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Research paper

Optimize building energy efficiency design and evaluation with machine learning

Chun Gu[1]

Abstract: With the increasing demand for energy efficiency optimization in the building industry, this study explores the application of machine learning technology in building energy efficiency design and evaluation. By comprehensively analyzing energy consumption data, environmental factors, building characteristics, and user behavior patterns, this paper proposes a machine learning-based approach aimed at accurately predicting and improving the energy efficiency of buildings. The study collected and pre-processed a large amount of data, built and trained multiple models, including neural networks, which showed a high degree of predictive accuracy in cross-validation. The results show that the neural network has obvious advantages in the task of building energy efficiency prediction. In addition, the interpretability of the model in practical applications and future research directions, such as the introduction of real-time monitoring data and in-depth study of the interpretability of the model, are also discussed. This study not only provides a new perspective for building energy efficiency optimization, but also provides a practical tool for intelligent building design and operation.

Keywords: building energy efficiency, energy consumption forecast, energy efficiency design and evaluation, machine learning

[1]Mas., Architectural Engineering Institute, Zhoukou Vocational and Technical College, Zhoukou 466000, China, e-mail: guchun188@outlook.com, ORCID: 0009-0004-8795-4794

1. Introduction

In the current construction industry, building energy efficiency has become an increasingly important issue. With the increasing global concern for sustainable development and environmental protection, the optimization of building energy consumption has become particularly critical. As one of the major sectors of global energy consumption, the construction industry has great potential for energy efficiency improvement, but also faces challenges. Traditional energy efficiency design methods rely on empirical rules and simplified models, which often fail to accurately predict energy consumption patterns in complex built environments. In addition, in recent years, machine learning technology has shown significant potential in several areas, especially in processing large amounts of data and solving complex pattern recognition problems. Its capabilities also show great application prospects in building energy efficiency optimization. Machine learning can process complex data from a building, such as environmental parameters, usage patterns, material properties, etc., to predict and optimize a building's energy consumption.

There has been a lot of research exploring the application of machine learning in the field of energy efficient building design and evaluation. Liang et al. emphasized the importance of energy efficiency models in the carbon neutral design of buildings, indicating that considering energy efficiency at the building design stage can significantly improve the sustainability of buildings [1]. Similarly, Buzatu et al. showed through experimental evaluation that an integrated design approach is crucial to improving the energy efficiency of buildings [2]. These studies highlight the need to consider energy efficiency from the design stage. Yu and Liu and Ning discussed the application of remote sensing technology and building information modeling (BIM) in improving building energy efficiency [3,4]. These techniques provide an effective tool for collecting building performance data and lay a foundation for the development and application of machine learning models. In particular, Razmi et al. demonstrated the potential of machine learning methods in practical building design by integrating PCA and ANN frameworks to optimize dormitory building design [5]. In addition, Tran et al. explored the impact of photovoltaic integrated multistory facade (PV-MSF) design on improving building energy efficiency, suggesting that combining renewable energy technologies and energy efficient design is an important direction for the future [6]. On the other hand, Zhao et al. conducted a BIM-based analysis on the energy efficiency design of building thermal system and HVAC system, and put forward specific design optimization suggestions [7]. Existing research highlights the need to improve energy efficiency in buildings from multiple perspectives, including design, technology application and building management.

The core objective of this study is to explore and validate the effectiveness and innovative applications of machine learning techniques in optimizing building energy efficiency design and evaluation. Different from traditional methods, this study proposes an innovative methodology based on machine learning that focuses on improving the accuracy and efficiency of building energy efficient design. By utilizing advanced machine learning algorithms to analyze and process large amounts of building-related data, such as energy consumption patterns, environmental impact factors, and user behavior patterns, this research aims to provide a more accurate and efficient means to predict and optimize building energy consumption. The innovation of this approach lies in its ability to take many factors into account to achieve a comprehensive assessment and optimization of building energy efficiency.

