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Application of CNN-DAE Deep Learning for Economic Cost Prediction in Construction Engineering

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Abstract: This paper aims to explore the effectiveness of constructing the construction economic cost prediction model of construction engineering by using CNN-DAE algorithm combined with CNN-DAE. As the construction cost of construction engineering is affected by a variety of complex factors and has high nonlinear and dynamic changes, traditional prediction methods are often difficult to achieve ideal prediction accuracy. Therefore, this paper proposes an innovative predictive model to address these challenges. Simulation prediction is carried out on Matlab platform through actual cases, sample data is normalized, and then sample data is quantified and predicted in Matlab environment. The relative error of prediction results obtained through data analysis of test samples is strictly controlled below 2%. At the same time, the stability analysis of the model obtained that the maximum relative error of the prediction was only 1.96%, which verified that the CNN-DAE algorithm based on the construction economic cost prediction model of construction engineering could more accurately capture the change trend of construction cost in terms of prediction accuracy and provide strong decision support for project managers. In addition, the model has strong generalization ability, and can adapt to different scales and types of construction projects.

Povzetek: Raziskava predlaga CNN-DAE algoritem za napoved stroškov v gradbeništvu. Model zmanjšuje napake, izboljšuje odločanje pri projektnih stroških in virih.

1 Introduction

In the field of construction engineering, construction economic cost forecast is the key link of project management, which is directly related to the project budget preparation, investment decision and the overall economic benefit. With the rapid development of the construction industry and the increasingly fierce market competition, how to predict the economic cost of construction scientifically and accurately has become an important topic for construction enterprises to enhance their competitiveness and optimize the allocation of resources. In recent years, the rapid rise of artificial intelligence technology and big data has opened up novel and efficient ways and strategies for solving complex problems such as construction project cost prediction. The research on using artificial intelligence technology to predict engineering cost is quite abundant at home and abroad, mainly around two major paths. First, by adjusting or optimizing neural network parameters to achieve accurate prediction of construction cost and construction cost; Second, the neural network is improved by other mathematical analysis methods to achieve the purpose of prediction. The specific research is shown in Table 1. However, these research methods are generally faced with the problem of improper selection of theoretical methods or imperfect construction of influencing factor index system, thus affecting the accuracy and stability of prediction. It is worth noting that currently no scholars in China have applied deep learning to construction cost prediction, and relevant researches mainly focus on the modeling of deep learning network and the exploration of improvement strategies.

Table 1 Analysis of existing research results

Sajadfar [1] combines linear regression and data mining techniques to propose an informatics framework-based engineering feature applied to data mining and the cost estimation supported by the algorithm. The principle of linear regression method is to use mathematical statistics to study the functional relationship between variables. The prediction accuracy is greatly affected by the data.
Xie [2] established a database by collecting the comprehensive unit price of the list of priced quantities of similar projects, and used the grey prediction model to predict the cost of sub-projects. Grey profit determines whether the relationship is close according to the similarity of geometric shapes of the series curves. Suitable for short-term forecast, the forecast accuracy is not high.
Putra [3] proposes an artificial intelligence calculation method based on BP neural networks to model the direct and indirect costs of typical completed projects in order to reduce uncertainty. This method is especially suitable for evaluating the cost of installation projects, and the total uncertainty of project cost estimation is greatly reduced. The neural network is a multi-layer feedforward neural network, which adjusts the connection weight between a large number of internal nodes by simulating the behavior characteristics of the animal neural network. The prediction result is easy to fall into

the local minimum, and the prediction accuracy is high.

Since the construction cost of construction engineering is affected by multiple complex factors and the collection of relevant data is difficult, its cost prediction has become a typical large sample, high dimension and nonlinear challenging problem. In addition, rapid and accurate prediction of construction costs is very important for the cost management of enterprises, and there are high requirements for the accuracy and timeliness of prediction. Traditional forecasting methods, such as regression analysis and grey theory, are often unable to meet the accuracy and time requirements of prediction when dealing with such problems. In contrast, the deep learning network model, with its advantages, can effectively avoid these problems, while showing good generalization ability. On the basis of in-depth analysis of traditional construction engineering cost prediction methods, this study chooses an advanced algorithm combining convolutional neural network (CNN) and noise reduction autoencoder (DAE), and uses its powerful learning and prediction mechanism to build a prediction model and train and learn the sample data. This model can accurately and quickly predict the construction cost of nonlinear engineering projects.

