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Research Article

Building Protection Data Release Planning Based on Multifeature Deep Learning

Chunhuan Guo,[1] Yajun Zang,[2] and Yu Gao[3]

[1]*School of Architecture and Civil Engineering, Chongqing Metropolitan College of Science and Technology, Yongchuan 402167, Chongqing, China*
[2]*School of Public Administration, Chongqing Technology and Business University, Chongqing, Chongqing 400067, China*
[3]*School of Artifical Intelligence and Big Data, Chongqing Metropolitan College of Science and Technology, Yongchuan 402167, Chongqing, China*

Correspondence should be addressed to Yu Gao; gaoyu@cqcst.edu.cn

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With the rapid development of China's economy, the protection of buildings has attracted the attention of many researchers. Although there is no such massive demolition in the past, natural damage still exists. Identify the collected historical building protection data through multifeature deep learning, and provide protection plans through the information in the database. In order to solve the problem of restoration of natural damage more professionally and efficiently, this paper collects the architectural features and restoration methods of each building in different processes through multifeature deep learning based on the current state of building information in China. Based on the collected information, this paper establishes the building information model, and stores and manages the building information. According to the Newton deep learning optimization algorithm, this paper enhances the algorithm to accurately collect building information and uses the collaborative filtering algorithm to provide users with a repair plan. This paper uses the GRU-based recommendation model to pass the threshold cycle unit algorithm for the probability of each building being selected in the list of similar buildings at a time point. Under the two conditions of 10 and 20 recommended numbers, the user coverage rate of the recommended case of deatomized building photos can reach 100%. And this paper recommends high-probability solutions for users to achieve automation, diversification, and intelligence.

1. Introduction

Architecture is an important part of the development process of human civilization, reflecting the way of life and habits of local people in the era, and carrying the local cultural atmosphere. With the rapid development of China's economy, the pace of urbanization has accelerated, and the scale of the renovation of old cities has been expanding. This not only damages the historical buildings but also destroys the local life atmosphere. The disappearance of historical value is irreversible. Therefore, the protection of historical buildings is particularly important. By archiving historical building materials, such as photos and videos of historical buildings, this paper proposes a new idea of using multifunctional deep learning to accurately protect and study historical buildings.

When researching and accumulating knowledge on methods, techniques, and practical interfaces of historic building preservation have substantial significance for the harmonization of scientificity and authenticity of building preservation that can be used in the future. It also plays a key role in interprofessional, cross-platform historic building conservation practice. Model and analyze the protection methods and special technologies of historical buildings through multifeature deep learning, and truly restore the effect of historical buildings after protection.

Based on multifunctional deep learning to explore the protection of historical buildings, this paper uses geodetic maps, tables, text, or pictures to preserve historical building information to achieve the protection of historical buildings. The scope is large, but even if these methods are more specific and accurate, they can fully and accurately reflect the historical style of the building.

2. Related Work

As one of the state-of-the-art techniques, deep learning has been highly valued in the field of an object retrieval. Litjens et al. survey the application of deep learning in image classification, object detection, segmentation, registration, and other tasks, and provide a brief overview of research in each application area [1]. Chen proposed a novel deep learning framework to merge these two features, from which the highest classification accuracy can be obtained [2]. Shen introduced the basic principles of deep learning methods and reviewed their success in image registration, anatomical and cellular structure detection, tissue segmentation, computer-aided disease diagnosis, and prognosis [3]. Oshea and Hoydis used the concept of radio transformer networks as a means of incorporating expert domain knowledge into machine learning models [4]. Hou et al. proposed a blind IQA model that directly learns qualitative assessments and outputs numerical scores for general use and fair comparison [5]. Zhao established a test bench to verify the filtering algorithm and applied MATLAB software to design the moving average filtering algorithm, the IIR filtering algorithm, and the moving-IIR filtering algorithm [6]. Yang et al. proposed a new nonlinear state estimation algorithm, which has high accuracy while ensuring robustness [7]. They utilize a learning denoising based approximate message passing (LDAMP) network, a neural network that can learn channel structure and estimate channels from a large amount of training data [8]. Tom et al. review important deep learning-related models and methods that have been used for many NLP tasks, and summarize, compare, and contrast various models [9]. These studies have certain guiding significance, but the studies are too single and need to be further improved.

3. Building Protection Analysis Based on Multifeature Deep Learning

A historical building has left imprints of old-time information in the development of the city, and these imprints are the carriers of recording urban civilization. The safety of historical buildings and the rational use of protection technologies can preserve and inherit local culture and life.

3.1. Current Situation and Analysis of Protection of Building Information. According to the principle of historical building protection, the protection of historical buildings should preserve the original historical information as much as possible, and use the physical object as the carrier to protect the environment as much as possible. The overall protection of historical buildings includes not only the protection and development of the physical environment of the historically left space but also the protection and development of the urban historical context.

The first stage is the census, the second stage is the analysis and evaluation stage, the third stage is the current situation investigation and thorough investigation stage, and the fourth stage is the filing stage. According to Table 1, the normal conservation process can be divided into several well-defined work steps according to the depth and completeness of the census [10]. There is a gradual one-way process between these stages, with little exchange of information between each stage of the work. The features of this protection process are as follows:

However, with the increase of various problems faced by building protection, the content of building protection has gradually become more complex and diversified. However, the mentioned advantages of building protection have turned into shortcomings in the current building protection.

At present, the security process of historical buildings is becoming more and more complex, and the circle of participants in the security process has expanded significantly, not only involving professional security personnel but also manufacturers and users. Decision-making and technical assistance at all stages of the conservation base should be provided. It is precise because of the joint participation of all employees that the original routine can no longer meet the needs of the current work [11]. The participants in the protection of historical buildings are shown in Table 2.

In addition, China's awareness of historical building conservation is weak. Major parts of the historic buildings are mostly dilapidated, severely or even collapsed. Historical buildings have their own uniqueness, and their safety issues are more important than general buildings, including the safety problems of historical buildings themselves, the fire bank problems of historical buildings, and the environmental impact of historical buildings' protection [12].