In addition, this study not only explores the potential and limitations of machine learning-based approaches in practical applications, but also focuses on evaluating the model's performance under different building types and environmental conditions. This includes the adaptability, extensibility and feasibility of the model in practical applications. Through this comprehensive study, the project aims to provide the building industry with a more flexible and accurate tool for energy efficiency design and assessment, marking a major step forward compared to traditional methods.

In terms of expected impact, this study provides a more efficient and accurate method to evaluate and optimize the energy efficiency of building design and operations. This not only significantly reduces energy consumption and operating costs, but also has important implications for mitigating the negative impact of buildings on the environment. In the long term, the results of this research are expected to drive the construction industry towards a more sustainable and intelligent direction, while providing valuable insights and methods for urban planning, environmental engineering and other fields, demonstrating its contribution and novelty in the broader field of smart buildings.

The research involves the selection, development, and implementation of machine learning models and their ability to analyze building energy efficiency data. The research process began with a comprehensive review of building energy efficiency challenges and machine learning applications, and then focused on collecting and pre-processing key data such as energy consumption, environmental parameters, and user behavior to ensure data quality and analysis accuracy. The core is to select and construct a machine learning model suitable for building energy efficiency optimization, and achieve the best performance through training and tuning, so that the model can accurately predict energy consumption and provide effective energy-saving recommendations. Through independent test data sets and practical case studies, this study will verify the prediction accuracy and practicability of the model, aiming to provide innovative machine learning application strategies for building energy efficiency design and evaluation, and promote technological progress in the field of building energy efficiency by combining theoretical research and empirical analysis.

2. Theoretical basis and application prospect

2.1. Concept and importance of building energy efficiency

Building energy conservation, that is, reducing energy consumption and improving energy efficiency through effective means during the design, construction and operation of buildings, is the core issue of modern architecture and urban planning, especially in the context of global efforts to promote energy conservation, emission reduction and sustainable development [8, 9]. It is not only of great significance for reducing environmental burden and mitigating climate change, but also significantly reduces energy costs and promotes economic efficiency.

In the discussion of building energy efficiency standards and evaluation methods, this study emphasizes the role of international energy efficiency standards such as LEED and BREEAM in promoting the development direction of the construction industry. By combining quantitative and qualitative evaluation methods, from energy consumption simulation to evaluation of energy-saving technologies, the aim is to predict and improve the energy efficiency performance of buildings [10, 11].

In-depth study and implementation of effective building energy conservation strategies are not only crucial to protecting the environment and promoting low-carbon development, but also contribute to sustainable economic and social development [12].

2.2. Basic knowledge of machine learning

Machine learning, a key branch of artificial intelligence, gives computers the ability to learn and improve themselves through data experience. It relies on statistical techniques to allow computers to recognize patterns and make predictions without specific programming [13, 14]. Machine learning is divided into supervised learning, unsupervised learning and reinforcement learning. Supervised learning learns the relationship between input and output by labeling data and is suitable for classification and regression tasks [15, 16]. Unsupervised learning explores structure in unlabeled data and is often used for clustering and market analysis. Reinforcement learning optimizes decisions through feedback and is applied to games and real-time decision scenarios. In the field of building energy efficiency, machine learning analyzes energy consumption, environment and user behavior data to optimize energy efficiency performance [17]. With the advancement of technology, machine learning is driving the evolution of the construction industry towards intelligent and sustainable development.

2.3. Application and ethical considerations of machine learning in building energy efficiency optimization

Machine learning is revolutionizing the field of building energy efficiency optimization. It significantly improves the accuracy and efficiency of energy efficiency design by analyzing complex data such as energy consumption history and environmental conditions [18]. However, ethical considerations cannot be ignored, especially issues of privacy, data security and algorithmic bias. With the growth of construction data, protecting personal privacy and ensuring data security is particularly critical, and strict privacy protection standards need to be followed [19, 20]. At the same time, preventing algorithmic bias from exacerbating inequality and ensuring fairness and transparency become necessary measures when designing and implementing machine learning algorithms. By solving these ethical problems, machine learning can not only improve the accuracy of energy efficiency assessment, but also promote the development of the building industry in a more sustainable and intelligent direction, showing its broad application prospects and accompanying ethical responsibilities in building energy conservation [21].