Convolutional neural network (CNN) and Deep autoencoder (DAE), as two important tools in the field of machine learning, have achieved remarkable results in many fields such as image recognition and natural language processing due to their powerful feature extraction and data processing capabilities. By simulating the hierarchical structure of the human visual system, CNN can automatically extract high-level abstract features from the original data, which is especially suitable for processing data with spatial structure, while DAE learns the compressed representation of the input data through unsupervised learning and reconstructs the original data in the decoding process, thus achieving data reduction and denoising. By combining CNN and DAE, a CNN-DAE algorithm based economic cost prediction model of construction engineering is constructed, aiming to make full use of the advantages of these two algorithms to improve the accuracy and efficiency of cost prediction [4]. The model automatically extracts the features of key cost factors in construction projects through CNN and uses DAE to further reduce and de-noise these features to eliminate redundancy and noise in the data and improve the generalization ability of the model.

This study aims to explore and introduce an innovative, scientific and rigorous cost forecasting method into the field of construction engineering, which is expected to significantly improve the accuracy of construction cost control, optimize the project management process, and further enhance the economic benefits of construction enterprises. It is expected that this study can provide practical cost control tools for practitioners in the construction industry [5]. It can also open up new research perspectives for academic researchers, promote the integration and application of interdisciplinary knowledge, and jointly promote the progress and development of the field of construction engineering cost forecasting.

2 Analysis of the influencing factors of the economic cost of construction of building projects

In the complex process of building construction, cost control is faced with dual challenges from predictable and unpredictable factors. For the predictable factors, it is feasible to control them through active management strategies, while the sudden occurrence of unpredictable factors becomes a big problem in cost control. In-depth analysis of the key factors affecting the cost of construction projects, mainly covering the following aspects.

2.1 Management system factors

Management system is the core support of construction project cost control. If there are loopholes in the management system, it will not only aggravate the uncertain events in the construction process, but also disrupt the original cost budget, resulting in a significant increase in project cost [6]. Specifically, the imperfection of the material management system will push up the cost of materials and affect the accuracy of the cost budget, while the defects of the personnel management system may delay the construction progress, and even cause mechanical damage due to improper operation, indirectly increasing the cost of mechanical loss in the construction.

2.2 Construction factors

The management efficiency in the construction process directly affects the cost control. Frequent rework not only directly increases the cost of the project, but also reflects the lack of management responsibility system of the construction site. If the project supervision fails to strictly follow the guidance of construction organization design, and the acceptance and supervision of concealed works, division works and individual projects are not in place, it will be difficult to find and solve problems in time, resulting in frequent rework phenomena and increased difficulty in cost control [7]. In addition, if the importance of safe and civilized construction is ignored, it may lead to quality and safety problems, forcing the suspension of the project, extending the construction period and interfering with the smooth implementation of the cost control program.

2.3 Construction material factors

Material cost occupies the core position in the cost control of construction engineering, and its increase is often attributed to the rise of material price or the increase of consumption. Market price fluctuations, especially the price changes of key materials such as steel bars and cement, are external factors that are difficult to predict completely in cost management [8]. The increase in the amount of materials may be related to the structural changes or design adjustments of the project, which further aggravates the pressure of cost control. In addition, the problem of material waste in the construction process can not be ignored, which may be caused by improper construction technology, methods or loose material management.

2.4 Other factors

In addition to the above factors, project supervision is not in place, personnel responsibility consciousness is weak, the rationality of construction organization arrangement and the strength of enterprise technical strength are all important factors affecting the cost control effect of construction projects [9]. These factors interweave and work together in the whole process of cost control, requiring construction units to take comprehensive consideration and comprehensive policies in project management.