When interpreting historical building information, the aggregation of historical building information is the protection of historical buildings, and the value of historical buildings lies in the information provided and transmitted by historical buildings. Therefore, in order to better protect the historical buildings, it is necessary to clarify the protection status and existing problems of the historical building information at this stage.

Due to the inadequate implementation of digital information work, the historical building information collected and organized lacks integrity and coherence, and the work functions of local governments and various research institutions are unclear. It causes the historical building information to present an island state and even a large number of repeated links [13]. This virtually hinders the application of digital information technology in the protection of historical buildings and deviates from the original intention of protecting and inheriting real and comprehensive historical building information [14]. Once the information transformation and analysis takes a long time, it will lead to low protection efficiency and easy to cause information failure. It can be seen that the construction of a complete historical building information system has become the key to the protection of historical buildings, as well as the

Table 1: Building preservation process.

The first stage preliminary research	Background research Photo compilation Building survey Building inspection Various identifications
The second stage design stage	Concept Design Extended design Construction design
Phase 3 construction phase	Construction preparation Construction collaboration Construction management
The fourth stage is the data compilation and archiving stage	Data collection into a book

protection of historical buildings and inheritance of excellence The development trend of historical building culture and innovative historical building protection methods [15] as shown in Figure 1.

At the same time, the historical building protection model is only implemented on a two-dimensional basis, the visualization and correlation of data are relatively poor, and the technical level is low, which seriously affects the development of protection work, and problems are not easy to be found.

3.2. Newton Deep Learning Optimization Algorithm. The Newton iteration method, also known as the Newton–Raphson method, is a method proposed by Newton in the 17th century to approximately solve equations in real and complex fields. In deep learning, the so-called optimization algorithm is an iterative method for finding the optimal solution to the objective function. In the convex optimization task, in order to solve the time-consuming problem of gradient calculation caused by a large amount of data, iteration may reduce the calculation amount of each step instead of the convex problem, and the iterative method is used to continuously approach the optimal solution function of the target [16].

Second-order methods use second-order derivatives to improve optimization compared to first-order methods, of which the most widely used second-order method is Newton's method. For the constraint problem f (a), the minimum value of the objective function is a*. The second-order Taylor expansion of f (a) is given as follows:

$$f(a) = f(a_k) + b_k^T (a - a_k) + \frac{1}{2}\left(a - a^k\right)^T H\left(a^k\right)(a - a_k). \tag{1}$$

Among them, b_k is the gradient of f (a) function at a_k, $H(a^k)$ is the Hessian matrix of f (a) at point a_k; and the gradient of the function at the extreme point is 0, that is, given as follows:

$$\nabla f(a) = 0. \tag{2}$$

In the process of finding the minimum value, it is assumed that in the k^{+}1th iteration, $\nabla f(a^{k+1}) = 0$. So from the formula, we get as follows:

$$\nabla f(a) = g_k + H_k\left(a - a^k\right). \tag{3}$$

That is: $g_k + H_k(a^{k+1} - a^k) = 0$, so we can get Newton's method iterative formula gradient descent method is a common optimization algorithm. In addition to the challenges posed by certain characteristics of the objective function, Newton's method for training large neural networks is also limited by its significant computational burden. Assuming that f (a) has a first-order continuous partial derivative, in solving such unconstrained optimal problem min f (a), a* is the minimum value of the objective function. The first-order Taylor expansion of f (a) is given as follows:

$$f(a) = f(a_k) + g_k^T (a - a_k). \tag{4}$$

Among them, $g_k$is the gradient of the f(a) function at x_k, then the k+1th iteration satisfies:

$$a^{(k+1)} \longleftarrow a^k + \lambda_k p_k. \tag{5}$$

3.3. Feature Perception Enhancement Algorithm for Fog Scene Based on Generative Adversarial Mapping Network. The first method of feature augmentation is to identify missing values in the data, which can better understand how to use the data in the real world. In natural scenes, due to the existence of fog or haze, the scene information is weakened during the image acquisition process [17]. Affected by the scattering of light by fog or haze in the environment, part of the reflected light in the scene cannot be received normally. It causes the loss of some details and color differences in the image, and the loss or change of the feature information in the image, which leads to image distortion. For ordinary perceptual networks, it cannot abstract the perspective for restoring hazy images [18]. The perception network uses two kinds of multilayer deep neural networks to construct an adversarial training framework to ensure the effective implementation of training rules. It fuses multiple features more accurately and obtains a perspective rate, that is, more in line with the real scene. The specific implementation algorithm is shown in Figure 2.

Feature augmentation is in the sense of identifying problematic areas and determining repair method is most effective, rather than removing things. A foggy environment

Table 2: Various participants in building protection.

	The first stage of preliminary research					The second stage design stage				The second stage construction phase			The fourth stage is the data compilation and archiving stage	Total
Protection process	Background research	Photo compilation	Building survey	Building inspection	Various identifications	Concept	Design	Extended design	Construction design	Construction preparation	Construction collaboration	Construction management	Data collection into a book	
Participants														
Owners and managers	√	√				√	√	√	√	√	√		√	10
Architect	√	√	√	√	√	√	√	√	√	√	√		√	13
Architectural historian	√	√				√	√						√	5
Contractor										√	√	√	√	5
Department of historic preservation	√	√	√	√	√	√	√	√	√	√	√		√	13
Historic building restorer	√	√		√	√	√	√	√	√	√	√	√	√	13
Structural engineer	√	√	√	√	√	√	√	√	√	√	√		√	12
Environmental engineer	√	√				√	√	√	√	√	√		√	5
Landscape engineer	√	√	√	√	√	√	√	√		√	√		√	13
Craftsman	√	√								√		√		4
Materials scientist	√	√				√	√							4
Surveyor	√	√	√										√	4
Planner						√	√						√	3