3. Data collection and preprocessing

3.1. Sources and types of data

In this study, the accurate assessment and optimization of building energy efficiency is based on diverse data types and sources. Key data include:

1. Energy consumption data: such as electricity consumption and energy consumption of heating and cooling systems, obtained from building management systems, smart metering equipment or energy suppliers.
2. Environmental data: meteorological information such as temperature and humidity that affect building energy conservation can be obtained through public meteorological services.
3. Building characteristics data: covering floor area, number of rooms, etc., collected during the design and construction phase.
4. User behavior data: including the number of occupants and electricity consumption habits, collected through surveys or intelligent systems. These comprehensive data provide a solid foundation for accurate assessment and effective optimization of building energy efficiency.

As shown in Table 1.

Table 1. Data sources and types

Data type	Data item	Description	Data source
Energy consumption data	Power consumption	Electricity consumption per hour (KWH)	Building management system
Environmental data	Outdoor temperature	Hourly outdoor temperature record (degrees Celsius)	Meteorological station
Building characteristic data	Floor area	Gross floor area (m2)	Architectural design document
User behavior data	Room frequency	Duration per room per day (hours)	Sensor recording or smart home systems

3.2. Data cleaning and integration

In this study, data cleaning and integration are key to ensuring data quality and providing an accurate basis for machine learning model analysis. Data cleansing involves dealing with missing values by deleting, filling or predicting them; Detect and process outliers, using statistical methods such as box charts to identify and decide on outliers; And perform conformance checks to ensure that data formats and units are consistent.

Data consolidation aims to combine data from multiple sources into a unified data set, including formatting uniformity and timestamp alignment to ensure that information from different data sources is accurately matched. For example, the date and time format of energy consumption data needs to be harmonized with meteorological data for full analysis. As shown in Fig. 1.

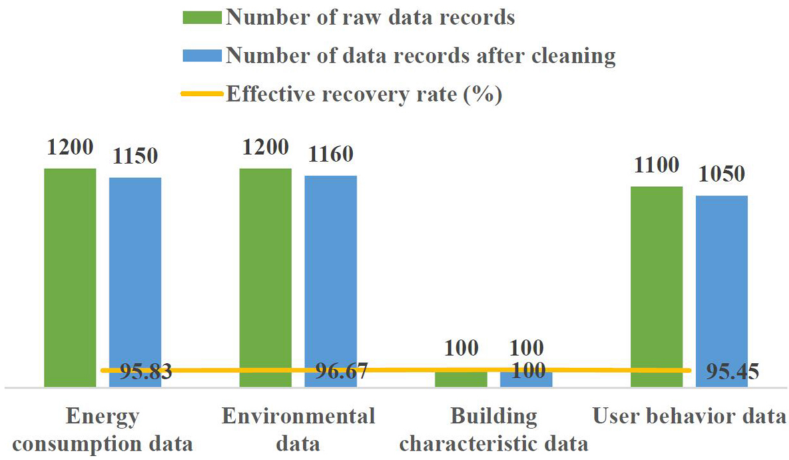

Fig. 1. Data cleaning and integration

The Fig. 1 above shows the effective recovery rates of different types of data during the cleaning and consolidation process, thus providing a visual indicator of data quality.