3 CNN-DAE algorithm modelling

3.1 CNN network model

Convolutional neural networks (CNN), as a pillar of deep learning, show remarkable efficiency in processing data with grid structure due to their unique structural design, especially for time series data and image data. Such data can be regarded as one-dimensional grid formed by regular sampling in time dimension and image grid composed of pixels in two-dimensional space respectively. Through its powerful feature extraction and learning ability, CNN has achieved excellent performance in many application scenarios [10]. The core advantages of CNN come from its three core ideas: sparse interaction, parameter sharing and isovariant representation. Sparse interaction means that each output neuron is only connected to a portion of the input data, which effectively reduces the number of network parameters, reduces computational complexity and also helps to extract local features. Parameter sharing means that all neurons in the same layer use the same convolution kernel for convolution operations, which further reduces the number of parameters and increases the generalization ability of the model. Equivariant representation makes the model invariant to some transformations of the input data, which is particularly important for tasks such as image recognition. The basic framework of convolutional neural networks is shown in Figure 1.

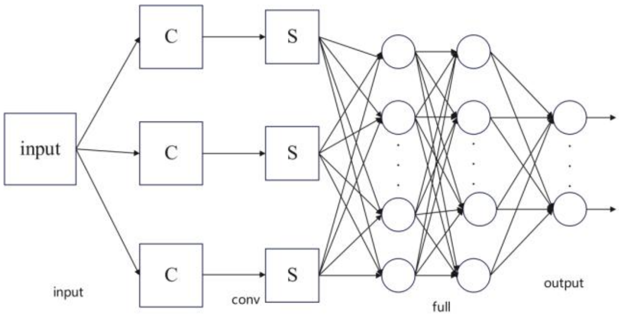


Figure 1: Basic framework of convolutional neural networks

The basic framework of CNN consists of several layers, the core of which is the convolution layer and the pooling layer. The input image or the feature map of the previous layer in the convolution layer will undergo convolution operation with multiple convolution cores. This process can be visually understood as sliding a window (i.e. convolution kernel) on the image or feature map, calculating the sum of the product of the elements in the window and the convolution kernel each time it slides to a new position, and obtaining the output value of the position [11]. As the whole image or feature map is traversed with the sliding of the window, each convolution kernel will generate a corresponding feature map, reflecting the feature information of the image at different angles or levels. The use of multiple convolution kernels can capture richer and more diverse features in the image. The operation formula of the JTH feature map of layer l is shown in Equation (1), which is expressed as x_j^l.

$$x_j^l = f\left(\sum_{i \in Mj} X_i^{l-1}\right) \times K^l + b_j^l \quad (1)$$

In Equation (1), l represents the number of layers in the convolutional neural network; K stands for convolution kernel; M_j represents receptive field; b_j represents a bias value.

The main purpose of the pooling layer is to reduce the complexity of the network by reducing the dimension (i.e. height and width) of the feature graph, thereby reducing the computational effort and avoiding overfitting. This process, often referred to as pooling or sampling, is an important step in the feature extraction process [12]. Pooling operation realizes dimensionality reduction by statistical calculation of local areas of the input feature map. There are various statistical methods, but the most common ones with significant effects include Max Pooling, Average Pooling and L2-norm pooling. And the weighted mean pooling based on the distance of center pixels. The calculation formula of pooling is shown in Equation (2).

$$x_j^l = \beta_j^l downsample\left(X_j^{l-1}\right) + b_j^l \quad (2)$$

3.2 DAE network model

Deep autoencoder (DAE) is a deep learning model that utilizes unsupervised learning. It automatically extracts features of high-dimensional complex input data from a large number of unlabeled data by performing greedy pre-training layer by layer and subsequent parameter optimization process [13]. The core architecture of DAE consists of three main parts: Encoder, Hidden Layers and Decoder.

The encoder part maps the raw input data x to a lower-dimensional implicit representation h, expressed as Equation (3). This mapping process is non-linear and aims to capture key information or features in the input data while removing or ignoring unimportant details or noise. In this way, the encoder is able to efficiently compress data and achieve feature dimensionalization while retaining enough information for subsequent reconstruction processes.

$$h = f_\theta(x) = S(W_x + b) \tag{3}$$

In Equation (3), S is the Sigmoid activation function.