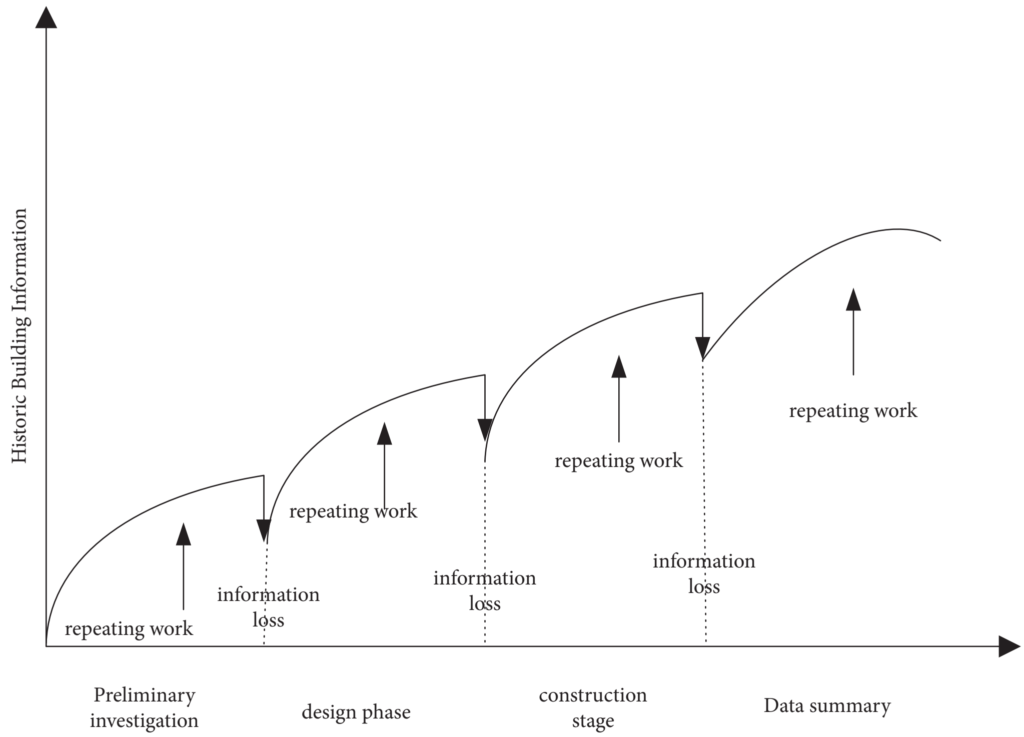


Figure 1: Information transfer process in historic building protection.

is the scattering of light by atmospheric particles, the light reflected from the target surface in the scene is scattered, and its light intensity decreases and expands exponentially, and the light source increases with the propagation distance [19]. According to the atmospheric light scattering theory, a widely used atmospheric light scattering model is formed in computer vision and graphics:

$$I(a) = J(a)t(a) + X(1 - t(x)). \tag{6}$$

Among them, I is the blurred image, J is the faded scene image, t is the transmittance $t = e^{-\beta d(x)}$ of the light propagation medium, X is the atmospheric light value, and a is the image pixel. However, in a real blurry scene, there is no single light source, and the light reflected from the target also has slow reflections, as shown in Figure 3, thus defining multiple light source scattering models:

$$I(a) = J(a)t(a) + X^*(1 - t(a)). \tag{7}$$

Among them, $X^* = \partial_0 X + {}^n \sum \alpha_i X_i$. X_* is the value of the rest of the interference light in the scene except atmospheric light, including the interference light after the diffuse reflection of the reflected light between the independent light source and the target, and the light source intensity coefficient.

In order to realize the dehazing processing of the foggy image, the fog-free image J in the scene is estimated, which can be obtained according to the formula as follows:

$$J(a) = \frac{I(a) - X^*}{t(x)} + X^*. \tag{8}$$

At this point, the attenuation image transformation is converted into an estimate of the ratio of perspective to atmospheric light A. During the propagation of light, the speed of light loss at different wavelengths is different. Channels in RGB space, relevant perspective metrics are evaluated accordingly and satisfy:

$$0 \le \overline{t}^c \le 1, \forall c \in \{r, g, b\}. \tag{9}$$

where $\overline{t}^c$ is the c-channel perspective in RGB space. In the computed fluoroscopy, $\sum (a) \sum J(a)$ occurs due to overestimation of fluoroscopy velocity due to limitations of fluoroscopy velocity or insufficient prior information. Assuming both blur and smoke images in the same scene in the same scene, there are:

$$t^c_{dist}(a) = \frac{X^* - I^c(a)}{X^* - J^c(a)}, 0 \le t^c_{dist}(a) \le 1. \tag{10}$$

Among them, t^c_{dist} is the optimal perspective ratio of the c channel. To solve the perspective relationship under limited conditions, the traditional method cannot precisely define it. To address this poor design, a method of natural image statistics is used to estimate the perspective ratio. It is further transformed into the minimum value problem in convex optimization, satisfying:

$$\min L(, t_{dist}) = \min L(G(F(I)),). \tag{11}$$

Among them, L is the loss function in image statistics, G is the mapping function from the input image I to the perspective, and F is the fog-related feature extracted from the input image I.

