Energy-Saving Design of Smart City Buildings Based on Deep Learning Algorithms and Remote Sensing Image Scenes

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The building of urbanization has encouraged the ongoing expansion of the city's scale in tandem with the ongoing development of the economy and society. The disorderly and rough land acquisition and construction have brought about the problems of inefficient use of many resources, which are in line with the concept of green and smart construction. Violated. In response to these shortcomings and needs, this article introduces deep-learning algorithms and remote-sensing image scenes. Based on the business logic of smart city building energy-saving design, the data set is analyzed by category according to different types of supervision and deep learning to realize the smart city. Effective analysis of building energy efficiency, and a simulation quantitative experiment for evaluation using BIM technology to assess buildings with energy efficiency designs in order to maximize energy-saving design. The simulation experiment results show that the deep learning algorithm and remote sensing image scene are effective and can support the energy-saving design of smart city buildings.

Povzetek: Algoritmi globokega učenja uporabljajo prizore daljinskega zaznavanja za oblikovanje energetsko varčnih stavb v pametnih mestih.

1 Introduction

Urbanization is growing in scope and demand for assets including land has been steadily rising as a result of the social economy's continued expansion. From the initial extensive use of land resources to the intensive and economical use of land to the concept of "harmonious symbiosis between man and nature", it fully reflects people's understanding and respect for nature [1-2]. For the transformation of nature and resource utilization, the traditional monitoring methods are all through manual on-site inspection. On the one hand, this method cannot achieve specific scope coverage, on the other hand, it increases the cost. The development of remote sensing imaging technology allows people to view the utilization or transformation of various buildings and resources from the air. Especially in recent years, spatial resolution and time resolution have been improved, allowing remote sensing images to be viewed clearly and intuitively in a short period. Resource distribution or change, the effective interpretation of these remote sensing images can be deeply applied in disaster monitoring and early warning, environmental monitoring and analysis, and traffic monitoring and analysis. In the process of continuous development of the construction industry, it also needs the support of natural resources such as land, which affects or even destroys the ecological environment to a certain extent, and even more affects the specific development and utilization of natural resources and energy [3-4].

The development of information technology and computer technology has made intelligent construction more mature and in-depth, especially in specific construction projects. As far as the building is concerned, it is a common project in the development of urbanization, and whether the building is energy-efficient and green determines the impact on the natural environment [5-6]. As one of the modern buildings, intelligent buildings provide users with a healthy, safe, and environmentally friendly environment. Therefore, buildings with smart environments are often equipped with more electrical equipment. The operation of these electrical equipment requires a large amount of power resources as support. Therefore, the power consumption of smart buildings is increasing. For the current situation where power resources are still scarce, effectively maintaining the utilization of smart buildings is a relatively large expenditure. Therefore, only by optimizing the construction of the building, innovating the construction management mode, strengthening the energy-saving design, and realizing the intelligent control and power system configuration [7-8].

In response to these shortcomings and limitations, this article attempts to introduce remote sensing image scenes to monitor the implementation, status, land occupation, and other information of construction projects in the air. Through the use of deep learning methods for in-depth characterization and analysis of feature capabilities, it is possible to distinguish effective scenes. , According to different supervision classification methods to achieve effective analysis of different data sets, further explore the design of energy-saving buildings in smart cities, and use simulation experiments for evaluation, aiming to improve the design of energy-saving buildings in smart cities.

2 Related work

Here, we discuss the related energy-saving design of smart city buildings based on deep learning algorithm machine learning and remote sensing image scenes are presented. Table 1 shows the summary of the related works.

Table 1: Related studies

References	Method used	Dataset	Key results	Limitations
[9]	Utilizing cutting-edge energy-efficient technology, consideration was given to the building's design, architecture, water supply and treatment system, exterior framework, ability to be constructed, and prospective LEED-credited components according to meteorological study.	Chicago weather analysis data	Three main aspects were found: water consumption reduction, on-site renewable energy, and yearly energy saving rate. Potential LEED credit points were obtained.	It fails to identify the specific changes or the amount of energy saved. Possible difficulties in putting into practice.
[10]	The model was evaluated using DesignBuilder and EnergyPlusTM	Information about the energy efficiency of a self-sufficient home in the suburbs of L'Aquila, Italy	Superior exterior economy and subpar warming system functionality may be distinguished; five scenarios are examined; energy savings of up to 67.1% are found	Considering the study is restricted to a single building in a single location, its findings might not apply to other structures or areas. Accuracy could be impacted by modeling assumptions.
[11]	Using dynamic modeling tools, passively solar systems (such as Trombe walls) and appropriate airflow methods are examined by DesignBuilder	Information about the energy efficiency of two distinct residential houses under different climate conditions	Trombe wall lowered cooling energy consumption by 36.1% and heating requirements by up to 71.7% in warm areas. In colder regions, there was an 18.2% savings in heating and a 42.4% reduction in cooling energy.	When suitable airflow strategies are not designed based on climatic characteristics, the system's performance may be severely restricted, which might result in interior overheating problems,

