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ORIGINAL

Urban energy management system based on intelligent linker

Sistema de gestión energética urbana basado en enlazador inteligente

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ABSTRACT

Introduction: the use of machine learning (ML) approaches to improve energy utilization in smart urban environments has garnered significant attention in recent years.
Objective: this research presents an innovative structure called a bi-fold mechanism-driven convolutional deep network (BMCDN) for estimating the energy performance of urban public facilities in urban energy management systems.
Method: the suggested method includes two significant phases: (1) feature extraction and fusion, and (2) energy significance estimation. The attention fine-tuned ResNet (N1) processes street-view images to evaluate anticipated market significance levels, while the attention-based Bi-LSTM (N2) integrates cross-domain features using input attention. A decision tree (DT) is used to combine and evaluate the fused information and estimated values, serving as the energy value estimator to determine energy values. Data gathered related to public facilities' energy efficiency from various sources is used to analyze the effectiveness of the suggested framework.
Results: the research presents an analysis of the performance gains using image-only representations and a proposed approach with morphological traits. The findings demonstrate that incorporating smart urban-related façade images improves the accuracy of the proposed framework and highlights the connection between energy usage and public facilities.
Conclusions: this study shows the potential for significant precision along with rapid inference time in predicting the energy performance of urban public facilities by combining data from numerous sources.

Keywords: Urban Energy Management; Public Facilities; Machine Learning (ML); Multi-Source Data; Bi-Fold Mechanism-Driven Convolutional Deep Network (BMCDN).

RESUMEN

Introducción: el uso de enfoques de aprendizaje automático (ML) para mejorar la utilización de energía en entornos urbanos inteligentes ha ganado una atención significativa en los últimos años.
Objetivo: esta investigación presenta una estructura innovadora denominada bi-fold mecanim-driven convolutional deep Network (BMCDN) para estimar el rendimiento energético de instalaciones públicas urbanas en sistemas de gestión de energía urbana.
Método: el método sugerido incluye dos fases significativas: (1) extracción y fusión de características, y (2) estimación de la significación energética. El attention fine tuned ResNet (N1) proceslas imágenes de la vista de la calle para evaluar los niveles de significación de mercado previstos, mientras que el Bi-LSTM (N2) basado en la atención integra características de dominio cruzado usando atención de entrada. Un árbol de decisión (DT) se utiliza para combinar y evaluar la información fusiony los valores estimados, que sirve como el estimde valor de energía para determinar los valores de energía. Para analizar la eficacia del marco

propuesto se utilizan los datos recogidos relacionados con la eficiencia energética de instalaciones públicas de diversas fuentes.
Resultados: la investigación presenta un análisis de las ganancias de rendimiento utilizando representaciones de sólo imagen y una propuesta de enfoque con características morfológicas. Los hallazgos demuestran que la incorporación de imágenes de fachadas urbanas inteligentes mejora la precisión del marco propuesto y destaca la conexión entre el uso de energía y las instalaciones públicas.
Conclusiones: este estudio muestra el potencial para una precisión significativa junto con un tiempo de inferencia rápido en la predicción del rendimiento energético de las instalaciones públicas urbanas mediante la combinación de datos de numerosas fuentes.

Palabras clave: Gestión de la Energía Urbana; Instalaciones Públicas; Aprendizaje Automático (ML); Datos Multifuente; Red Profunda Convolucional (BMCDN).