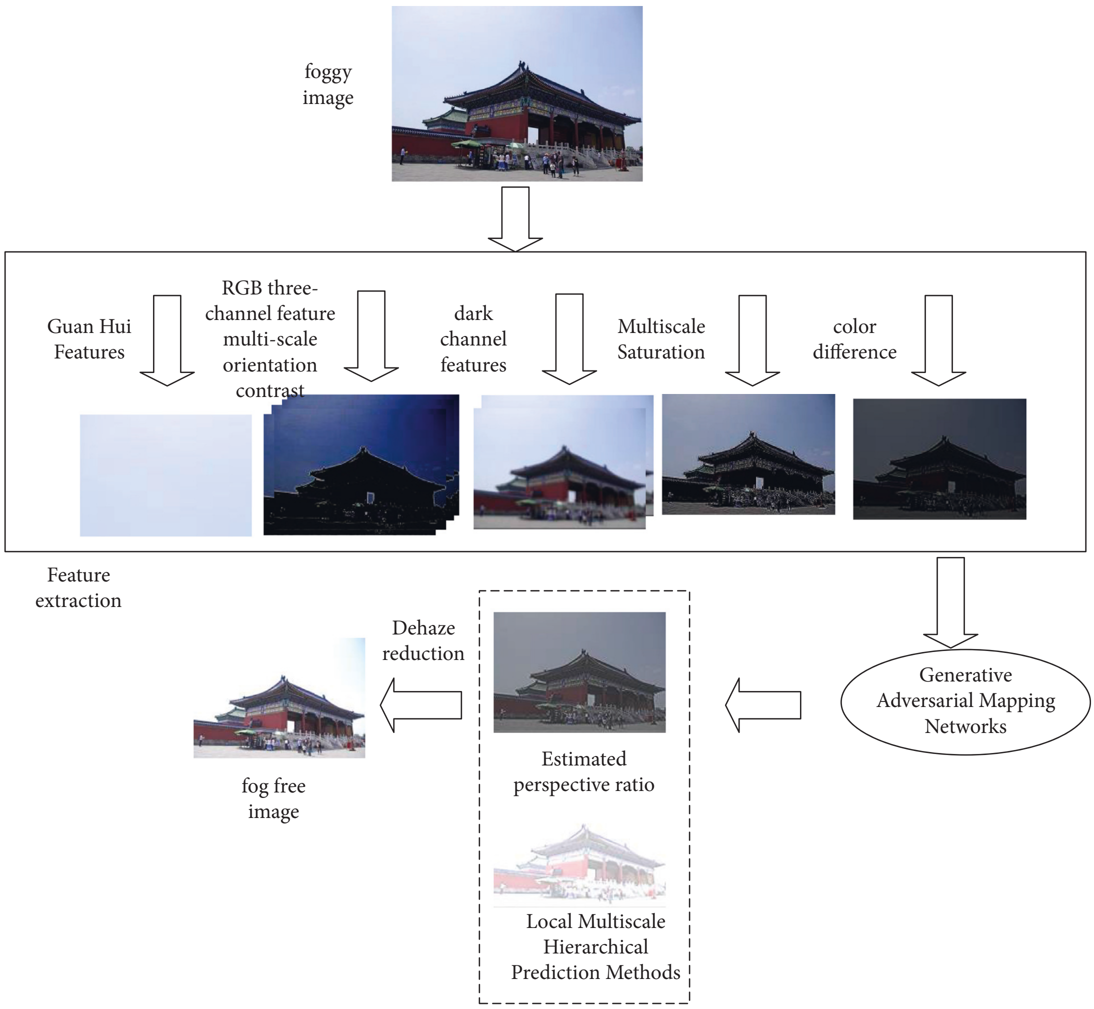


Figure 2: Framework diagram of multilayer perceptual dehazing algorithm based on generative adversarial mapping network.

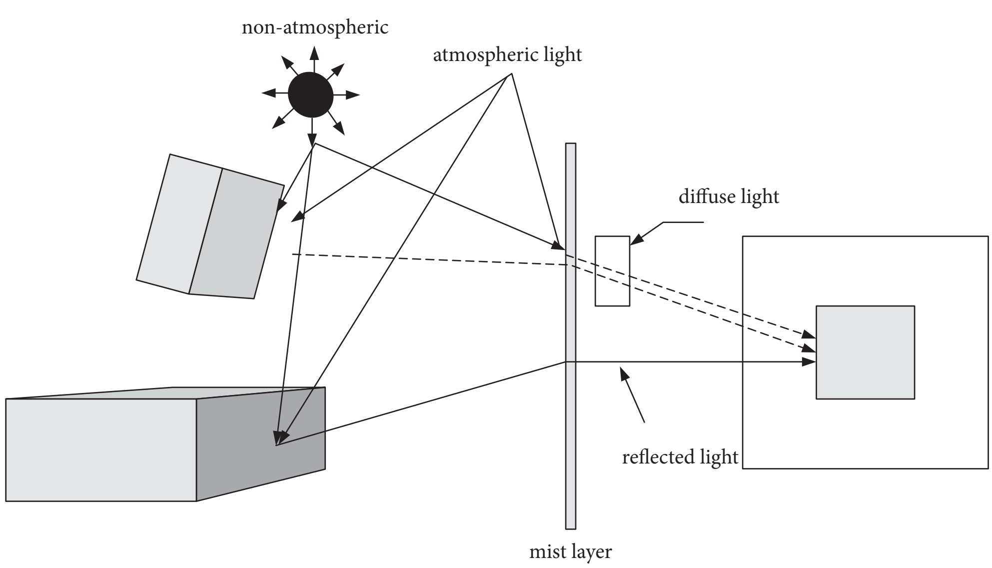


Figure 3: Multisource scattering model.

3.4. Item-Based Collaborative Filtering Algorithm. The so-called collaborative filtering is to recommend items to users based on their previous product preferences and the choices of other users with similar interests. Product-based collaborative filtering algorithms have been widely used in the industry since they were proposed, and are still the basis for reference algorithms used by many companies [20]. The idea is very intuitive, that is, recommend the most similar scheme to the user, that is, recommend according to the user's historical interest, as shown in Figure 4.

When a user needs a personalized building protection scheme, he/she can first find other users, who have similar interests to him/her and then recommend those novel schemes that the user likes to the user. Building i represents $R = \{r_{ij}\}$ of the user-item matrix in the i-th column, then the formula for calculating the cosine similarity of the angle between building i and building j is given as follows:

$$sim(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \bullet \vec{j}}{\vec{i}_2 * \vec{j}_2}. \tag{12}$$

The formula to express the Pearson correlation is given as follows:

$$\begin{aligned} sim(i, j) &= \frac{\sum_{u\in U}(r_{ui} - r_i)(r_{u,j} - r_i)}{\sqrt{\sum_{u\in U}(r_{ui} -)^2}\sqrt{\sum_{u\in U}(r_{u,j} -)^2}}, \\ sim(i, j) &= J(i, j) = \frac{|U_i \cap U_j|}{|U_i \bigcup U_j|}. \end{aligned} \tag{13}$$

3.5. Algorithms Based on Threshold Cyclic Units. A simple recurrent unit is a variant, what they have in common is that each neuron is a processing unit, and each processing unit contains several thresholds, which are used to control the flow of information. The recurrent threshold cell model was proposed in 2014. And it performs well in speech recognition and machine translation [21]. The entire GRU process is shown in Figure 5.