				particularly during the middle seasons.
[12]	Deep learning (DL) used the BP-DCHP Data Fusion Algorithm to design BIM energy-efficiently.	Beijing Intelligent Communities' environmental statistics	Develops DTs for urban scene applications by utilizing deep learning to assess ecological pleasure. Analysis of energy usage evaluating components to determine the best and most energy-efficient choices.	Restricted to the extent and precision of the BIM models' accessible building data. Dependence on node dispersion and initial network architecture; possible computing energy cost.
[13]	Applications of artificial intelligence (AI), machine learning (ML), and DL in Industry 4.0 Building and Construction	Many datasets about the stages of the construction lifecycle	Cutting-edge reviews in structural analysis, material optimization, architectural design, etc.	Problems with data collecting, model creation, and scalability of implementation.
[14]	The use of pattern recognition technology in the intelligent building environment's visual analysis is examined in the research.	Consistently and swiftly collecting information about urban structures from satellite or aerial photos is crucial for monitoring recently built structures and other new theme material. It also helps to update geospatial data.	Large-scale visualization, the collecting of GIS data, and other uses for remote sensing are made easier. enhanced ability to identify and categorize urban buildings	Difficulties managing diverse building kinds and complicated urban settings; large training data sets may be needed for reliable performance
[15]	The benchmark utility learning technique by utilizing Deep Learning end-to-end training with deep bi-directional Recurrent Neural Networks in the study presented to increase forecasting performance.	The effectiveness of the suggested approaches on ground truth data by forecasting patterns of resource utilization using information collected from occupant behaviors for resources like room illumination.	study's findings demonstrate that it is possible to obtain a very precise depiction of the actual ground truth for occupant resource utilization.	Presumes familiarity with utility features and perhaps reliance on the standard of the information provided
[16]	Energy conservation, the incorporation of sources of sustainable energy, and a simplified management framework are the three factors that are most important to take	Gather information on actions, successes, and conditions while at the work location, then forward it over to the centralized platform for evaluation.	Lower environmental impact, better social services, reduced utility bills, and more effective resource utilization. enhanced effectiveness in resolving building-related problems, such	Considerable disadvantages of Model Predictive Control and scaling issues with DRL

	into account while creating intelligent electrical grid systems using Deep Reinforcement Learning (DRL) in Smart Buildings (SB) (DRL-SB-IoT) technology.		as security, wellness tracking, and energy consumption prediction	
[17]	Convolution Recurrent Neural Networks for Deep Reinforcement Learning (DRLCRNN) offer creative ideas for reducing energy use and running heating, ventilation, and air conditioning (HVAC) systems.	Time series data from Houston, Texas, USA's extremely productive office district	8% possible energy savings through HVAC system optimization with CRNN and DRL	Previous studies' lack of comprehensive end-to-end management and their restriction to certain building and climate circumstances
[18]	A novel approach to the gathering of multi-dimensional information is offered by computer vision (CV) technology. It examined the most recent developments in the construction sector from global sources, concentrating on the state of research in four HVAC fields.	Occupant information monitoring provides data regarding the state and behavior of the inhabitants.	When compared to current sensing technologies, CV technology improves data dimension, resolution, and accuracy by efficiently detecting very dynamically constructed environments. 95% accuracy for information related to occupants and 86% accuracy for information related to comfort were attained.	Rapid processing and incorporation in a variety of built environment situations provide hurdles for the technology. Effective cross-research interaction between construction management and CV is lacking.

2.1 Overview of deep neural networks

For neural networks, they have sprouted since the 1940s. From the initial artificial neuron models to the perception algorithms in the 1950s, they can effectively analyze the dichotomy of multi-dimensional data, indicating that these models can only be effective Deal with linear classification problems. The emergence of the BP propagation algorithm can realize non-linear processing and local processing of non-linear classification problems through the model, but there may be problems such as long network construction time and partial optimization.

The emergence of deep network training can solve the local problem of gradient disappearance, that is, the initial training of the network through unsupervised classification, to ensure that the weight of the network is a good initialization value, and on this basis, the use of supervised classification to the network Continue the second round of optimization to ensure the improvement of network performance. On this basis, industry scholars have introduced a series of new architectures and new technologies, such as the ReLU activation algorithm, AlexNet function, etc., making the neural network gradually enter the mature stage.

From the perspective of specific deep neural network applications, it can generally be divided into two categories, one is the input deep neural network, which is a one-dimensional vector; the other is the DNN value of a two-dimensional or three-dimensional image. The former type often has a deep belief network, while the latter type is a neural network that represents a Convolutional type.

3 Research status of deep learning in remote sensing image classification

From the perspective of supervision methods, the classification of remote-sensing image scenes based on deep learning can be divided into three classification methods: full supervision, semi-supervision, and weak supervision. The proposed flow is depicted in Figure 1.