3.3. Data preprocessing technology

In this study, data preprocessing is a key step in transforming raw data to fit machine learning model analysis, covering the following techniques:

- Normalization or normalization: The process of adjusting data at different scales (e.g., floor area, temperature) so that the algorithm can process it more efficiently, usually converting values into a range of 0 to 1 or giving data a zero mean and unit variance.
- Feature coding: Converting non-numerical features (such as date and time) into a digital format, often through unique thermal coding or sequential coding.
- Time series data processing: such as rolling averages or seasonal adjustments to help capture time-related patterns.
- Feature engineering: Extracting or constructing new features from data, such as week and hour features based on time stamps, to identify energy consumption patterns.
- Data cleaning: Correcting errors or inconsistencies in the data set, for example, filling in missing outdoor temperature readings with the average of adjacent time points.
- Data integration: Combining data from different sources or formats into a unified set, such as combining building energy consumption and weather conditions data to analyze the impact of temperature on energy consumption and create a comprehensive view for in-depth analysis.

As shown in Table 2.

Table 2. Data preprocessing

Raw data item	Data preprocessing description
Outdoor temperature	Normalization: conversion to a value between 0 and 1; Data cleaning: Fill in missing values
Timestamp	Feature encoding: Converted to a numeric representation of the hour and week
Floor area	Normalization: Converted to a value with 0 mean and unit variance
Data integration example	Merge energy consumption data with weather conditions data

3.4. Analysis of the impact of data quality on the model

Data quality plays a key role in building machine learning models, directly affecting the accuracy and reliability of the models.

Data integrity issues, such as mishandled missing values, can lead to faulty model predictions. Data accuracy is significantly affected by outlier processing, and unrecognized outliers may lead to incorrect energy consumption correlation. Data consistency, especially the unity of unit and format in data integration, is very important for model learning. Inconsistencies can cause models to fail to interpret features correctly. In addition, the features extracted in feature engineering need to be highly correlated with the target variables, for example, time stamp features should reveal changes in daily energy consumption patterns. As shown in Fig. 2.

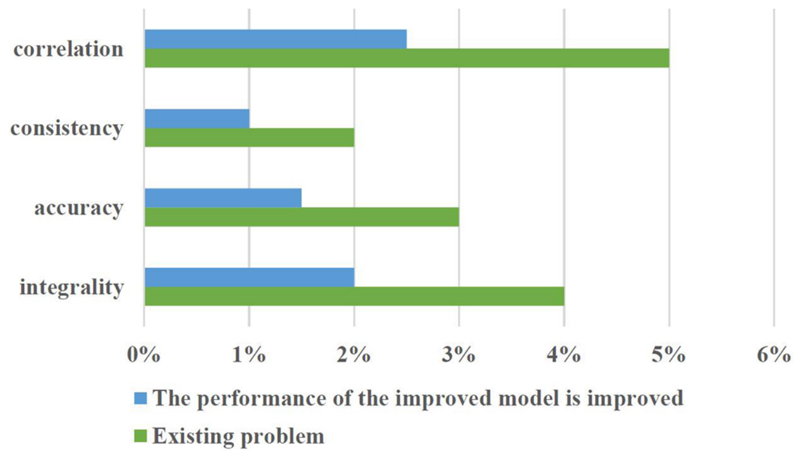

Fig. 2. Analysis of the influence of data quality on the model

The diagrams provide a quantitative perspective on the specific impact of various aspects of data quality on model performance. For example, improving data integrity and accuracy can directly lead to improved model performance. At the same time, improving data consistency and correlation also helps to improve the prediction accuracy of the model.