The hidden state of the recurrent neural network changes the activation function to a nonsaturated activation function, thereby avoiding the problem of gradient disappearance caused by the saturated activation function, and at the same time, it can also speed up the network convergence speed. The activation function value at time t is the weighted average of the activation function value $h_{t-\mathrm{i}}^j$ at the moment before $h_t^j$and the candidate activation function value at the current moment.

$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j. \tag{14}$$

Among them, z_t^j is called the update gate to determine the update proportion, and the formula is given as follows:

$$z_t^j = \sigma(W_z x_t + U_z h_{t-1})^j, \tag{15}$$

where σ is the sigmoid activation function. When is the hanging value after the time, the calculation formula is given as follows:

$$= tabh(W_z x_t + U_z h_{t-1})^j, \tag{16}$$

where tanh is the hyperbolic tangent function.

$$\begin{aligned} tanh(x) &= \frac{e^x - e^{-x}}{e^x + e^{-x}}, \\ r_t^j &= \sigma(W_r x_t + U_r h_{t-1})^j. \end{aligned} \tag{17}$$

To avoid overcustomization, a dropout layer is added between the two layers, and the parameters disconnect the split-add neurons on each update. In other lists of similar buildings of the time, the partial formula:

$$L(\{x, y\}_1^N) = -\sum_n \sum_i y_i^{(n)} * \log(f(x^{(n)})i). \tag{18}$$

Figure 6 shows the model forward propagation flow chart. Suppose there are four types of buildings, numbered 1, 2, 3, and 4. They are represented as vectors in the input layer as shown in Figure 6 according to their encoded form.

Set the hidden layer node to 3, then the 1*3 vector exits the GRU structure function in the hidden layer. Finally, the fully connected layer provides the probability that each product may appear at different times and uses the output probability and the maximum N products as recommendations to the user.

4. Building Conservation Planning Test Based on Multifeature Deep Learning Model

By scientifically and rationally protecting the building's information model throughout its life cycle, a history is also an object in the information model, seamlessly conveying the protection of all historic buildings. It is better communicated to future assets, and professionals can also join the work earlier [22]. Depending on the division of labor, it can bring its own technology and experience to contribute to the preservation of historic buildings [23]. The project is shown in Figure 7.

4.1. Deep Neural Network Model Based on RPN. RPN (region proposal network) is a fully convolutional neural network used to extract target candidate boxes in detection [24]. In order to solve this bottleneck, some scholars proposed to use the CNN network to extract the target area, that is, the RPN to extract the target detection area. The detection network of the proposed algorithm is shown in Figure 8. The task of finding relevant features through deep learning is part of the algorithm that automates the feature engineering that reduces the problem.

4.2. Precision, Recall, and T-Score. The concepts of classification accuracy and recall (recall) were proposed in 1968 and are still in use today [25]. The accuracy rate is P, which is defined as the ratio of the number of products recommended

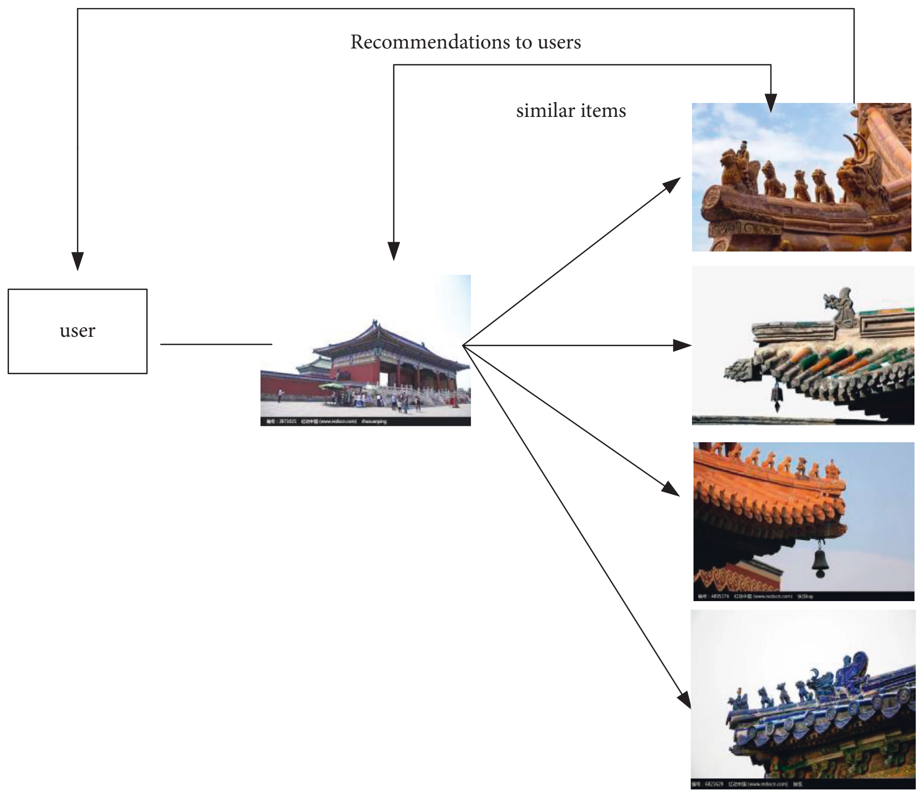


Figure 4: User usage history product recommendation.