INTRODUCTION

The current real smart city level represents among the greatest considerations in people's regular existence. Individuals generally explore the current city values on appraisal internet pages earlier making actual settle down.[1] Individual settlers value cities for affordable rates and smart lighting systems, valuing energy efficiency and enhancing ambiance. City administrators use massive data and algorithms for smart solutions.[2] Commercial and educational researchers are utilizing ML approaches like Random Forest (RF) and regression trees to train industrial AVMs on smart city characteristics for improved effectiveness.[3] Urban areas with high crime rates, recognition, and academic achievements attract more visitors, while wireless connectivity infrastructure is crucial for property appraisal.[4] Smart lighting enhances property charm and protection, while POIs and appearance significantly impact market worth. People often prefer more attractive smart cities with similar features.[5] Street perspective images offer wireless communication and city layout information, but current research lacks an approach to incorporate urban data into energy value estimates.[6] The goal is to improve urban energy management by offering the BMCDN framework, which uses street-view images wireless communication, and data characteristics to accurately assess urban public implementation energy performance while increasing efficiency and precision.

Related works

The accuracy of urban public implementation energy estimates was multidimensional, regarding geographical, temporal, and error resolutions presented in the article.[7] The integration of energy systems and climate resilience necessitated, as large mistakes were reported by computational approaches. To provide effective urban environment monitoring, research suggested sophisticated wireless sensor networks, artificial intelligence (AI), and communication protocols.[8] Research explored IoT integration in smart cities to address energy consumption issues, discussed energy management in IoT-based cities and challenges with energy harvesting.[9] The SHapley Added Clarification method and Machine for Boosting Light Gradient were utilized to create a deep learning (DL) model that accurately predicted energy consumption and emissions in green smart city facilities.[10] Research introduced a hybrid deep transfer learning approach, combining DANN and LSTM, to forecast short-term public facilities energy, enhancing prediction performance and recommending efficient use of available data resources.[11] Research presented a demand-side smart energy system that integrates energy storage devices, load types, and renewable sources, using modern technologies like data mining, IoT, and ML for smart lighting management.[12] The IoT enabled energy-efficient smart meter effective SWIPT for transmission of the smart grid wireless communication was presented in the article.[13] With an emphasis on overall power consumption and energy limits, it suggested an ideal power allocation algorithm. The algorithm displayed enhanced EE under EH constraints. DL methods for energy prediction utilizing real-world data were examined in the work.[14] The research demonstrated their proficiency in addressing corruption, dimensionality reduction, and complexity to enhance predictive modeling by bridging knowledge gaps among DL and smart city specialists. The research examined the benefits of ML feature selection-derived energy consumption estimates, focusing on filter, wrapper, and embedding techniques.[15] The wrapper approach enhanced model accuracy, to the results, and high gradient boosting in conjunction with the wrapper method yielded the greatest accuracy. Research demonstrated a Cat Boost-based prediction technique for accurately estimating public facilities' energy use.[16] The model, verified on Seattle's energy efficiency dataset, differentiates between normal and abnormal energy use, aiding city managers and facility owners in making more energy-efficient decisions. A data-driven ML approach for predicting energy consumption in metropolitan infrastructure was presented in the research.[17] A data-driven MPC for quick DR incidents in urban public facilities using ensemble-based training and end-user demand segregation approaches for accurate decision-making was examined in.[18] The GA's control performance was improved by optimizing hyper parameters and reducing searching range, resulting in reduced labor expenses and model development time.

METHOD

Research gathered the dataset of public facilities view images (https://github.com/MaoranSun/buildingEnergyEfficiency) and metadata (https://www.kaggle.com/code/sasakitetsuya/energy-efficiency-model-for-building). This section outlines the bi-fold mechanism-driven convolutional deep network (BMCDN) algorithm's details as well as the framework's general architecture. The suggested method comprises these two main steps: First, feature extraction and fusion; second, an estimator of energy value. Even though the project uses a variety of data sources, the street-view image serve as the smart city's image data, thus the characteristics of the smart city, and spatial elements constitute its metadata. Figure 1 shows the general flow diagram.