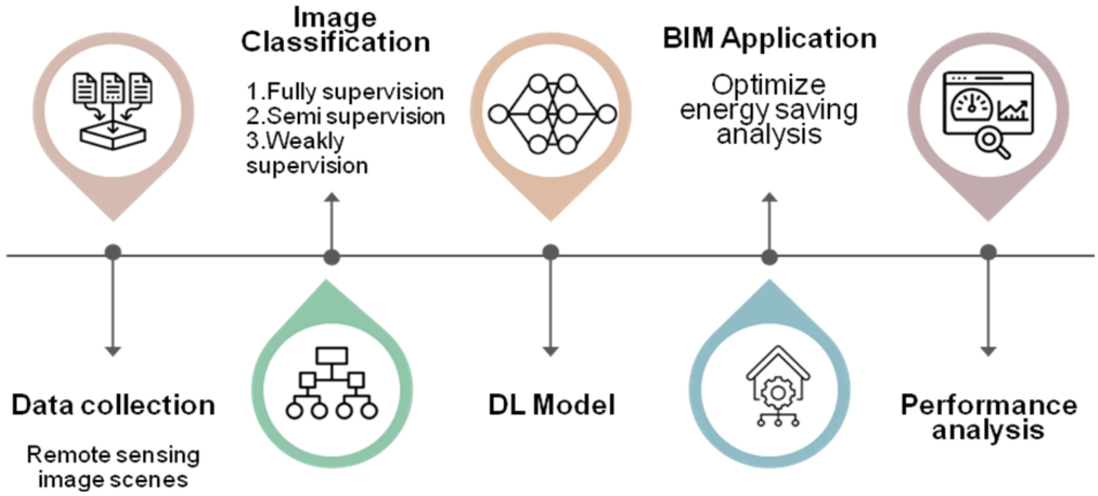

Figure 1: Proposed methodology

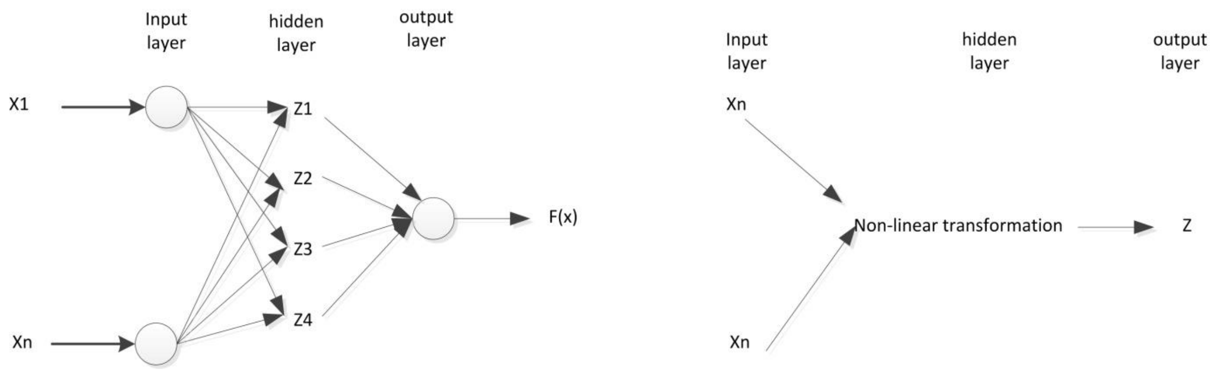

Figure 2: Neural network and neuron structure.

3.1 Remote sensing image scene classification method based on fully supervised deep learning

For fully supervised learning, its essence is supervised learning, that is, one of the methods of network training using known data and corresponding labels. The current methods of using deep learning for scene classification can be regarded as a fully supervised kind one. For topic models, it is an effective way of fully supervised classification, such as using sparse semantic models for adaptive deep learning, realizing effective fusion of topic models and convolutional neural networks, and fully analyzing the multi-layered semantics of remote sensing images. Realize the fusion at the semantic level, analyze the classification of specific sparse topic features and deep models, realize the analysis of feature capability representation, and improve the level of classification.

On this basis, some scholars try to introduce metric learning and deep learning and use the loss function to realize the deep neural network fusion of specific training models. This method can effectively analyze the diversity and classification in the specific analysis and classification of remote sensing image scenes. The problem of similarity between the two, at the same time, also achieved an effective improvement in classification accuracy.

It is a relatively common way to use deep-level fusion multi-feature algorithms to achieve remote sensing image scene classification upgrades. For example, some scholars perform effective scene classification for the feature vector of the connection layer, but although this method has high computational efficiency, it ignores part of the image information. Although the calculated result is similar to the global feature, it belongs to the corresponding categories are still different. In terms of specific reasons, it may be closely related to local features, rather than more sensitive to global features. Therefore, while analyzing the local and global features of the deep neural network, the first is to use specific clustering methods to cluster the features into different sample sets and realize the local features through the local features and the index values of the cluster centers. Sequence reconstruction, and finally, use the fusion of local features and cluster center similarity to replace the final feature of the image [12-13].

In addition to the corresponding transformation of the characteristic data layer, some scholars use the transformation of multiple network structures to improve the efficiency of calculation. Typical examples include automatic learning of CNN architecture, CapsNet architecture, skip connection covariance network and CNN network mechanisms. The specific visual attention mechanism carries out the fusion of feature extraction to achieve a significant improvement in classification accuracy.

3.2 Remote sensing image scene classification method based on semi-supervised deep learning

For semi-supervised learning, its essence is to use a large number of unordered label samples, so this algorithm does not have a high demand for data samples, and to a certain extent alleviates the defect of insufficient sample data.

Scholars in the industry use the corresponding tags to effectively expand the scale. By constructing a semi-supervised learning framework, the number of labeled samples can be automatically expanded. That is, first make minor adjustments to the trained network architecture based on the sample labels. On this basis, perform deep feature support vector machine training on the fine-tuned structure. After the training is completed, the sample category is predicted and analyzed, and the label is marked the sample is directly integrated through the original sample, and the continuous iterative operation realizes the gradual iteration of the specific sample, which effectively improves the accuracy of label data training and classification, and ensures the effective improvement of generalization ability and classification accuracy.

To use unsupervised classification for feature classification and learning, it is first necessary to establish a corresponding feature extraction model and implement specific semi-supervised learning analysis by training and labeling samples [14-15].

3.3 Deep learning model structure

A layer for input, multiple hidden layers, and an output layer make up the deep learning model utilized in this investigation. The input layer receives the feature set and applies non-linearity by processing via hidden layers using the ReLU activation function. The output layer uses softmax activation for multi-class classification or a sigmoid activation for binary classification, depending on the assignment. Using the binary or categorical cross-entropy as the loss function, the gradient descent technique is used to optimize the model. The input, hidden, and output layers make up the deep learning model. The input feature (independent variable) of the deep learning model is transformed by the hidden layer non-linearization, and then the output label (dependent variable) is shown in the left image of Figure 2.