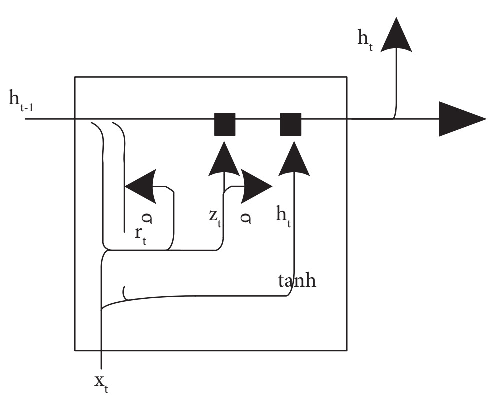


Figure 5: GRU structure diagram.

by the user to the number of products that the user actually uses. It can reflect the possibility that the user will use a recommended product [26].

When a user is recommended to be specified, the user is an active user, denoted as U_a. After sorting the purchased items by purchase time, it is called the user's purchase sequence, denoted as S_a, and N represents the number of recommended items. When the data are implicit feedback, if user i has acted on item j, $r_{ij} = 1$, otherwise $r_{ij} = 0$. Common symbols and their meanings are shown in Table 3.

Often mentioned together with precision is recall. The recall rate is recorded as R, and the user's historical behavior data are regarded as time series data, so the data S_a^{t-1} of the usage sequence S_a of the user U_a before time t is generally used as the historical data. The data S_a^{t+1} after time t is used as unknown data to evaluate the model. Table 3 presents the recommended results based on S_a^{t-1} and the number of user favorite products in S_a^{t+1}. Then the calculation Formula of the precision rate and recall rate of the available user U_a from Table 4 is:

$$W = \frac{P_{rs}}{P}, R = \frac{P_{rs}}{P_{\mathrm{r}}}. \tag{19}$$

T-score is a comprehensive consideration of precision and recall, and its calculation formula is given as follows:

$$T = \frac{2 * W * R}{W + R}. \tag{20}$$

The calculated precision, recall, and T-score are averaged over all users. The T-score is mainly used for the selection of hyperparameters in the model.

4.3. Feasibility Analysis of Historical Building Protection Based on Multifeature Deep Learning. Strategies for crawling user rating data for usage scenarios and details of subsequent data processing. Then enter the personal homepage of each user, if the user has reviewed more than 50 buildings, then crawl its building list and the corresponding score, and the crawling fields are the same. Repeat the process several times to achieve the desired amount of data.

It can be seen from the strategy of crawling the data of building ratings that the crawling is mainly for popular buildings, so the crawled data belongs to a class of extreme

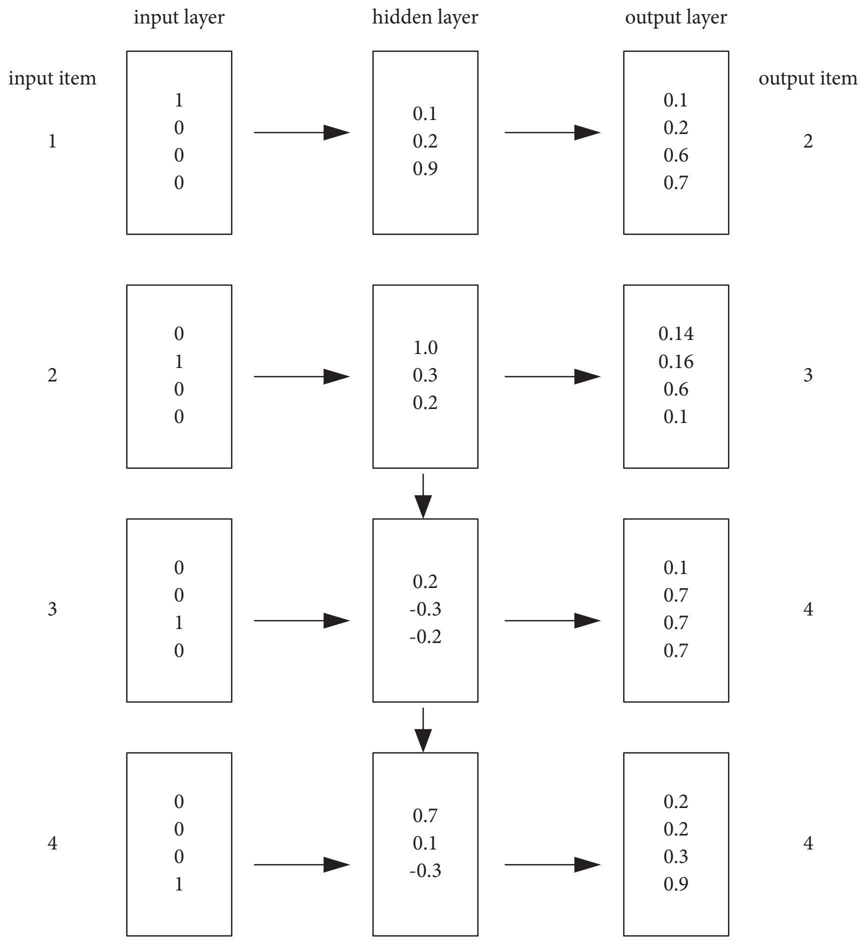


Figure 6: Model forward propagation flow chart.

data. It crawls the scores of popular building data relatively completely, but the scores of other buildings are very incomplete. Figure 9 is a graph of user evaluation data of the top 5 popular buildings in 2018.

First, the duplicate samples in the dataset are removed; secondly, due to the crawling strategy of the building rating dataset, the number of recommendations in the dataset is too large, so it is processed and the building entries with less than 10 comments are deleted. Then, change the time in the dataset to timestamp format and sort user reviews chronologically. Finally, unify the field names in the two datasets. The fields included in the final dataset are given as follows:

As can be seen from Table 5, from the perspective of data density, the user-recommendation number matrix dataset of the building rating dataset is relatively sparse.