4. Construction and implementation of machine learning model

4.1. Model selection and reasons

In this study, choosing the right machine learning model is crucial to ensure the accuracy and efficiency of energy efficiency optimization. The model is chosen based on the characteristics of the data, the nature of the prediction task, and the interpretability of the model. Here are some common machine learning models and their applicability:

1. Linear Regression: It is suitable for predicting the linear relationship between building energy consumption and various factors. The model form is shown in Eq. (4.1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \tag{4.1}$$

   where y is the target variable (such as energy consumption), $x_1, x_2, \ldots, x_n$ is the feature (such as temperature, time, etc.), $\beta_0, \beta_1, \ldots, \beta_n$ is the model parameter, and ϵ is the error term.
2. Decision trees: Simulate the decision process to understand the nonlinear relationship between data features and target variables.
3. Random Forest: An integrated approach to decision trees that enhances prediction accuracy and stability through voting or averaging of multiple trees, suitable for complex nonlinear and high-dimensional data analysis.
4. Neural network: mimics the structure of human brain, specializes in processing large and complex data sets, and can reveal deep patterns of data, which is very suitable for analyzing complex building energy saving models.

Machine learning model selection analysis is shown in Table 3.

Table 3. Model selection analysis

Model type	**Advantages**	**Cons**	**Applicability analysis**	**Application scenario Example**
Linear regression	Simple and easy to understand, high computational efficiency	It can only handle linear relationships	Predict the linear relationship between building energy consumption and temperature	Predict the linear relationship between building energy consumption and temperature
Decision tree	Easy to interpret and handle nonlinear relationships	Easy to overfit	Energy efficiency rating according to building characteristics	According to the characteristics of the building divided into different energy efficiency levels

Table 3. [cont.]

Model type	Advantages	Cons	Applicability analysis	Application scenario Example
Random forest	High accuracy, strong anti-overfitting ability	The model is large, but the explanation is relatively weak	Deal with complex relationships and multi-factor combination forecasting	Multi-factor combination predicts energy consumption
Neural network	Powerful modeling capabilities for large-scale data	The training time is long, requires a lot of data, and the interpretation is poor	Analyze complex building energy efficiency models	Analyze complex building energy saving model

4.2. Feature selection and engineering

Feature selection and engineering are important steps in machine learning model construction. By selecting features that are highly correlated with the target variable (e.g., energy consumption), such as Pearson correlation coefficient is used to evaluate the linear relationship between features.

1. Feature selection: Aims to reduce the data dimension and eliminate irrelevant data. For example, Pearson Correlation Coefficient $\rho(X,Y)$ is used to evaluate the linear relationship between feature X and energy consumption Y.
2. Feature engineering: including the creation of new features and the conversion of existing features. For example, new interaction features can be created by combining timestamp and environmental data, or nonlinear relationships can be captured using Polynomial Expansion X^2, X^3.

As shown in Table 4.

Table 4. Feature selection and engineering

Original feature	Feature selection	Feature Engineering	Description
Power consumption	High correlation	–	Directly as the target variable
Outdoor temperature	Medium correlation	Temperature squared $Temperature^2$	Capture the nonlinear relationship between temperature and energy consumption
Floor area	Low correlation	–	May not be a major predictor Improve the interpretability of time information
Timestamp	Medium correlation	Time coding $Hour$, $Weekday$	
Room frequency	High correlation	–	Direct as an important feature

4.3. Model training and optimization

1. Model training: Assuming that random forest is selected as the main model, model training involves estimating model parameters according to the training data set. A random forest consists of several decision trees, and its training involves the construction of each tree. The training of each tree can be expressed as the process of building a decision tree based on the training set D.
2. Hyperparameter tuning: The random forest has multiple hyperparameters that need to be adjusted, such as the number of trees (n_{trees}) and the maximum depth of each tree ($depth_{\max}$). Hyperparameter tuning can be done using methods such as Grid Search or Random Search.
3. Cross-validation: In order to evaluate the generalization ability of the model, cross-validation (e.g., k-folding cross-validation) is used to evaluate the performance of the model on different subsets. This involves dividing the data set into k subsets, training the model with $k-1$ subsets at a time, and using the remaining subset to verify model performance.

Data examples of model training and optimization are shown in Table 5.