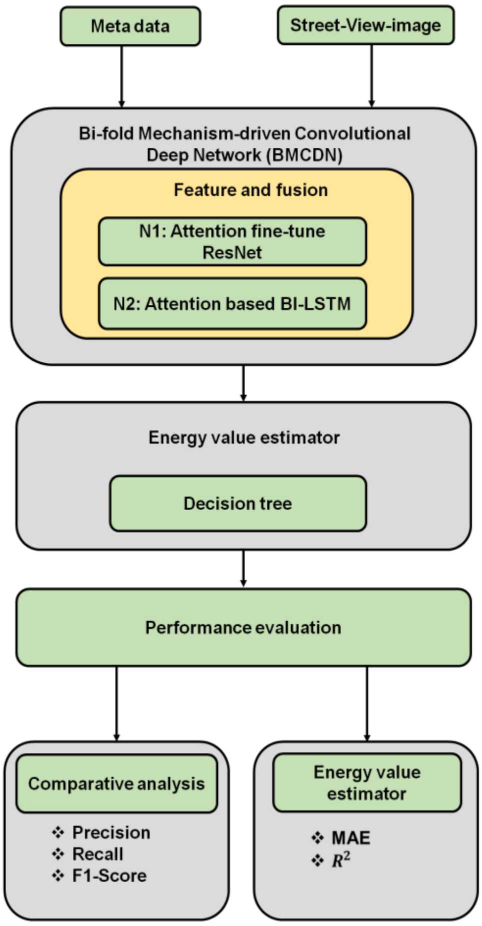

Figure 1. The general framework

Bi-fold mechanism-driven convolutional deep network (BMCDN)

Bi-fold mechanism-driven convolutional deep network (BMCDN) integrates attention fine-tune ResNet and attention based Bi-LSTM. There are two methods for processing the images and metadata separately. Initially, the attention fine-tune ResNet (N1) receives street-view images as input to assess the anticipated market value levels, considering elements like smart lighting when assessing the public facility's overall appeal and usability. Conversely, the attention based Bi-LSTM (N2) that focuses on fusing data features through input attention, integrating energy-efficient smart lighting solutions into consideration in order to improve the city manager's appeal. Ultimately, a decision tree (DT) is employed to concatenate and assess the fused information and expected levels in the energy value estimator having determined energy values.

Feature extraction and fusion

Attention fine-tuned ResNet

A fine-tuned ResNet model improves energy management systems by increasing prediction accuracy and effectiveness, employing deep learning to enhance real-time evaluation, prediction, and decision-making procedures in energy consumption and distribution. This concept makes use of smart lighting and wireless communications to enable smooth data interchange and transmission across different system components, allowing for quick reaction and adaption to changing energy demands. The optimizing energy usage, smart lighting integration makes the framework for energy management more flexible and economical.

A layer of input, activating function, batch normalization, frequency-band focusing unit, smart lighting, dropout and globally mean pooling, fundamental residual block, layers of fully linked soft-max, and a layer of output make up the mainframe of the model. The wavelet values of the unprocessed vibration signals are inputted into the input layer of the suggested networks. Numerous residual fundamental blocks make up the stage module residue and smart lighting in structure to enhance the data processing. The mapping patterns that are similar between the first platform modules and the remaining fundamental components differ slightly. An extra "global pooling-convolution-batch regularization" architecture is present in the identity mapping of the initial fundamental residual block to correspond with the number of filters. It is important to note that the ResNet employed adds batch normalization in between both the activation function and convolution to expedite training and avoid over-fitting. In order to give sufficient illumination for precisely recording the signals of vibration and maximizing the model's performance, smart lighting can be quite important. Vibration signals may be used to notify equipment failures or abnormalities in wireless sensor networks, which could lead to proactive maintenance and improved network dependability. This is one way that the model in wireless communication may be applied to predictive maintenance.

$$y_i^{k+1} = \sigma\left(AM\left(\sum_j w_j^k * x_{ji}^k\right)\right) \quad (1)$$

Where, the BN is used. Figure 2 illustrates the main model framework of this paper, which is 34-layer ResNet architecture.