Hidden layers lie between the encoder and decoder, and they make up the “depth” part of the depth autoencoder [14]. These layers further process the encoded data through nonlinear transformations to extract deeper, more abstract feature representations, and the number of hidden layers and the number of neurons in each layer can be adjusted according to the specific task and the characteristics of the data set.

The decoder function g (h) is responsible for mapping the implicit representation h back into the original input space, and reconstructing the original input data y as much as possible, expressed as Equation (4) [15]. This process verifies the validity of the features extracted by the encoder, and also provides a training signal to the entire network through a backpropagation algorithm to optimize the parameters of the encoder and decoder so that the reconstruction error is minimized.

$$y = g(h) = S_g(Wh + b_y) \tag{4}$$

In Equation (4), S_g represents the activation function of the decoder, Sigmoid function.

The training process of DAE is an optimization problem, which aims to find the optimal value of network parameter $\theta = \{W, \ b_y, b_h\}$ on a given set of unlabeled data sample set X through unsupervised learning to minimize the reconstruction error. Reconstruction error is a measure to measure the difference between the input data reconstructed through the coding-decoding process and the original input data. It is usually used as a Cost Function or Loss Function in the training process. The expression of reconstruction error is shown in Equation (5).

$$J_{AE} = \sum_{x \in D} L(x, g(f(x))) \tag{5}$$

In Equation (5), L is the reconstruction error function, which is represented by the square error function as shown in Equation (6).

$$L(x, y) = \|x - y\|^2 \tag{6}$$

Stack noise reduction autoencoders are an important component of deep learning architecture. It builds a hidden layer of deep learning model by stacking multiple noise reduction autoencoders [16]. By extracting the high-level feature representation of the data layer by layer, this structure realizes the effective reduction and denoising of the input data. The calculation formula of the coding process of the modified denoising automatic encoder is shown in Equation (7).

$$y = f_\theta(x) = s(W_x + b) \tag{7}$$

Compared with traditional autoencoders, noise interference is introduced in the training process, that is, artificial noise is added to the input data, and then the model is required to reconstruct or purify the noise-polluted data through learning [17]. This process forces the autoencoder to learn more robust and useful feature representations, thereby improving its ability to understand the intrinsic structure of the data.

3.3 Prediction algorithm process

A construction economic cost prediction model based on CNN and DAE algorithm is established, and these two deep learning technologies are combined to improve the accuracy and efficiency of cost prediction [18]. The following is a detailed analysis of how CNN and DAE combine to achieve this prediction algorithm process, as shown in Figure 2.

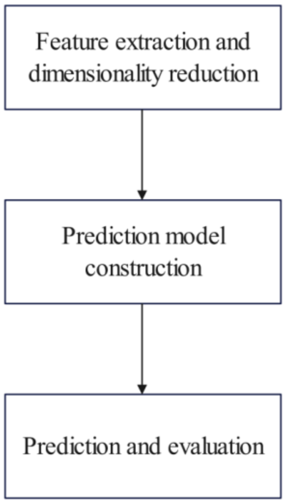


Figure 2: Predictive flow chart

(1) Feature extraction and dimension reduction

In the processing of economic cost data, feature extraction and dimensionality reduction are the key steps to build efficient prediction models. First, the powerful capability of convolutional neural network (CNN) is used to automatically capture local features in the data through its convolutional layer, which may be hidden in the timing changes of cost data, periodic fluctuations, or complex interactions between different cost items [19]. By combining the nonlinear activation function with the sliding window, the convolutional layer can extract the deep features that are critical to cost prediction, and then the pooling layer further down-samples these features to reduce the space size of the data while retaining the key information to improve the robustness and computational efficiency of the model. Next, the high-dimensional features extracted by CNN are input into the encoder part of the denoised autoencoder (DAE), which forces the encoder to learn a more robust and abstract feature representation by introducing noise into the input data and attempting to reconstruct the original clean data [20].