The distribution of the number of user reviews and the number of building reviews in each dataset is shown in Figure 10. It can be seen from the figure that the number of ordinary photo users with less than 10 comment data are far more than the number of users, who use the case scoring dataset for dehazing photos, and the number of comments in the two datasets is similar. But when the number of comments is greater than 20, the number of people in the normal photo use case dataset is significantly smaller than the number of people in the dehazing photo using rating data.

According to the comparison and analysis of the results of the recommendation algorithm on the test sets of the two data sets with large differences in characteristics, Figure 11 shows the results when the number of recommended items N is 10 and 20, respectively.

On the two datasets, under the conditions that the recommended number is 10 and 20, the coverage rate of the enhancement algorithm against fog scene feature perception is the highest. When the number of recommendations is 20, the user coverage rate of the recommended case for dehazing photos can reach 100%. Fill in the missing values of the test set with the mean of the training set in the test set to achieve the effect of data enhancement, so as to achieve the purpose of feature enhancement.

5. Discussion

By collecting, sorting, summarizing, and establishing relevant systematic procedures for extensive theoretical data and case data on historical building protection measures, this paper analyzes the comprehensive problems of historical buildings. Aiming at these problems, this paper proposes to use the algorithm in multifeature learning to optimize the system. Therefore, it innovatively proposes to create a system suitable for the protection of historical buildings, and this

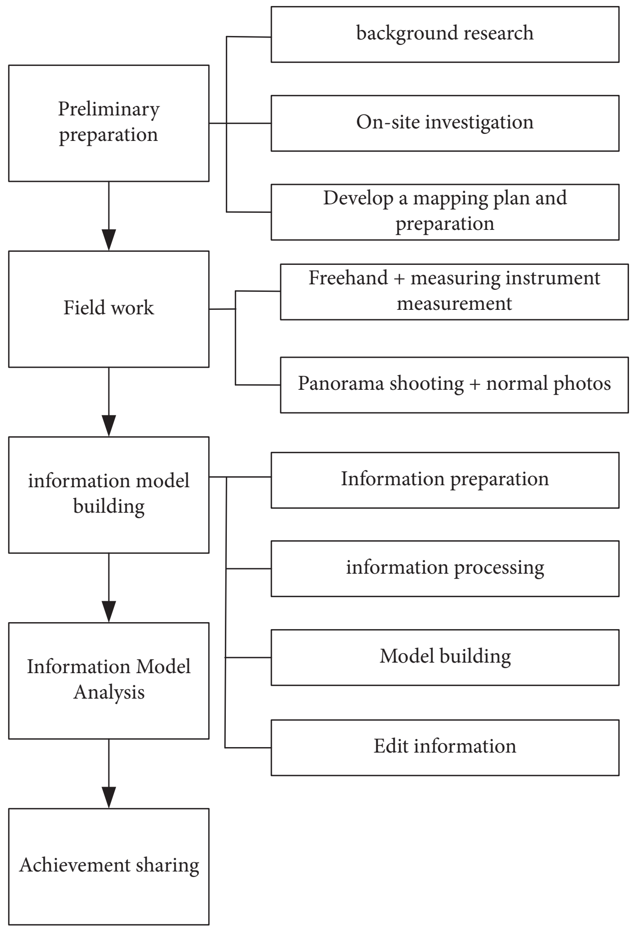


Figure 7: Project practice process.

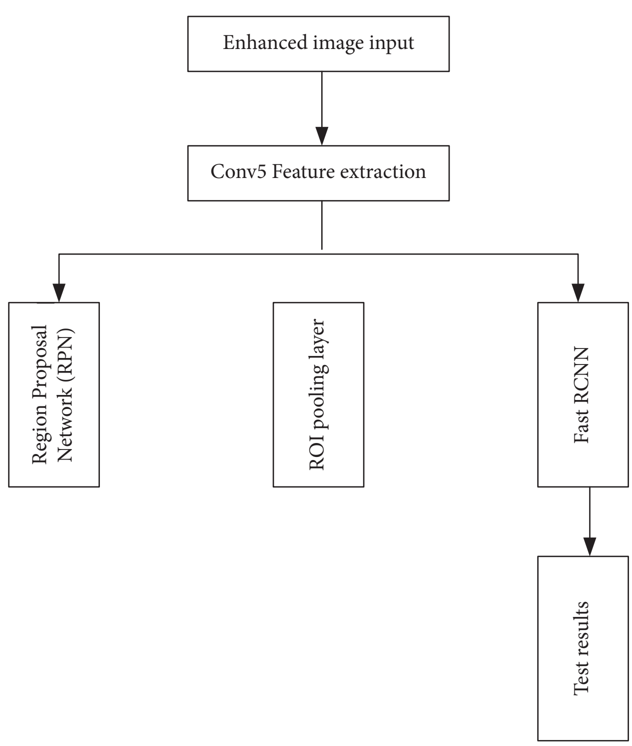


Figure 8: Network model framework diagram.

Table 3: Common symbols and their meanings.

Symbol	Meaning
U_a	Active user
S_a	Purchase sequence of active users
N	Number of recommended items
n	Number of users
m	Number of item types
R	User-item matrix

Table 4: User preference and number of recommended products.