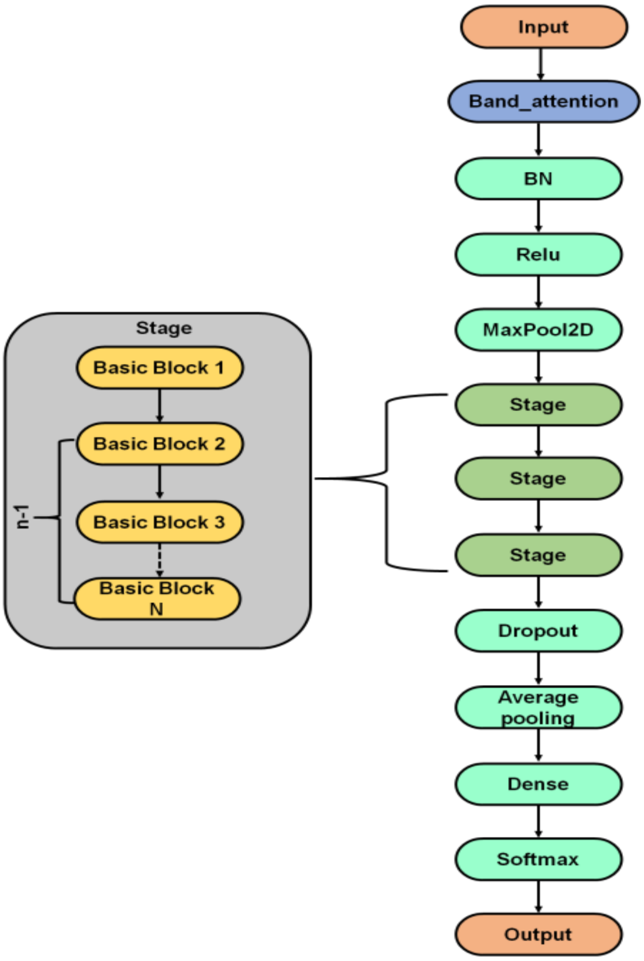

Figure 2. The suggested attention to ResNet architecture

Another method that sets the ResNet apart from the conventional CNN is that smart lighting global average pooling is used to replace the fully linked layer. Enforcing connections using feature maps and classifications renders global average pooling natural due to its convolution structure, which gives it an advantage over entirely linked layers. This tactic simultaneously lowers the network's overall parameters.

Attention based Bi-LSTM

By dynamically prioritizing important information, attention-based Bi-LSTM improves energy management systems by increasing forecasting accuracy and decision-making efficiency for the best possible energy allocation and consumption. Adding smart lighting to the mix increases this efficiency even further by enabling consumer tastes and real-time data to inform adaptive lighting level changes.

Our model's primary classification component was constructed using an attention-based Bi-LSTM. The correlation among each word and the final classification varies depending on which input word is utilized. In this research, we want to utilize the benefits of Bi-LSTM. It is possible to efficiently encode long-distance word connections using the Bi-LSTM.

After receiving the features produced, it extracts the final hidden layer to produce new features. The contextual data obtained by the Bi-LSTM can be thought of as two distinct textual representations because it can access both the prior and following contextual data. A Bi-LSTM model is fed with smart lighting and it generates an approximate model of the series. An attention layer receives this final representation of features and determines which characteristics are highly connected, significantly in the context of smart lighting. The Bahdanau attention with scores for attention that follows is used by the suggested model's attention mechanism:

$$core(querry,\ key)\ = U^{S}tang\ (X_{1key} + X_{2query}) \qquad (2)$$

Decision tree as energy value estimator

For energy management systems, a decision tree-based estimator increases efficiency through cost reduction, resource allocation optimization, energy value prediction, and improved overall energy consumption management. By improving energy usage in lighting systems, smart lighting integrated into this structure further increases efficiency by dynamically modifying the amount of light based on usage, daylight accessibility, and customer preferences.