(2) Prediction model construction

A series of fully connected layers are cleverly connected behind the decoder of DAE to build the final predictive model. These fully connected layers act as the "decision layer" of the model and are responsible for mapping the low-dimensional potential spatial vectors output from the DAE to specific cost predictions. The design of the fully connected layer needs to consider the number of layers, the number of neurons in each layer and the choice of activation function to balance the expressiveness and training efficiency of the model [21]. RELU function is a typical linear rectification function. In neural networks, activation function is the existence of the ability to make the neural network nonlinear, which can transform the results of each layer of neural network after linear calculation into nonlinear. The calculation formula of RELU function is shown in Equation (8), the learning rate is 0.001, which takes both convergence speed and convergence stability into account. The learning rate of network training attenuates according to the number of iteration rounds. The specific attenuation Equation (9) is shown.

$$y = \max(0, w^T x + b) \tag{8}$$

$$lr = lr_{init} * 1/\left(1 + decay * epoch\right) \tag{9}$$

Where, $\mathrm{lr}_{\mathrm{init}}$ is the initial learning rate, decay is the attenuation coefficient, and epoch is the number of rounds.

The random drop neuron ratio is 0.5. Since neurons sometimes have binding update parameters, in order to make full use of all neurons, dropout can randomly drop some neurons, break the binding update, and avoid falling into overfitting.

The training of the prediction model is an iterative optimization process, which relies on a large number of historical cost data as a training set [22]. Through the backpropagation algorithm, the model can automatically adjust the weight and bias of each layer in the CNN and DAE to minimize the error between the predicted cost and the actual cost, such as the mean square error (MSE) or the mean absolute error (MAE) [23].

(3) Prediction and evaluation

In order to verify the accuracy and generalization ability of the prediction model after the training, it is necessary to use a test set independent from the training set for evaluation. Evaluation measures include not only direct error measures between predicted costs and actual costs, but also more complex evaluation methods such as coefficient of determination (R^2), root mean square error (RMSE), and confidence levels of forecast intervals. Through these indicators, the performance of the model in different scenarios can be comprehensively evaluated, and the direction for model optimization can be provided. In practical application, prediction model has become an important tool for cost control and decision-making of construction projects. When new economic data is input, the model can quickly provide the corresponding cost forecast value, helping project managers to identify potential cost overruns in time, adjust resource allocation, optimize project plans, and thus achieve effective cost control. In addition, the forecast model can also be integrated with other management tools, such as cost estimation software, project management information system, etc. Form a more comprehensive and intelligent cost management system [24].

4 Example analysis

4.1 Data source and processing

4.1.1 Data collection

In order to ensure the accuracy of the model prediction results, it is necessary to collect engineering data that is highly similar to the engineering cases to be predicted as a training set. In view of the significant differences between regions in labor costs, prices of main materials, construction techniques and technical solutions, the scope of sample selection was strictly limited [25], and only residential projects in a certain city and its neighboring cities were included. Through the comprehensive use of engineering cost information network, professional cost information journals and other authoritative resources carefully selected and collected a total of 20 groups of high-rise residential project data from 2018 to 2023. These projects are residential buildings of 22 to 30 storeys and are geographically concentrated in and around Nanchang, thus ensuring a high degree of uniformity and comparability of the samples in terms of geography and type [26].

Then the preliminary data statistics and analysis of these samples were carried out. The construction process of a construction project often takes a long time and is affected by a variety of factors, and the diversity of its design scheme is also an important aspect that determines the project cost. In general, the cost of construction project is affected by four categories of factors: engineering attribute, environmental attribute, market attribute and management attribute. The engineering attribute focuses on the uniqueness of the structural design of the building project itself, including the building area, the floor area, the standard floor area, the foundation type, the structure type, the staircase construction mode, the seismic grade, the facade decoration style, the number of floors and the height and other key parameters. The environmental attributes focus on the specific conditions of the construction site, such as the availability of the construction site, the convenience of sewage treatment, the difficulty of earthwork excavation and foundation treatment. Market attributes are closely related to market economy environment, including labor cost, price level of basic building materials such as concrete and steel bar and its change trend; The management attribute relates to the main management party in the implementation process of the construction project, as well as the arrangement and control of the construction cycle [27].