	Number of recommended products	Number of products not recommended	Total
User likes the number of products	P_{rs}	P_{rn}	P_{r}
User dislikes the number of products	P_{is}	P_{in}	P_{i}
Total	P	P_{n}	m

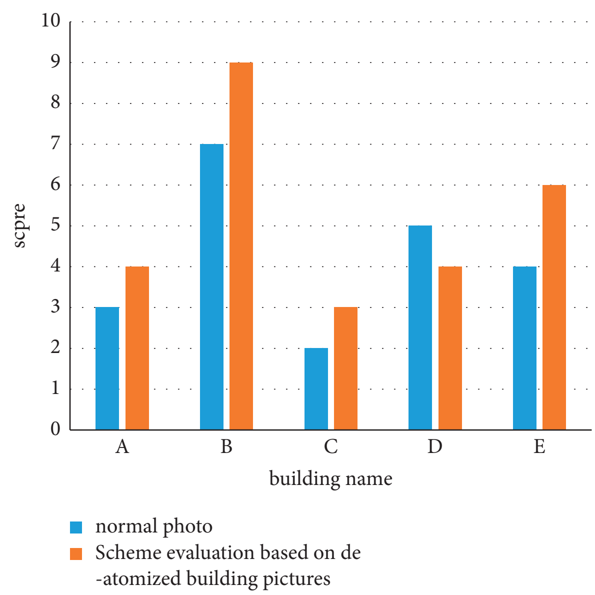


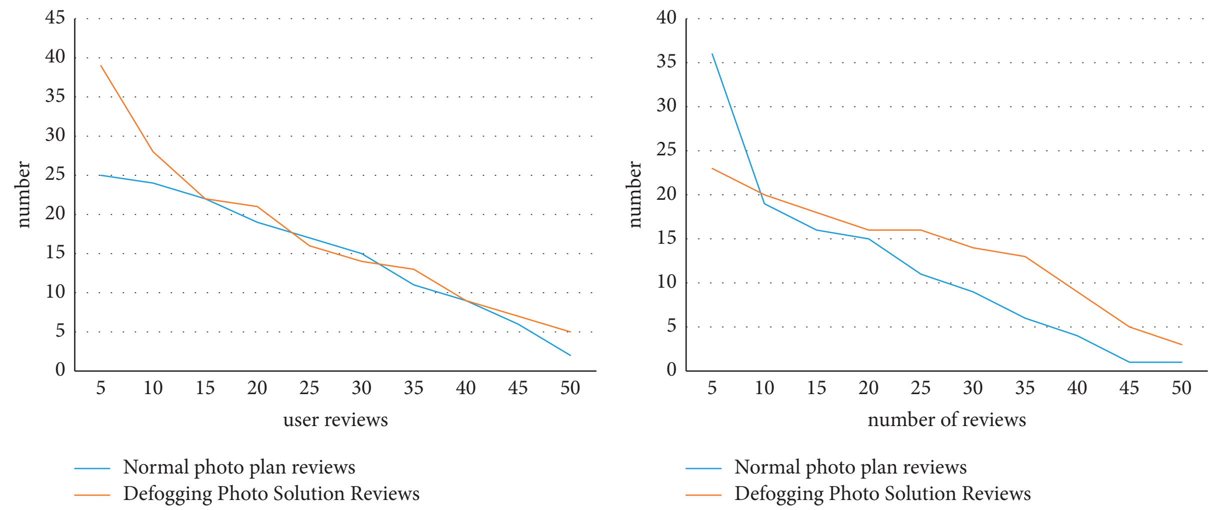
Figure 9: User evaluation data graph.

Table 5: Dataset features table.

	Ordinary photo dataset	Dehazed photo dataset
Number of users	50	60
Number of buildings	130	135
Total number of transactions	310	321
Data density	6.77%	7.13%
Average number of evaluation plans per user	12	15
The average number of evaluations for each program	17	20

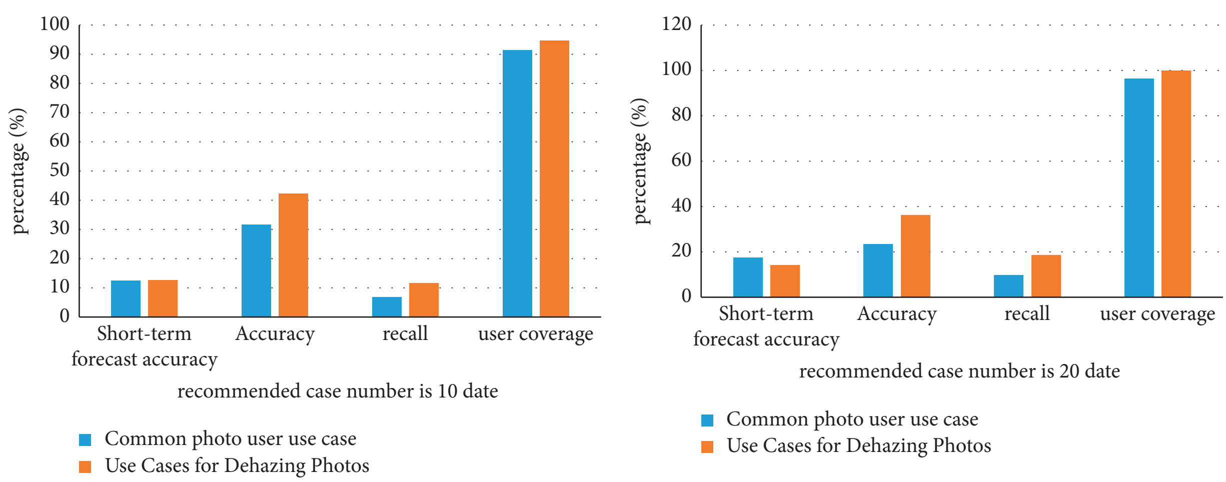
paper organizes and categorizes various parameter information required by the comprehensive research of historical buildings. It builds a relatively complete, scientific, and universal parameter library.

According to the elements and characteristics contained in historical buildings, this paper stores digital information. According to the deep neural network model of RPN, the building information is connected, and this paper together constitutes a complete and clear information system model. It is provided to research units, construction units, investment units, and government departments at all levels to truly realize automated, intelligent, and seamless management.



(a) (b)

Figure 10: The number of user reviews and the number of recommended case reviews in two cases.



(a) (b)

Figure 11: The number of user reviews and the number of recommended case reviews in two cases.

6. Conclusion

As an important part of the machine learning field, the recommendation algorithm not only has academic value but is also a marketing method in the business economy, so both the academic and industrial circles have paid great attention to it. The building protection test has only done a preliminary study on the classic recommendation algorithm, and there are still many deficiencies. The scoring data are not considered in the model, and how to apply the scoring data to deep learning is also a problem that needs to be considered.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no potential conflicts of interest in this study.

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