To separate the nodes into meaningful functions, let's construct an objective function. Every division in which the increment is maximized is:

$$JH(C_o, e) = J(C_o) - \sum_{i=1}^{n} \frac{M_i}{M_o}(C_i) \qquad (3)$$

Where e is the attribute that is used to conduct the splitting; I is a measure of heterogeneity, and C_o and C_i are parent and i-th child nodes, respectively. M_i is the quantity of samples in the i-th child node; M_o is the overall amount of data in the parent node. We use binary decision trees for simplicity and to shrink the combinatorial search space. The child nodes C_{left} and C_{right} in our scenario are:

$$JH(C_o, e) = J(C_o) - \frac{M_{left}}{M_o} J(C_{left}) - \frac{M_{right}}{M_o} J(C_{right}) \qquad (4)$$

Here is heterogeneity metric; M_{left} and M_{right} are the numbers of patterns in the left and right child nodes. Entropy calculation for all non-empty classeso(j|s) ≠ 0^2:

$$J_G(s) = -\sum_{j=1}^{d} o(j|s)log_2 o(j|s) \qquad (5)$$

Where o(s) is the percentage of samples that are associated with a single node s. Therefore, if every sample in a node is a member of the same class, the entropy is zero, and if the arrangement of classes is uniform, the entropy is maximal. One way to think of the Gini measure of heterogeneity is as a condition that reduces the possibility of misclassification:

$$J_H(s) = \sum_{j=1}^{d} o(s)\big(1 - o(s)\big) = 1 - \sum_{j=1}^{d} o(s)^2 \qquad (6)$$

Where K_H(s) the Gini is a measure of heterogeneity and o(s) is the proportion of samples that belong to a class and a single node. Classification error is an additional metric for heterogeneity.

$$J_\varepsilon(s) = 1 - max\ \{o(s)\} \qquad (7)$$

Where s is the single node and o(s) is the fraction of samples that correspond to a class; $J_\varepsilon(s)$ is the classification error. Because it is less susceptible to alterations in the capabilities of the groups in the nodes, this criterion is appropriate for pruning trees but not for growing trees.

RESULTS

The research implemented the proposed approach in Python (v 3.11) on Windows 10 OS. The system is driven by an Intel Core i5 processor and features a high-performance IRIS graphics card, delivering strong capacity for executing demanding machine learning applications. The effectiveness of the suggested method BMCDN was analyzed by applying a set of parameters, including f1-score, recall, and precision are compared with existing methods such as KNN, SVM, and MLP Head.[19] Then the DT for energy value estimators was analyzed and error parameters were evaluated that are MAE and R^2 were compared with the existing methods KNN, RF BRT.[20]

The degree to which the estimated values of the model agree with the actual values is referred to as prediction accuracy. High prediction accuracy is a sign of the validity and dependability of the model's predictions. By using real-time data and customizing lighting levels depending on customer preferences and surroundings, smart lighting can further improve prediction accuracy. The result of the overall accuracy is displayed in figure 3. In that evaluation, the training set has shown the best results for urban energy management systems.