This study identifies and extracts five key engineering features (i.e., influencing factor X) that affect the economic cost of construction projects, namely, structure type, number of building floors, building height, construction period and construction area. At the same time, a corresponding project cost data (i.e., the affected factor Y) is collected as the target value predicted by the model. Through this series of rigorous data collection and collation work, the training sample set containing all feature vectors is successfully constructed, which lays a solid foundation for the training and optimization of the subsequent model.

4.1.2 Data processing

In order to ensure that the self-coding network will not encounter the output saturation problem due to the large absolute difference of the input data when processing data, which may lead to low training efficiency or premature convergence to the local optimal solution, it is crucial to normalize the input and output vectors in the training data sample set X . This step aims to uniformly adjust the range of data to the interval [0, 1] to promote the stability and efficiency of network learning. Linear normalization (also known as min-max normalization) is adopted as the method of data transformation, which is implemented by the following Equation (10).

$$\bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

In Equation (10), $\bar{x}_i$ represents the data after normalization; x_i represents the data collected now; $x_{\min}$ represents the minimum value of such data; $x_{\max}$ represents the maximum value of such data. This transformation ensures that all data points are mapped linearly to the interval [0, 1], thus effectively avoiding the adverse impact on network training caused by excessive difference in data scale. For each input vector and output vector in the training data sample set X, the above linear normalization formula will be applied for processing to ensure that the entire data set has a consistent scale at the input and output levels, which provides a good basis for the subsequent self-coding network training.

At the same time, in order to improve the efficiency and accuracy of the model's processing and analysis of sample data, the data obtained by preliminary statistics were quantified, and the quantified results were presented in the form of input vectors in Table 2.

Table 2: Engineering feature vector quantization table

Influencing factor/unit	Sample 1	Sample 2	…	Sample 20
Structure type (X1)	3	3	…	3
Number of floors (X2)	23	25	…	30
Height of building (X3)/m	3.00	3.02	…	2.98
Construction period (X4)/d	230	450	…	120
Area of structure (X5)/m²	10319.95	9.555.54	…	14.631.6

4.2 Prediction operation of data

Equation (9) is applied to transform the quantized data, and then these processed data are imported into the Matlab environment for further processing and predictive analysis.

The training process of predictive analysis was performed on these data in Matlab, and the training process showed a convergence trend of the predicted data in about 80 to 100 iterations. Specifically, when the number of training iterations reaches the 88th time, the global error in the unsupervised learning stage reaches 0.05, indicating that the model has learned certain data features at this time, and the global error further decreases to 0.042 at the 100th iteration, indicating the continuous improvement of the model performance.

Entering the supervised learning phase, the model is trained on more detailed labeled data to further improve the prediction accuracy. After several iterations, when the number of iterations reached 424 times, the global error reached 0.001, which indicates that the prediction accuracy of the model has basically met the requirements. When the training continued to the 500th iteration, the global training error was reduced to 0.0008, which further proved the efficiency and accuracy of the model in the prediction task.

4.3 Model accuracy analysis

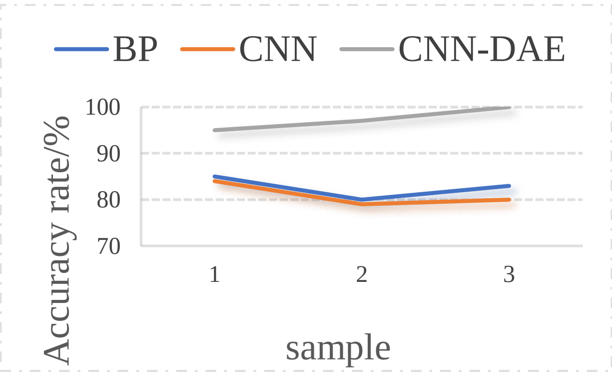
By redrawing and comparing and analyzing the predicted and actual construction cost of the test samples, the relative error data shown in Table 3 was obtained.