Table 5. Training and optimization of the model

Procedure	**Description**	**Parameters/Technology**	**Goal**
Model training	Train a random forest model	Build a decision tree based on data set D	Minimizing training error
Hyperparameter tuning	Adjust model hyperparameters	Grid search n_{trees}, $depth_{\max}$	Find the best combination of hyperparameters
Cross verification	Evaluate model generalization ability	$k-$ Fold cross verification	Verify the performance of the model on different data subsets

4.4. Challenges and coping strategies in model construction

1. Challenge: Multi-dimensional and complex data
   Working with multi-dimensional and complex data can lead to overfitting of the model, where the model performs well on training data but poorly on new data.
   Strategy: Introduce regularization terms (for example, Lasso (L_1) or Ridge (L_2) regularization). For example, in a linear regression model, add the L_2 regularization term, as shown in Eq. (4.2):

$$\min \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{m} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{m} \beta_j^2 \tag{4.2}$$

   where λ is the regularization parameter.
2. Challenge: unbalanced data
   In some cases, there may be an imbalance in building energy efficiency data, for example, the amount of data for high and low energy consumption varies greatly.

Coping strategy: Use resampling techniques, such as oversampling a few classes or undersampling a majority of classes. Or use cost-sensitive learning methods to give different weights to different categories.

3. Challenge: model interpretability
   Complex machine learning models, such as deep neural networks, may lack interpretability, which can be a problem for building energy efficiency assessments.

Strategies: Use more explicable models (such as decision trees), or introduce model interpretation tools (such as SHAP values) to explain the predictions of complex models.

As shown in Table 6.

Table 6. Challenges and coping strategies in model construction

Challenge	Coping strategy	Description
Data complexity	regularization	L_2 regularization is added to the linear model to reduce the risk of overfitting
Data imbalance	resampling	Oversample a few classes or undersample a majority to balance the data set
Model interpretability	Use interpretable models	Use models that are easier to interpret, such as decision trees

5. Verification and evaluation of the model

5.1. Verification methods and implementation steps

1. In machine learning projects, model validation assesses model performance through two main methods.
   Cross validation: The data set is equally divided into training and test sets, such as 50-fold cross validation, which trains the model with four copies of the data at a time and tests the remaining one, iterating to ensure that each piece of data is verified.
   Performance evaluation indicators: mean square error (MSE) and other evaluation indicators are used to quantify the accuracy of model prediction, providing an intuitive evaluation standard for model performance. MSE, as shown in Eq. (5.1):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5.1}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value
Or the coefficient of determination (R^2), as shown in Eq. (5.2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{5.2}$$

where $\overline{y}$ is the average of y_i.

2. Implementation steps.

As shown in Fig. 3 cross validation process, the data set is randomly divided into $k$subsets; For each subset, use it as a test set and the rest as a training set; The model is trained on the training set and performance is evaluated on the test set; Calculate the average performance metrics for k of tests.

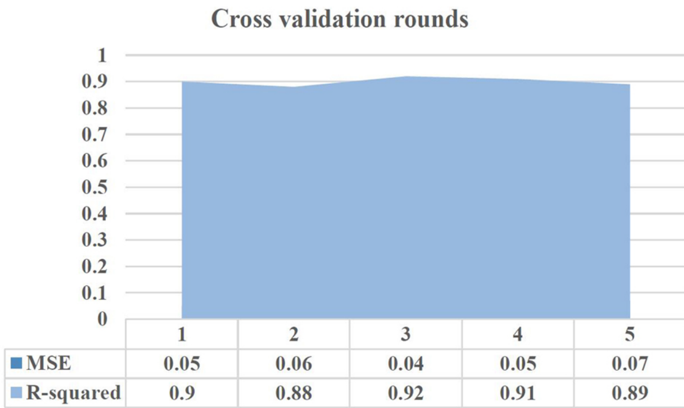

Fig. 3. Cross-validation

5.2. Performance evaluation indicators

1. Mean Squared Error (MSE): Measure the mean of the square of the difference between the predicted and actual values of the model, as shown in Eq. (5.1).
2. Coefficient of determination (R-squared, R^2): reflects the degree to which the model explains the data variation, as shown in Eq. (5.2).
3. Mean Absolute Error (MAE): The mean of the absolute value of the difference between the predicted value and the actual value. The following Eq. (5.3) is shown:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5.3}$$

The performance evaluation index data of the model are shown in Fig. 4.