A neuron is a node in a neural network, and its structure is shown in the right figure of Figure 1. Let the neuron input $x' = \left[x'_1, x'_2, \cdots, x'_n\right]^T$, weight $w = \left[w_1, w_2, \cdots, w_n\right]^T$, and output z. The specific calculation is shown in formula (1).

$$z = \phi\left(w^T x'\right) \tag{1}$$

Among them, $\phi(\cdot)$ is an activation function, including sigmoid, hyperbolic tangent function (Tanh) modified linear unit (ReLU), etc. The specific calculation is shown in formula (2).

$$\begin{aligned} &Sigmoid(x) = \frac{1}{1+e^{-x}} \\ &Tanh(x) = \frac{2}{1+e^{-2x}} - 1 \\ &\operatorname{Re}LU(x)\max(0, x) \end{aligned} \tag{2}$$

3.4 Deep learning (DL) model parameter estimation

The DL model's estimation of variables is an optimization procedure, and formula (3) provides the detailed computation, Where N defines the entire amount of instances, y symbolizes the correct rate of the label, $f(x_i;\Theta)$ reflects the predict rate, x_i demonstrates the i_{th} signifie, and Θ indicates the parameter of the DL approach.

$$J(\Theta)=\frac{1}{N}\sum_{i=1}^{N}\left(y-f(x_i;\Theta)\right)^2 \qquad (3)$$
$$\arg\min_{\Theta} J(\Theta)$$

The gradient descent technique is the DL model's parameter optimization method. The specific algorithm is as follows: ①initialize the parameter at random Θ; ②The parameter of control Θ moves against the gradient of the goal function, as well as the amplitude of movement is α, as as shown by formula (4). Where α is referred to as the learning rate θ_i, which stands for the parameter i; ③Repeat until the parameter is reached Θ correlations.

$$\theta_i=\theta_i-\alpha\frac{\partial}{\partial\theta_i}J(\Theta), i=1,2,\cdots \qquad (4)$$

The hyper parameters of the technique of gradient descent consist of the number of repetitions (epochs) and the degree of learning α. Over fitting may readily result from many iterations, while underfitting can easily result from few iterations. When α is little, the model will converge slowly, and when α is big, the deep learning model could not converge at the entire [16-17].

This work addresses the issue of over-fitting of the model and convergence speed by employing the early halting approach and the learning rate decay method. In order to successfully prevent over fitting, several academics have developed the early stopping approach, which ends the iteration when the objective function stops decreasing after continuous iterations. The term "learning rate decay" refers to the dynamic reduction in the learning rate α with an increase in the number of model iterations. This phenomenon might expedite the rate of model convergence. The formula (5) shows the specific computation. In this case, epoch denotes the number of iterations, represents the starting learning rate, and α_0 denotes the learning rate.

$$\alpha=\alpha_0\times a^{\frac{epoch}{10}}, epoch=0,1,2,\cdots;0<a<1$$
(5)

Use the following inference rules to infer user interests:

1) $u_i\in T(c_k)\Rightarrow u_i\in I(c_k)$;

2) $u_i\in A(c_k)\Rightarrow u_i\in I(c_k)$;

3) $u_i\in L(c_k)\Rightarrow u_i\in I(c_k)$;

4) $u_i\in P(c_k)\Rightarrow u_i\in I(c_k)$.

According to the aforementioned principles, a user is assumed to be interested in a certain category ck if they participate in it (e.g., Top Re-viewer, Advisor, and Category Lead).

Each position has a category, as was previously indicated, and qualities also have categories.

Based on the pre-defined ontology, it is easy to conclude that you are automatically interested in the field of film (see Figure 3). The block diagram of the fuzzy deep learning network algorithm recognizer is shown in Figure 3:

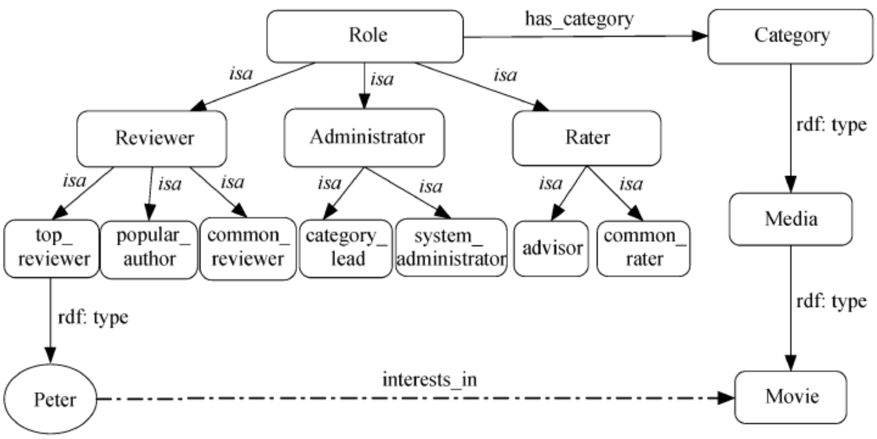

Figure 3: Role-based reasoning about user interests.