Table 3: Relative error between actual construction cost and predicted value of test sample

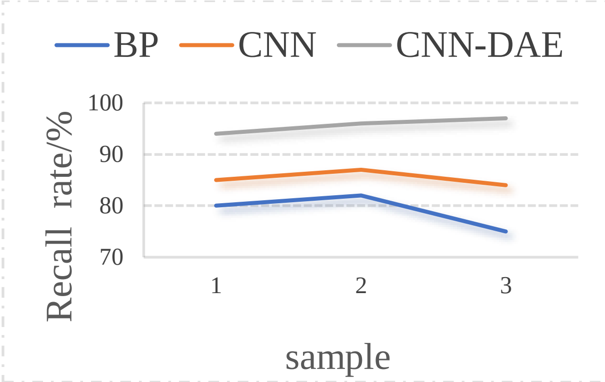
			(Ten thousand)
Engineering sample number	Actual construction cost (a)	Projected construction cost (b)	Relative error/% (b-a)/a
15	750.66	760.22	1.27
16	2125.31	2083.65	1.96
17	1123.64	1132.83	0.82

Through in-depth analysis of the information in Table 3, it can be clearly observed that in the three groups of selected prediction data, the relative error of all prediction results is strictly controlled below the threshold of 2%, which fully demonstrates the high-precision performance of the prediction model. Specifically, the relative error range of these three forecast samples is excellent, with the maximum error being only 1.61% and the minimum error being less than 1.00%. In the cost management of the construction phase of the project, it is generally believed that when the relative error of the forecast can be kept within 2%, the forecast result can be used as an important basis for construction organization decision-making. Therefore, based on the above analysis, it can be confirmed that the construction cost prediction model constructed by CNN-DAE algorithm has excellent prediction effect and ideal performance in relative error control, which fully verifies the high reliability and accuracy of this model in practical application.

BP and Convolutional neural network (CNN) are two common neural network algorithms. In order to verify the feasibility of the CNN-DAE neural network proposed in this study, the accuracy and recall rate of the three algorithms in the predicted value of construction cost are compared. The result is shown in Figure 3.



(a) Accuracy comparison



(b) Comparison of recall rates

Figure 3: Comparison results of algorithm accuracy and recall rate

As can be seen from Figure 3, CNN-DAE algorithm is always higher than BP algorithm and CNN algorithm in terms of prediction accuracy and algorithm recall rate.

4.4 Model stability analysis

In order to further explore the stability of the prediction effect of the new model, the relative error data in Table 3 are presented graphically in Figure 3. Several key points can be intuitively summarized from the chart. The maximum relative error of the prediction is only 1.96%, while the minimum value is 0.82%. This data range highlights the excellent performance of the prediction model in accurately controlling the relative error and its significant advantages in stability. At the same time, the results of the graphical simulation prove the accuracy and reliability of the prediction model.