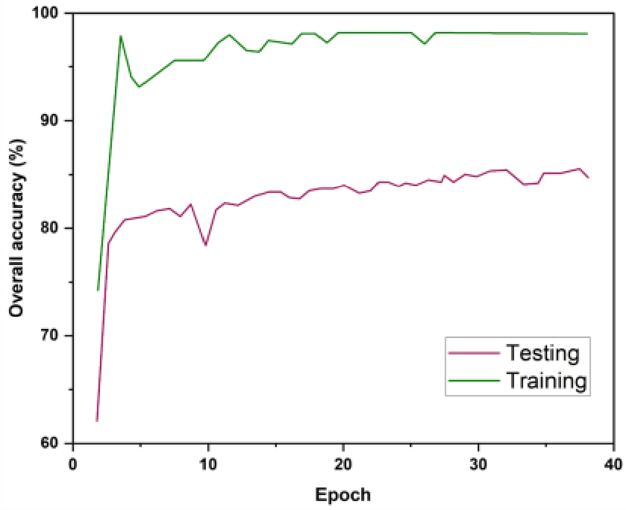

Figure 3. Result of overall accuracy

The percentage of correctly predicted favorable outcomes to the entirety of expected positives is known as precision and smart lighting explicate the path to higher precision. It is a gauge of how well the model has predicted the great outcomes. The comparison of precision is displayed in figure 4. Comparatively, the existing KNN, SVM, and MLP Head algorithms achieve 50,56 %, 52,97 %, and 68,30 % precision, while the proposed BMCDN achieves 91,42 %. The proposed method shows a higher precision score can perform effectively in urban energy management systems.

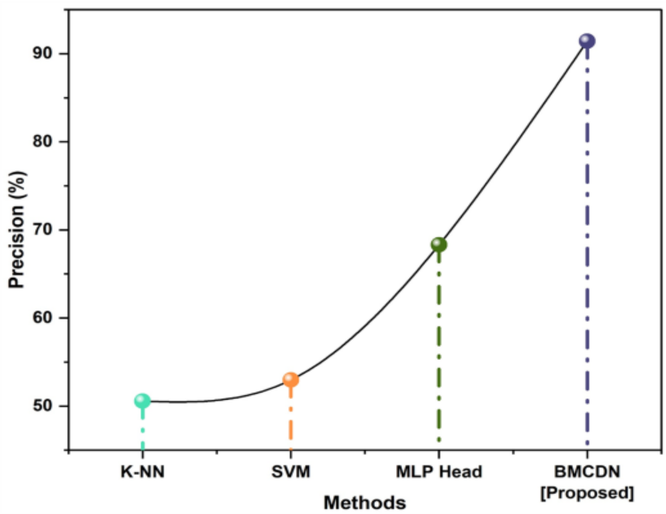

Figure 4. Comparison of precision

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The percentage of correctly anticipated positive discoveries to all assessments made throughout the actual class is termed recall. It gauges how comprehensive the optimistic forecasts remain. Smart lighting has the potential to greatly improve this procedure. The comparison of recall is displayed in figure 5. Here, compared to the existing KNN (50,60 %), SVM (53,87 %), and MLP Head (63,05 %) methods, the proposed method has a much higher recall value of 92,14 %. The suggested method demonstrates that a greater recall score can effectively perform in an urban energy management system.

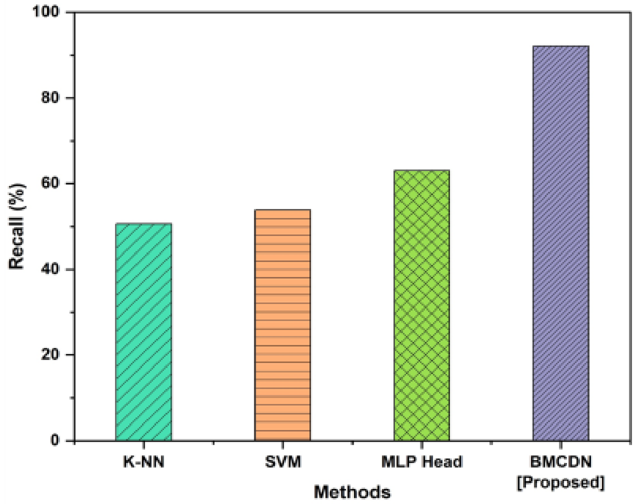

Figure 5. Comparison of recall

The smart lighting harmonic mean of recall and precision is referred to as the F1-score. It provides a balance between recall as well as accuracy, especially when the arrangement of classes is unequal. The comparison of the f1-score is shown in figure 6. The suggested BMCDN strategy has a high f1-score percentage of 93,23 %, while the existing KNN, SVM, and MLP Head methods achieve 50,51 %, 52,62 %, and 64,64 %, respectively. The proposed method shows a higher precision score and can perform effectively in urban energy management systems.