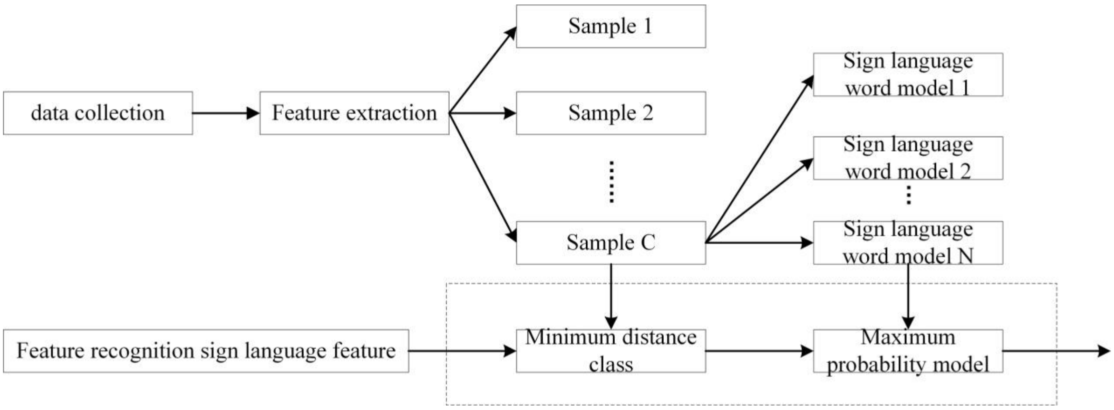

Figure 4: Block diagram of the recognizer.

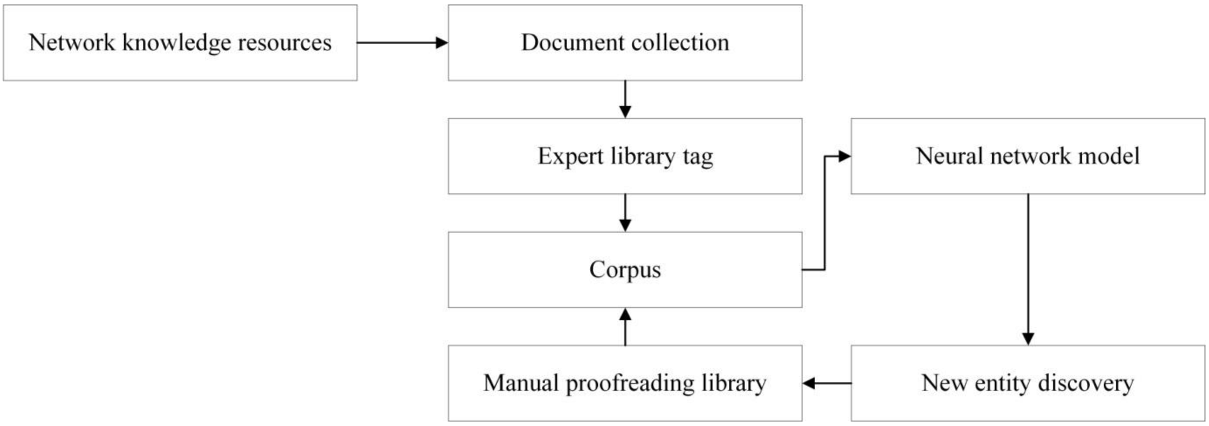

Figure 5: Overall framework of the model.

Through effective feature extraction of the part-of-speech features and corresponding combinations of the algorithm, the analysis of textual knowledge entities from the perspective of knowledge discovery, mining the relationship between context and specific knowledge entities, and renaming and renaming specific entities are realized. The new algorithm knowledge entity analysis, and then expands the expert database, carries on the specific setting of the test set, to realize the expansion *of* the expert database, especially realize the maximization analysis of the knowledge entity (Figure 5).

3.5 Definition of the model

Starting from the specific algorithm, the knowledge entity is recognized, the specific meaning of the semantics is analyzed from the perspective of knowledge recognition, and the deep neural network is set and analyzed as follows: To splice any string sequence $c_1c_2\cdots c_L$ into a long vector, the specific calculation is shown in formula (6):

$$X^{(i)} = X_{c_1}X_{c_2}\cdots X_{c_L} = \left(x_1, x_2, \cdots, x_d, x_{d+1}, \cdots, x_{3d}, \cdots, x_{Ld}\right) \quad (6)$$

For the sample of the training data set, the cost of the function is defined, and the accuracy learning effect is quantitatively analyzed through the input sample value and the actual output. The specific calculation is shown in formula (7):

$$J(W,b;x,y) = \frac{1}{2}\left(H_{W,b}(x) - y\right)^2 \quad (7)$$

In formula (7), the constant of the cost function can be expressed by x and y.

The k-th layer in the initial setup neural network is represented by z_i^k , and the activation output value of the node is represented by a_i^k . The specific calculation steps are as follows:

1) Realize specific model output according to specific forward propagation algorithm;

2) based on step 1, perform effective calculations on the nodes of the input layer, specifically as shown in formula (8):

$$\delta_i^{(2)} = \frac{\partial}{\partial z_i^{(2)}} J(W,b;x,y) = \frac{\partial}{\partial z_i^{(2)}} \left(\frac{1}{2} \left(a_i^{(2)} - y_i \right)^2 \right) = -\left(y_i - a_i^{(2)} \right) f'\left(z_i^{(2)} \right)$$
(8)

3) based on step 2, calculate the partial derivative value of the hidden layer node. The specific calculation is shown in formula (9):

$$\delta_i^1 = \left(\sum_{j=1}^{m} W_{ji}^{(2)} \delta_i^2 g'\left(z_i^{(1)} \right) \right) \quad (9)$$

4) Modify the parameters of layer l according to the given update rate η. The specific calculations are shown in ICBC Private (10) and formula (11):

$$W_{ij}^{(l)} = W_{ij}^{(l)} - \eta a_j^{(l)} \delta_i^{(l+1)} \quad (10)$$

$$b_i^{(l)} = b_i^{(l)} - \eta \delta_i^{(l+1)} \quad (11)$$

3.6 Remote sensing image scene classification method based on weakly supervised deep learning

For weakly supervised learning, it is also widely used. The use of specific remote sensing images for weakly supervised classification can realize a similar calculation of specific sample targets and perform feature classification. The classification of this algorithm can divide the specific data set into two domains: target and data source [18-19].