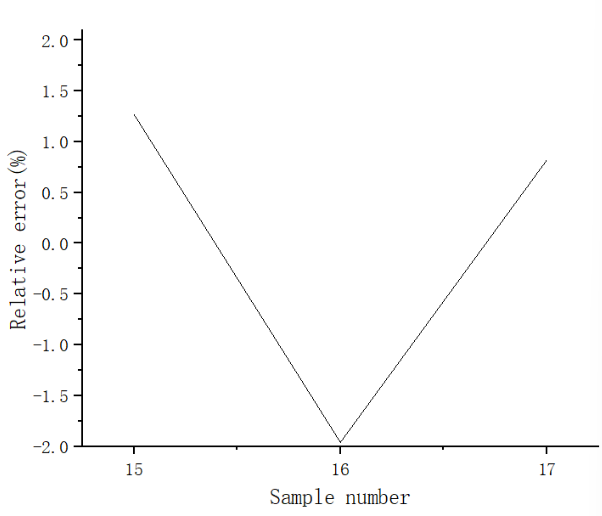


Figure 3: Predictive relative error stability

Furthermore, the mean absolute error (MAE), mean square error (MSE) and coefficient of determination (R^2) were used as evaluation indexes to quantitatively analyze the performance of the model, and the results were shown in Table 4. It can be seen that the average error of the BP model reaches 0.116, while the coefficient of determination of the CNN model is as high as 0.902, and its prediction accuracy is improved by 0.088 compared with that of the BP model. This significant improvement is mainly attributed to the inclusion of time delay effect in the input variables of the CNN model, which increases the dimension of the input variables. And a convolutional neural network (CNN) with better performance is adopted. Furthermore, the coefficient of determination of the CNN-DAE model reached 0.943, indicating that the prediction accuracy was again increased by 4.5% when the noise reduction autoencoder (DAE) structure was introduced on the basis of the CNN model.

Table 4: Comparison of evaluation indexes of prediction performance of the three models

Prediction model	RMSE	MAE	R^2
BP	0.172	0.116	0.814
CNN	0.122	0.083	0.902
CNN-DAE	0.093	0.071	0.943

It is worth mentioning that the construction of the entire CNN-DAE algorithm model and its practical application in the construction cost prediction of construction engineering all rely on Matlab, a powerful programming platform. Through a series of carefully designed programming operations, the prediction process can be efficiently realized. Compared with traditional cost estimation and prediction methods such as budget software or BP neural network, the model shows obvious advantages in the prediction speed, and reaches a new height in the stability and accuracy of the prediction results.

4.5 Discussion

With the increase of the complexity of CNN-DAE model, such as increasing the number of convolutional layers or enlarging the size of convolutional nuclei, although the prediction accuracy of the model may be improved, the computational amount will also be significantly increased, thus affecting the computational efficiency. When dealing with large data sets, even with efficient computing devices and algorithms, long computing times may be required. This may cause the model to fail to give timely prediction results in scenarios with high real-time requirements. In some cases, the available computing resources (such as cpus, Gpus, etc.) may not meet the needs of model training or prediction. This can lead to reduced computational efficiency and even inability to complete model training and prediction tasks. As the size of a construction project increases, the diversity of project data is likely to increase. This includes different types of construction projects, different geographical locations, different materials and technologies, etc. This diversity can make it difficult for the model to capture all relevant features during training, thus affecting the prediction accuracy. When construction projects vary widely in size, models may struggle to maintain consistent predictive accuracy across projects of all sizes. This may require training models separately for different types of projects, or adopting more complex model structures to improve generalization.

To sum up, the algorithm still has some potential limitations in practical applications, such as certain prediction delay when processing large-scale data sets or performing complex calculations, which depends on specific hardware configuration and data processing requirements. In addition, high-precision prediction is often accompanied by high computing costs, which may pose certain challenges to systems with limited computing resources. Therefore, in actual deployment, it is necessary to consider the balance between model performance and computing resources to ensure that accurate prediction results can be obtained in real-time applications, and the delay and computing cost in the prediction process can be effectively controlled, which remains to be further studied.

5 Conclusion

In the process of exploring the construction economic cost prediction model based on convolutional neural network (CNN) and deep autoencoder (DAE), the potential and advantages of this model in the field of complex engineering cost estimation are deeply analyzed. By integrating the powerful feature extraction capability of CNN and the excellent unsupervised learning capability of DAE, the model can not only capture hidden and deep-level cost influencing factors from massive construction data, but also effectively deal with noise and redundant information in the data, thus significantly improving the accuracy and robustness of cost prediction.

This study provides a new idea and method for the fine management of the economic cost of construction engineering, and also provides a valuable reference for the subsequent relevant research in the aspects of algorithm optimization, feature selection and data preprocessing. In the future, it is expected to further expand the application range of this model, such as combining more types of engineering data and introducing other advanced artificial intelligence technologies to build a more comprehensive and intelligent economic cost prediction system for construction engineering. Meanwhile, we will continue to pay attention to the performance of the model in practical applications, and constantly optimize the algorithm structure to improve the prediction accuracy. Contribute wisdom and strength to the high-quality development of the construction engineering industry.

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