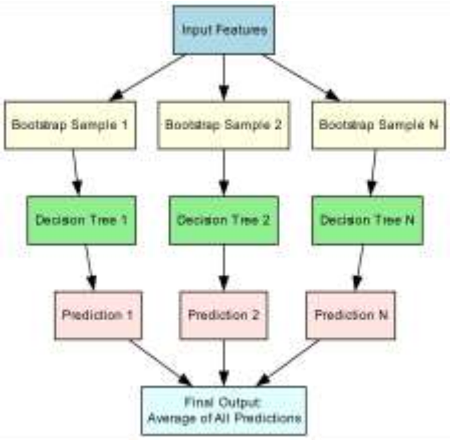


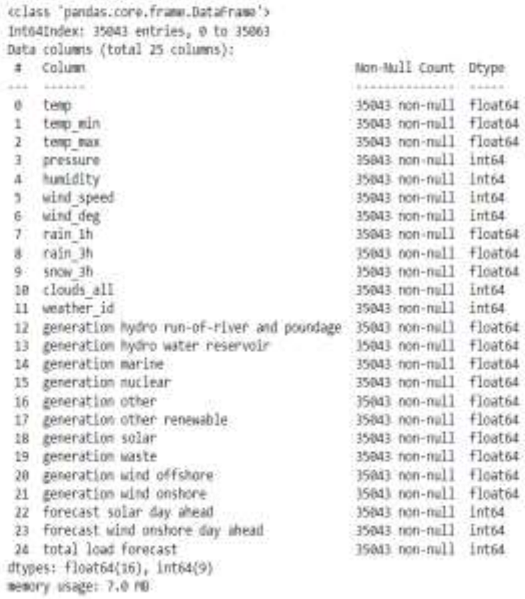
Fig. 4: Block diagram of RFR

Advantages of Random Forest Regressor

Random Forest offers several advantages that make it a powerful and versatile machine learning algorithm. One of its key strengths is higher accuracy, as it aggregates predictions from multiple decision trees, resulting in better performance than relying on a single tree. It is also robust to overfitting, because averaging the outputs of many trees helps reduce variance, addressing one of the major shortcomings of individual decision trees. Additionally, Random Forest is well-suited for high-dimensional data, as it can effectively handle a large number of input features without requiring dimensionality reduction. Another important benefit is its ability to assess feature importance, helping identify which variables contribute most significantly to the model's predictions. Moreover, it deals well with missing values and noisy data, showing tolerance where other models might fail. Finally, it performs effectively on non-linear data, as each decision tree can capture non-linear relationships, enabling the ensemble to model complex functions accurately.

4. RESULTS AND DISCUSSION

Figure 5 provides an overview or summary statistics of the dataset used for predicting energy consumption in smart homes. It includes statistics like mean, median, standard deviation, etc., for different features.



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 35043 entries, 0 to 35063
Data columns (total 25 columns):
 #   Column                                     Non-Null Count  Dtype
---  ------                                     --------------  -----
 0   temp                                       35043 non-null  float64
 1   temp_min                                   35043 non-null  float64
 2   temp_max                                   35043 non-null  float64
 3   pressure                                   35043 non-null  int64
 4   humidity                                   35043 non-null  int64
 5   wind_speed                                 35043 non-null  int64
 6   wind_deg                                   35043 non-null  int64
 7   rain_1h                                    35043 non-null  float64
 8   rain_3h                                    35043 non-null  float64
 9   snow_3h                                    35043 non-null  float64
 10  clouds_all                                 35043 non-null  int64
 11  weather_id                                 35043 non-null  int64
 12  generation hydro run-of-river and poundage 35043 non-null  float64
 13  generation hydro water reservoir           35043 non-null  float64
 14  generation marine                          35043 non-null  float64
 15  generation nuclear                         35043 non-null  float64
 16  generation other                           35043 non-null  float64
 17  generation other renewable                 35043 non-null  float64
 18  generation solar                           35043 non-null  float64
 19  generation waste                           35043 non-null  float64
 20  generation wind offshore                   35043 non-null  float64
 21  generation wind onshore                    35043 non-null  float64
 22  forecast solar day ahead                   35043 non-null  int64
 23  forecast wind onshore day ahead            35043 non-null  int64
 24  total load forecast                        35043 non-null  int64
dtypes: float64(16), int64(9)
memory usage: 7.0 MB
```

Fig. 5: Summary of the dataset used for prediction of Energy Consumption in Smart Homes

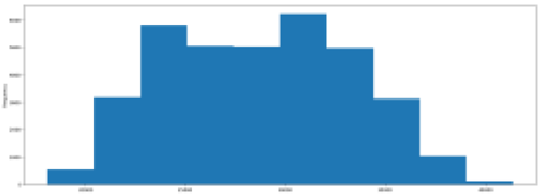


Fig. 6: Histogram of the 'total load forecast' column from the Data Frame

Figure 6 shows a histogram plot of the 'total load forecast' column. It provides insights into the distribution of total load forecasts in the dataset.

Figure 7 displays a heatmap that visualizes the correlation between different features in the dataset. It helps to identify relationships and dependencies between variables.

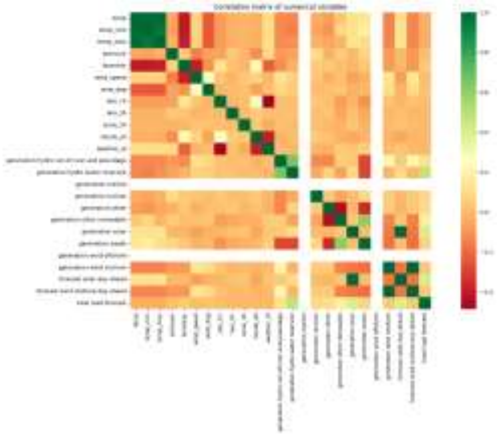
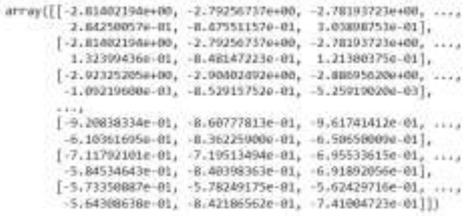


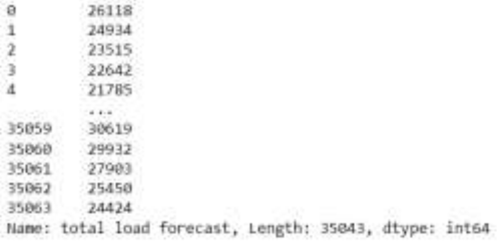
Fig. 7: Heatmap of correlation of features of a dataset