3.7 Qualitative comparison of supervision methods

Using a specific fully-supervised classification method, the classification effect obtained is more obvious, and the classification accuracy is higher, but the premise of fully-supervised classification requires a large number of samples as the support of network classification, but it should be noted that label samples are difficult to obtain, especially The labeling of disordered images requires a lot of manpower and material resources, which inhibits the in-depth application of the fully-supervised method to a certain extent[20].

The semi-supervised classification method is network training for a large number of unordered label samples, which can obtain more information through the network and improve the classification efficiency of the network. However, this kind of classification can only construct the corresponding space from the labeled samples, without adding additional pre-judgment information, so the accuracy of the classification is limited.

The weakly supervised classification method, in essence, uses data samples that are similar to the target but not the same for training and analysis, which not only reduces the need for sample labels but also improves the generalization ability of the network.

By comparing these three types of methods, it can be seen that the algorithm accuracy of fully supervised classification is high, but the premise is that a large number of sample labels are required. Although semi-supervised classification does not require high sample labels, its ability to network classification is not enough and is weak. Although supervised classification reduces the demand for target data samples, it cannot fit the gap between the target and the data source, so the accuracy of classification is difficult to improve.

Based on deep learning classification, scientific BIM technology is used to realize the construction of building office energy-saving informatization, and to realize the specific unification, standardization, and modelization of construction projects in different construction phases and different data acquisition phases. For example, in the elevator installation process, by using modern BIM technology to fully obtain and analyze the size and number of floors of the elevator to ensure that the data is safer and more comprehensive, the building planning is more reasonable, energy-saving and economic benefits are improved., It also raises the requirements for environmental protection. On the one hand, this approach simplifies the task of project implementation and ensures more flexible planning and design. On the other hand, it increases the design coordination rate [21-22].

The use of scientific BIM can realize the optimization of specific intelligent building designs, ensure that problems are found in the design, timely feedback on the existing problems in the intelligent building, and regularly optimize and adjust various parameters to achieve the improvement of the effectiveness of the specific design. , To better provide support for construction projects and improve the quality and corresponding efficiency of engineering construction.

Through the use of scientific BIM technology, the construction of specific management models is realized, the specific building energy-saving design is standardized and accurate management analysis, and the designers can perform timely and effective reading and data acquisition to improve the accuracy of the design. , Comprehensive and effective, avoid loss in the process of information transmission as much as possible, improve the acquisition, sharing, analysis, and utilization of data, and ensure that the design of the building is more complete and reasonable.

Use scientific BIM technology to realize the construction of specific 3D models. Based on the rendering of specific 3D models, we can analyze and display the architectural design more intuitively to ensure that the design is effective and scientific. By virtualizing the 3D model during construction, the specific construction party is simulated, and timely feedback and adjustment of the shortcomings in the construction plan, such as strengthening scientific lighting, optimizing the design of ventilation and water, etc., reduce the problems encountered in actual construction.

Through the use of scientific BIM technology, the specific building information database can be updated and perfected, the template database can be constructed to achieve standard selection, and standard analysis and evaluation can be performed on the requirements of the plan and the needs of customers. The relevant design personnel can be based on the specific Query related to the database to ensure the uniformity and standards of building energy-saving design, which can effectively improve design efficiency. Through specific computer technology, it can realize dynamic avoidance of collision avoidance and other problems, to ensure that the energy-saving design is more optimized and perfect, to achieve the quality of building energy-saving design, and to ensure the smooth realization of the project [26-32].

From the perspective of transformer use, it has its resistance. Therefore, when power resources are used, the voltage transformer will cause a certain amount of waste of electrical energy. Therefore, the optimized design of the transformer is actually to effectively reduce the effective power of the transformer., Improve the working efficiency of the transformer.

3.8 Reduce active power loss

From the specific point of view of the transformer, in the specific composition and operation process, it needs to be based on a fixed voltage and frequency, to ensure that the active loss does not change, especially for the load of the transformer, there is no corresponding relationship. Therefore, when selecting the corresponding transformer, it is necessary to choose a material with a smaller resistance value, such as copper. Through the new transformer, specific quality can be achieved, the loss of power consumption can be reduced, and a good energy-saving effect can be achieved [23].

3.9 Increase transformer capacity

When selecting the transformer capacity, it is necessary to make the operation of the transformer as close to the maximum load rate as possible according to the actual operation of the transformer, to ensure that the transformer achieves the best energy-saving effect, especially for buildings, which may often contain multiple transformers. Therefore, it is necessary to clarify the number of transformers. On the premise of meeting the demand, reduce the number of transformers and increase the capacity of transformers to achieve the greatest energy-saving effect.

3.9 Choose the right cable

Appropriate power cables can effectively reduce power loss and are also an important part of building electrical optimization design. When choosing a power cable, the most important thing is to choose a low-resistivity cable, of which communication cables are the most commonly used. This cable material has good conductivity and low resistivity. On the one hand, the specific cable length can be reduced, and on the other hand, the specific cable cross-sectional area can be increased [24-25].

4 Simulation analysis

4.1 Experimental Setup

To verify the effectiveness of DL and remote sensing image scene classification, this paper selects specific training samples for feature analysis to directly carry out the energy-saving design of smart city buildings. Using deep learning and remote sensing image classification, certain training samples were chosen for this work in order to assess attributes that are directly related to energy-saving design in smart city structures. An Ubuntu 16.04 operating system on a single 3.6 GHz 8-core i7-4790 CPU with 32GB of RAM was used in the testing arrangement. An NVIDIA GTX 1070 graphics processing unit (GPU) was used to speed up computations. Large datasets and intricate DL models could be processed more quickly and effectively thanks to this hardware setup, which was important for applications like image segmentation, feature extraction from BIM data, and energy usage prediction. The GPU's capacity for parallel processing greatly sped up the training and assessment of the model, allowing for prompt testing and reliable confirmation of suggested energy-saving techniques. This configuration allowed for thorough research and modeling of many scenarios to maximize energy efficiency in urban building contexts, in addition to meeting the study's technological requirements.