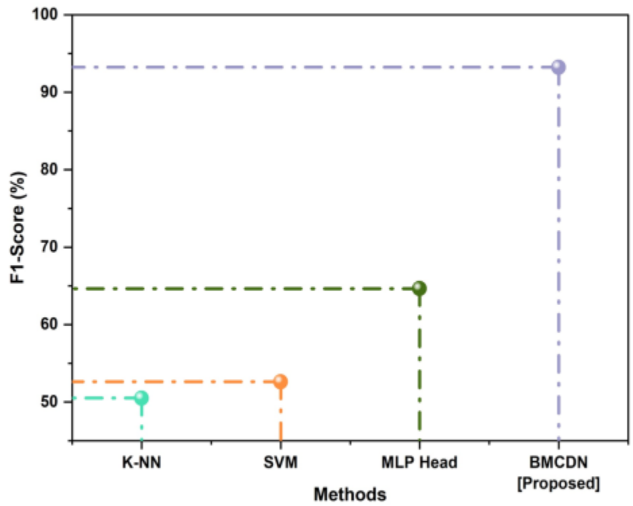

Figure 6. Comparison of f1-score

The MAE between the expected and actual values is calculated. It assesses how accurate continuous variables remain in the context of smart lighting. The comparison of MAE is displayed in figure 7. Here, compared to the existing KNN (13,68), RF (12,33), and BRT (12,23) methods, our DT method has a much lower MAE value of 10,64. The suggested method demonstrates that a lower MAE score can effectively perform in an urban energy management system.

The proportion of the variability of the dependent factor that can be forecast based on the variance of the independent variables is known as R^2. It gives a model's goodness of fit an indication. By influencing metrics like consumption of energy or efficiency, smart lighting can have a substantial impact on this ability to predict. The comparison of R^2 is displayed in figure 8. Comparatively, the existing KNN, RF, and BRT algorithms achieve 68,4, 77,5, and 78,2, while the DT achieves 89,6. The DT method shows the higher R^2 score and can perform effectively in urban energy management systems.