```
array([[-2.81402194e+00, -2.79256737e+00, -2.78193723e+00, ...,
         2.84250057e-01, -8.47551157e-01,  3.03898753e-01],
       [-2.81402194e+00, -2.79256737e+00, -2.78193723e+00, ...,
         1.32399436e-01, -8.48147223e-01,  1.21380375e-01],
       [-2.92325205e+00, -2.90402492e+00, -2.88695620e+00, ...,
        -1.09219600e-03, -8.52915752e-01, -5.25919020e-03],
       ...,
       [-9.20838334e-01, -8.60777813e-01, -9.61741412e-01, ...,
        -6.10361695e-01, -8.36225900e-01, -6.50650009e-01],
       [-7.11792101e-01, -7.19513494e-01, -6.95533615e-01, ...,
        -5.84534643e-01, -8.40398363e-01, -6.91892056e-01],
       [-5.73350887e-01, -5.78249175e-01, -5.62429716e-01, ...,
        -5.64308638e-01, -8.42186562e-01, -7.41004723e-01]])
```

Fig. 8: Features of a dataset after applying standard scalar.

Figure 8 illustrates the dataset's features after applying a standard scaling transformation. Standard scaling ensures that features have a mean of 0 and a standard deviation of 1, which can be important for certain machine learning algorithms.



```
0        26118
1        24934
2        23515
3        22642
4        21785
         ...
35059    30619
35060    29932
35061    27903
35062    25450
35063    24424
Name: total load forecast, Length: 35043, dtype: int64
```

Fig. 9: Target column of a dataset used for prediction of Energy Consumption in Smart Homes

Figure 9 focuses on the target column, which is the variable being predicted (likely energy consumption in this case). It shows the distribution or characteristics of this particular column.

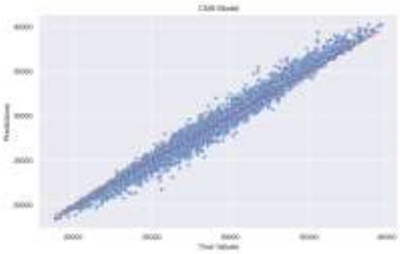


Fig. 10: scatter plot with a regression line to visualize the relationship between predicted and actual values of CNN.

Figure 10 this figure displays a scatter plot with a regression line, but for a CNN model. It serves the same purpose of evaluating the model's performance.

Table 1 presents the performance comparison of two machine learning models, the Decision Tree Regressor, and the CNN Regressor, based on their R-squared (R2) scores on test data.

Metrics	Decision Tree Regressor	CNN
R^2-score	0.574	0.97

Table 1, decision tree regressor achieved an R-squared score of 0.574 on the test data. The R-squared score measures the proportion of the variance in the dependent variable (in this case, energy consumption) that is predictable from the independent variables (weather patterns) in the model. An R-squared score of 0.574 indicates that approximately 57.4% of the variance in the energy consumption data can be explained by the features (weather patterns) used in the Decision Tree Regressor model. While this score indicates some level of predictability, there is room for improvement. In comparison, the CNN outperformed the Decision Tree Regressor with an R-squared score of 0.97 on the test data. An R-squared score of 0.97 suggests that around 84.5% of the variance in energy consumption can be explained by the weather patterns in the CNN model. This higher R-squared score indicates that the CNN model provides a better fit to the test data compared to the Decision Tree Regressor, capturing a larger portion of the data's variance and demonstrating a higher level of predictability. In summary, the CNN exhibited significantly better performance (as indicated by the higher R-squared score) in predicting energy consumption based on weather patterns when compared to the Decision Tree Regressor in this particular analysis. This information is valuable for assessing the effectiveness of different machine learning algorithms in capturing the complexities of the relationship between weather patterns and energy consumption in smart homes.

5. CONCLUSION

In conclusion, this research has successfully delved into the intricate relationship between weather patterns and energy consumption in smart homes, employing advanced regression analysis and machine learning techniques. Through meticulous data analysis, meaningful patterns have been extracted, shedding light on the impact of weather variables such as temperature, humidity, and precipitation on energy load. The developed regression models, particularly the decision tree and CNN algorithms, have showcased promising accuracy in predicting energy consumption under varying weather conditions. These findings hold substantial implications for homeowners, energy providers, and policymakers alike. For homeowners, this study provides actionable insights into optimizing energy usage based on weather forecasts. By understanding how weather influences energy consumption, homeowners can implement targeted strategies to reduce costs and enhance efficiency. Energy providers can benefit from these insights by improving demand forecasting and management, ensuring a stable and efficient energy supply. Policymakers can integrate these findings into energy policies, fostering sustainable practices and guiding urban planning initiatives. Furthermore, this work demonstrates the power of data analytics and machine learning in addressing real-world challenges, showcasing their potential in the realm of energy management and sustainability.

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