4.2 Quantitative comparison results

In the specific experimental part, three types of data are selected through an experimental comparison of the public urban building data set, as shown in Figure 6-8 respectively:

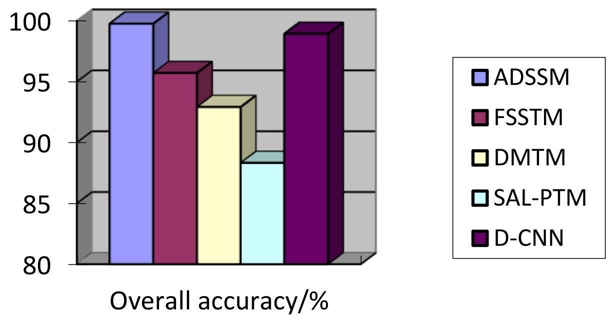

Figure 6: Accuracy analysis of full supervision.

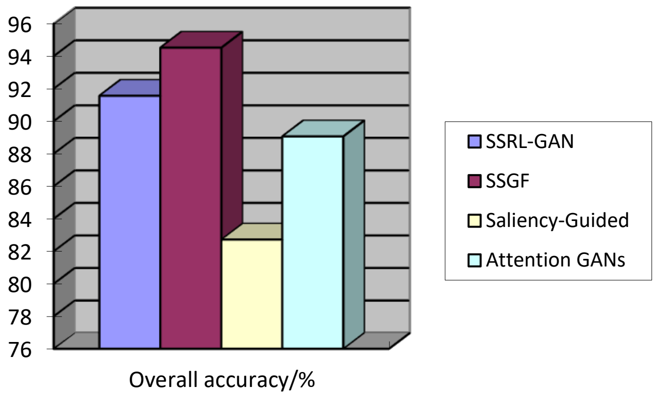

Figure 7: Semi-supervised accuracy analysis.

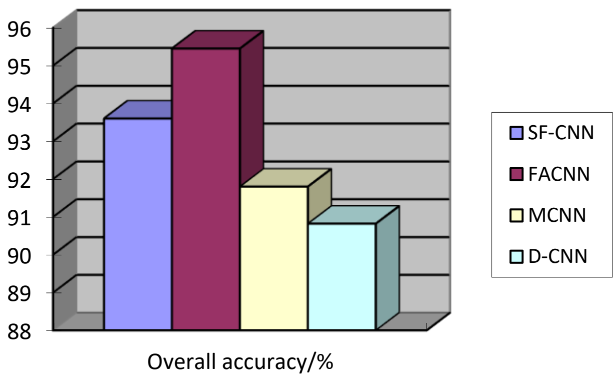

Figure 8: Quantitative comparison of the overall accuracy of the data set.

From the calculation results in Figure 6, it can be seen that based on the same amount of training data, the use of fully supervised classification to classify architectural scenes is better, but the results of different types of supervised classification methods are relatively small. This is mainly because the classification of building data in this dataset is relatively low, so semi-supervised classification can completely replace the fully-supervised classification method.

It can be seen from the results in Figure 7 that after the sample data volume reaches 2000, the accuracy of semi-supervised classification is the same as that of fully-supervised classification, which shows that the classification style of semi-supervised classification makes up for the deficiency of insufficient label data.

It can be seen from the results in Figure 8 that the fully-supervised classification method is better when applied to the classification of architectural scenes. When the amount of data is large, the fully-supervised classification method is still selected first. It can be seen from the results in Figure 9 that when the number of data sets is small, or when the task is relatively simple, the use of weakly-supervised classification methods can effectively improve the generalization ability of the network and achieve classification accuracy similar to that of fully-supervised classification. When faced with more complex data sets and actual classification tasks, the classification method based on full supervision is still the best. Therefore, the simulation experiment results show that the deep learning algorithm and remote sensing image scene are effective and can support the energy-saving design of smart city buildings.

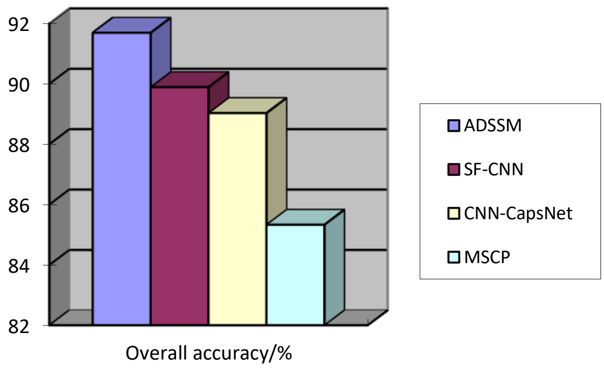

Figure 9: Quantitative comparison of the overall accuracy of the second data set.

4.3 Evaluation metrics

In this section we evaluate the proposed D-CNN with other existing methods Deep extreme learning machine (DELM) [33], Fused ML [33], and Intelligent Energy Management System (IEMS)[33] to detect accuracy. Precision, recall, and F1-score are evaluated with Root Mean Square Propagation (RMSProp)[34], Adam [34], and Enhanced DNN(E-DNN) [34].