In order to further verify the effectiveness of these performance evaluation indicators in practical application, a specific building energy efficiency renovation project is selected as a case study. The project involves an energy efficient renovation of the office building, including but not limited to updating insulation, installing more energy efficient HVAC systems and introducing smart lighting systems.

The performance of each model was evaluated using MSE, R-squared, and MAE. By comparing these indicators, it is possible to determine which model is better at predicting building energy efficiency.

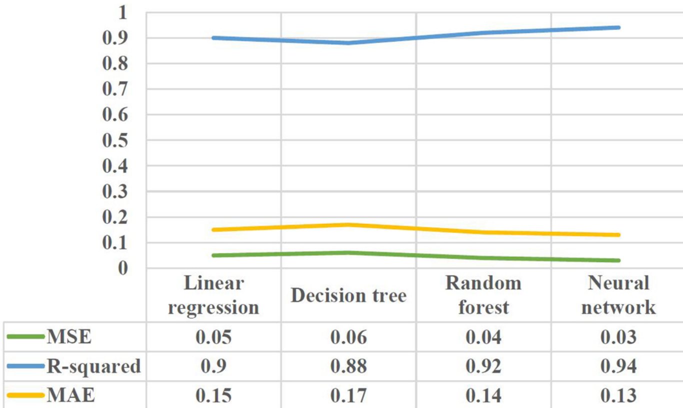

Fig. 4. Performance evaluation indicators

5.3. Limitations and potential improvements of the model

Limitations: data quality dependencies, risks of overfitting, and insufficient model interpretability.

Suggestion: Strengthen data pre-processing, adopt regularization technologies such as Dropout, increase the diversity of data sets, reduce overfitting, and introduce tools such as LIME and SHAP to improve model interpretability. Facing the challenges of adaptability and scalability in different architectural environments, microservices or containerization technologies are adopted to meet the needs of large-scale data processing by using cloud computing services.

Implementation strategy: requirements analysis, data preparation, model selection and customization, training and validation, deployment and monitoring in production environments.

Limitations and potential improvements of the model are shown in Table 7.

Table 7. Limitations and potential improvements of the model

limitation	Description	Potential improvement method
Data quality dependency	Inaccuracy of input data leads to prediction errors	Enhanced data cleaning and preprocessing technologies
Risk of overfitting	The model overperformed on the training data	Apply regularization techniques such as Dropout and early stop strategies
Model interpretability	Model predictions are not easy to understand	Introduce model interpretation tools such as LIME or SHAP

6. Conclusions

This study successfully applied machine learning technology to the optimization of building energy efficiency design and evaluation by comprehensively utilizing energy consumption, environment, building characteristics and user behavior data. In particular, the neural network model shows remarkable effect in predicting and optimizing building energy consumption. This not only improves forecasting accuracy, but also provides a new perspective on building design and energy efficiency assessment, providing the construction industry with an effective tool to support more accurate and sustainable energy decisions.

In terms of educational theory and practice, the research emphasizes the importance of data science in practical applications and pushes the education system to strengthen the education of data analysis and machine learning. The findings broaden students' and professionals' awareness of the potential of machine learning applications to advance their careers.

Future research will explore more data sources to improve the dynamic prediction ability of the model, further study the interpretability of the model, and extend to a wider range of building types and geographical environments to enhance the universality and adaptability of the model. The adoption of advanced machine learning algorithms and data processing technologies will further optimize the prediction accuracy and model efficiency, and promote intelligent and sustainable development in the field of building energy efficiency.

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