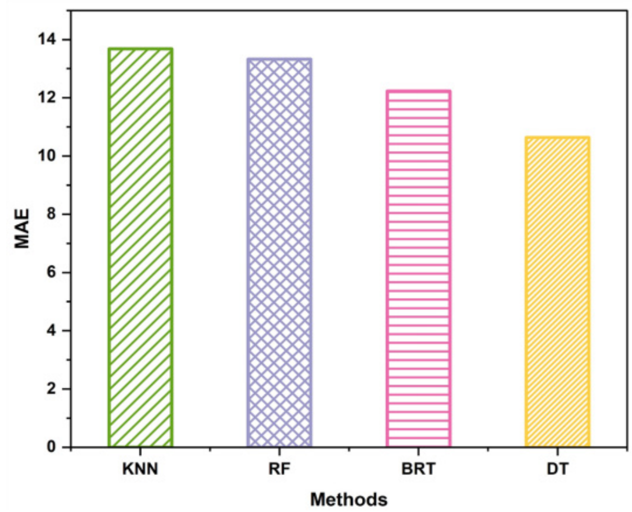

Figure 7. Comparison of MAE

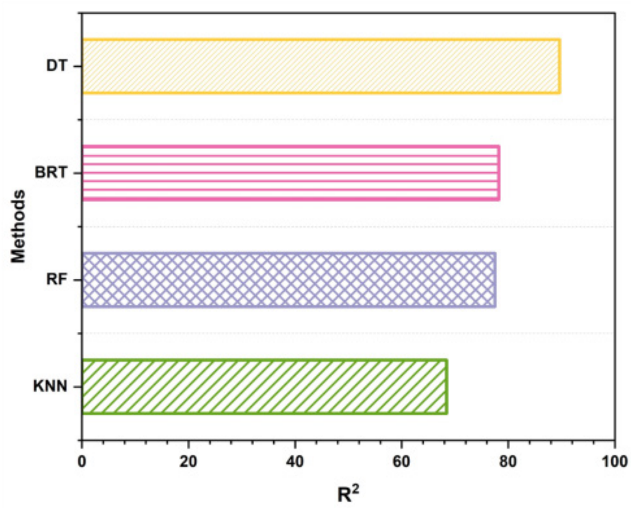

Figure 8. Comparison of R^2

DISCUSSION

The evaluation of the BMCDN approach shows that, when compared with additional traditional techniques like KNN,[19] SVM,[19] and MLP Head,[19] it performs better in urban energy management systems. Compared to other existing methods that assess precision and recall, the BMCDN method generates higher scores in both areas. It's F1 score demonstrates significantly how well-rounded and effective its prediction skill represents. The decision tree (DT) of the BMCDN approach outperforms the current KNN,[20] RF,[20] and BRT[20] in terms of energy value predictions, showing a lower MAE and a R^2 score. The improved accuracy, recall, MAE, and R^2 results suggest that BMCDN provides a more dependable and accurate method for energy management and smart lighting solutions. RF,[20] KNN,[20] MLP Head,[19] SVM,[19] and BRT[20] are various ML models that can handle large datasets but face challenges in accuracy, computational costs, and interpretability. KNN is sensitive to K-values and can be computationally expensive, while SVMs are inefficient and expensive. MLPs are prone to overfitting and require extensive data preprocessing. BRTs are more interpretable but sensitive to overfitting. To address the challenges, BMCDN is a robust and efficient network for urban energy management and smart lighting systems. Its dual-layered approach improves precision, recall, and F1-score, balancing overfitting and underfitting. Its adaptability to real-time data inputs allows for dynamic customization of lighting levels, optimizing energy consumption.

CONCLUSIONS

The utilization of machine learning (ML) techniques has attracted a lot of attention in recent years to enhance energy utilization in the smart public facilities industry. Smart lighting is an important instance of innovation, employing ML algorithms to adapt lighting according to population and available natural light. The proposed framework uses street-view images and features to accurately estimate energy consumption patterns in urban public facilities, promoting smarter, more energy-efficient lighting systems. The proposed framework BMCDN achieves high accuracy, making the presented model valuable in urban energy management. Experimental findings value such as precision (91,42 %), recall (92,14 %), and f1-score (93,23 %) were all found to be best achieved by the proposed BMCDN method. The energy estimator values resulted in MAE (10,64) and R^2 (89,6) were found better by DT. The integration of smart lighting solutions into the structure further improves its efficiency. Lack of accurate, consistent, and comprehensive data can lead to serious consequences affecting the system's performance. In Future work involves refining data ingestion and quality assurance methods, improving data reliability, and optimizing methods for tackling discrepancies. This will enhance the ability to become more reliable and efficient in managing systems that are related to energy in urban areas.

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CONFLICT OF INTEREST
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AUTHORSHIP CONTRIBUTION
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Software: Anton Louise De Ocampo, Rowell Hernandez.
Drafting - original draft: Hongjun Sun.
Writing - proofreading and editing: Felicito Caluyo.

ANNEXES

ML	Machine learning
BMCDN	Bi-fold mechanism-driven convolutional deep network
AVM	Automated valuation model
POI	Points of interest
DANN	Domain-Adversarial Neural Network
LSTM	Long Short-Term Memory
SWIPT	Simultaneous wireless information and power transfer
EE	Energy efficiency
EH	Energy harvesting
MPC	Model predictive control
DR	Demand response
SVR	Support Vector Regression
GA	Genetic algorithm
DT	Decision tree
BN	Batch normalization
CNN	Convolutional neural network
Bi-LSTM	Bidirectional Long Short-Term Memory
KNN	K-Nearest neighbor
SVM	Support vector machine
MLP	Multi-layer perceptron
MAE	Mean absolute error
RF	Random Forest
BRT	Boosted Regression Tree