4.4 Accuracy

The accuracy parameter indicates the percentage of all predictions made by a model were accurate. Figure 10 and Table 2 show the accuracy. The approaches that yielded the lowest accuracy, DELM (84.01%), and the best accuracy, 93.45%, were Fused ML (90.7%), IEMS (92.11%), and the D-CNN technique. This indicates that of the approaches studied, D-CNN which makes use of deep convolutional neural networks is the most successful way for assessing and improving energy-saving designs in smart city buildings.

Table 2: Accuracy

Methods	Accuracy (%)
DELM	84.01
Fused ML	90.7
IEMS	92.11
D-CNN (proposed)	93.45

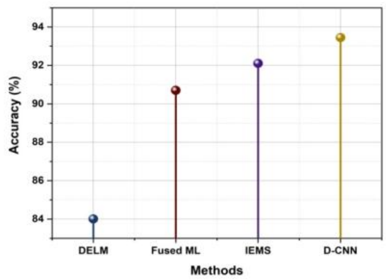

Figure 10: Comparison of Accuracy

4.5 Precision

The precision of positive forecasts is measured. The ratio of true positives to the total of true positives and false positives is used to compute. Less false positives in comparison to real positives are indicated by greater precision.

Table 3: Overall outcome of precision, recall, F1-score

Methods	Precision (%)	Recall (%)	F1-Score (%)
RMSprop	96.79	96.55	97.35
Adam	95.09	97.05	69.05
E-DNN	98.91	99.52	99.09
DCNN Proposed)	98.97	99.55	99.12

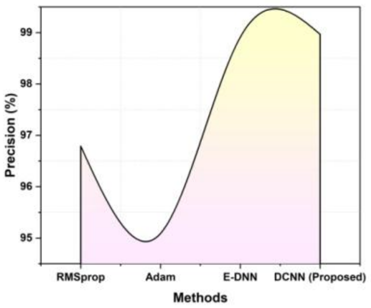

Figure 11: Comparison of precision

Figure 11 shows the precision and Table 3 depicts the overall outcome of precision, recall, and F1-score. The techniques produced RMSprop (96.79%), Adam (95.09%), E-DNN (98.91%), and the maximum precision of DCNN (98.97%) that was suggested.

4.6 Recall

Recall is often referred to as sensitivity or true positive rate, and assesses how well the classifier can recognize positive examples. The ratio of true positives to the total of false negatives and true positives is used to compute it. In comparison to genuine positives, fewer false negatives are indicated by a stronger recall. Figure 12 depicts the recall. While the techniques achieved RMSprop (96.55%), Adam (97.05%), and E-DNN (99.52%), the recommended DCNN reached the greatest D-CNN (99.55%).

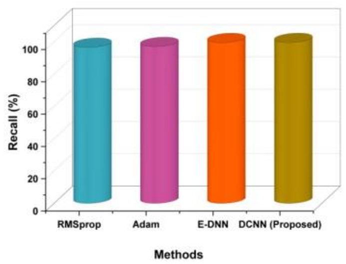

Figure 12: Comparison of recall

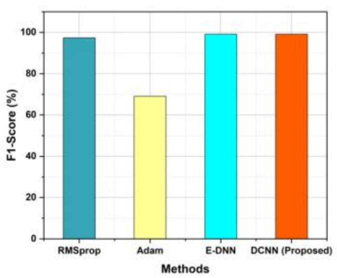

Figure 13: Comparison of F1-score

4.7 F1-score

The harmonic mean of recall and accuracy is known as the F1-score. It offers a solitary metric for evaluating the equilibrium between recall and accuracy. Better overall performance in terms of recall and precision is indicated by a higher F1 score. Figure 13 shows the F1-score diagram. The suggested DCNN achieved the maximum F1-score (99.12%), whereas the approaches achieved RMSprop (97.35%), Adam (69.05%), and E-DNN (99.09%).

4.8 Discussion

In discussion, an important step towards sustainable urban development has been made with the energy-efficient design of smart city buildings that incorporates deep learning algorithms and remote sensing pictures. This research advocates for more intelligent resource management in line with green building principles by addressing significant inefficiencies in urban construction processes. The research shows a methodological synergy that improves building energy efficiency by integrating remote sensing for accurate environmental monitoring and deep learning for thorough data analysis. The framework is different from other approaches because we combine deep learning algorithms with remote-sensing image scenes to analyze urban energy use more thoroughly and precisely. DL enables automatic and sophisticated pattern recognition in large datasets, while remote sensing provides real-time, spatially rich information. This combination improves the accuracy and efficiency of energy-saving designs, outperforming other approaches that do not have such sophisticated data processing capabilities. Moreover, the use of BIM technology for detailed simulations further refines the optimization process, resulting in superior energy efficiency outcomes. Optimal performance in office buildings is ensured by the implementation of Building Information Modeling (BIM), which further refines design ideas. The results of the simulation trials demonstrate how well these technologies work in urban settings to provide significant energy savings and enhance environmental sustainability in general. The findings demonstrate how well these approaches work to significantly increase energy efficiency in urban settings. The study not only finds potential for energy savings but also offers a framework for deploying scalable solutions across a variety of building types by classifying and analyzing data based on different monitoring levels.

5 Conclusions

With the continuous development of social economy, people have higher and higher requirements for building design. On the one hand, they have high requirements for living experience, and on the other hand, they are for better energy conservation and emission reduction. In response to these needs, this article is based on DL and remote sensing image scene methods and analyzes the business logic of smart city building energy-saving design. Through the analysis of electrical power consumption, transformer capacity measurement, and building classification accuracy analysis, smart city building energy saving is realized. Effective analysis, using BIM technology for energy-saving design analysis, and using simulation experiments for evaluation. The simulation experiment results show that the DL algorithm and remote sensing image scene are effective and can support the energy-saving design of smart city buildings.

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