Heliyon 10 (2024) e25950

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Integrated prediction and control of mobility changes of young talents in the field of science and technology based on convolutional neural network

Lianfeng Xia [a,b,*], Fanshuai Meng [a,b]

[a] *Henan Polytechnic, Zhengzhou, 450046, China*
[b] *Mongolian University of Life Sciences, Ulaanbaatar, 17024, Mongolia*

ARTICLE INFO

Keywords:
Convolutional neural network
Scientific and technological personnel
Flow change
Combination prediction method
Control measure

ABSTRACT

As the scientific and technological levels continue to rise, the dynamics of young talent within these fields are increasingly significant. Currently, there is a lack of comprehensive models for predicting the movement of young professionals in science and technology. To address this gap, this study introduces an integrated approach to forecasting and managing the flow of these talents, leveraging the power of convolutional neural networks (CNNs). The performance test of the proposed method shows that the prediction accuracy of this method is 76.98%, which is superior to the two comparison methods. In addition, the results showed that the average error of the model was 0.0285 lower than that of the model based on the recurrent prediction error (RPE) algorithm learning algorithm, and the average time was 41.6 s lower than that of the model based on the backpropagation (BP) learning algorithm. In predicting the flow of young talent, the study uses flow characteristics including personal characteristics, occupational characteristics, organizational characteristics and network characteristics. Through the above results, the study found that convolutional neural network can effectively use these features to predict the flow of young talents, and its model is superior to other commonly used models in processing speed and accuracy. The above results indicate that the model can provide organizations and government agencies with useful information about the flow trend of young talents, and help them to formulate better talent management strategies.

1. Introduction

With the rapid development of artificial intelligence technology, the utilization of convolutional neural networks (CNNs) in the scientific and technological fields is on the rise [1,2]. In this ever-changing era, it is particularly urgent to understand and study the changes in the flow of young talents in the field of science and technology [3,4]. Young people are the backbone of scientific and technological progress, and their innovative ability and vitality are crucial to scientific and technological development [5,6]. However, due to various factors, mobility among young talents is prevalent in the field of science and technology. On one hand, young talents often seek opportunities and challenges by transitioning between different institutions and enterprises; on the other hand, the highly competitive environment in the science and technology sector frequently presents attractive conditions that entice young talents to

* Corresponding author.
E-mail address: 13010@hnzj.edu.cn (L. Xia).

https://doi.org/10.1016/j.heliyon.2024.e25950
Received 9 August 2023; Received in revised form 31 January 2024; Accepted 5 February 2024
Available online 10 February 2024

explore alternative career paths [7–9]. Therefore, it is of great significance to comprehensively predict and control the flow of young talents in the field of science and technology for industrial development [10,11]. Firstly, by forecasting the trends in talent flow, science and technology enterprises can proactively strategize talent acquisition and training plans to adapt to future changes in the talent pool [12]. Secondly, by exerting control over talent flow patterns, science and technology enterprises can effectively retain exceptional individuals, thereby enhancing organizational stability and competitiveness. Lastly, comprehensive prediction and control of the flow of young talents in science and technology can aid governmental bodies and relevant institutions in formulating more rational talent policies, thus promoting sound development within the field of science and technology. To sum up, it is necessary to pay attention to the urgency of the flow of young talents in the field of science and technology, and actively take measures to deal with it. This will not only help the long-term development of enterprises, but also have a positive impact on the prosperity and progress of the entire technology industry.

CNNs, as powerful artificial intelligence technology, possess the capacity to efficiently process and analyze large-scale datasets [13,14]. Hence, their application in the comprehensive prediction and control of fluctuations in the flow of young talents within the science and technology domain holds great potential [15]. The application of CNNs, known for their efficacy in image processing, enables efficient processing of young talent flow data. CNN's excellent feature extraction ability and pattern recognition ability enable it to be applied to the flow change prediction of young talents in the field of science and technology. In this study, convolutional neural networks are used to predict the flow changes of young talents in the field of science and technology, mainly based on the following considerations: First, CNN can automatically extract and learn the deep features of the flow changes of young talents; Secondly, CNN has good performance when dealing with complex and nonlinear flow change problems. In terms of the parameters of predicting young talents, the following factors are mainly considered. First, the academic achievements of young people, including published papers and patents; The second is the youth's project experience, including the projects they have participated in and the importance of the projects. Finally, young people's skills and abilities, including professional skills, teamwork ability, innovation ability and so on. These factors are quantified into concrete parameters and used as input data to train the convolutional neural network model. Simultaneously, through analysis and mining of the forecast results, key factors affecting talent flow can be determined, leading to the formulation of targeted control strategies. Therefore, in order to accurately predict the flow trend of young talents in various fields, this study proposes a prediction model of young talents flow in science and technology based on convolutional neural networks, which is expected to help science and technology enterprises and government agencies better cope with the changes of young talents flow and promote the development of science and technology. Because convolutional neural network has good effect in the field of image processing, it can be applied to the processing of young talent flow data.

Traditional statistical models are often based on certain assumptions that may not hold true in real-world complex data. In contrast, CNNs are able to automatically learn and extract key features from data without the need for prior assumptions. Compared to other machine learning methods (such as decision trees, random forests, etc.), CNNs have much stronger capabilities when processing image and sequence data. While these methods perform well on certain tasks, the structure of the CNN makes it particularly well suited for working with spatio-temporal data like talent flow data. At present, most research on talent mobility focuses on sociological or economic perspectives. However, this study is the first to attempt to use CNN, an advanced artificial intelligence technique, to predict and control fluctuations in this area. This gives technology companies and government agencies a fresh perspective and tools to tackle this challenge. In conclusion, the convolutional neural network method used in this study to predict the flow of young talents in the field of science and technology has great advantages, and the research method and perspective are innovative.

The purpose of this study is to predict changes in the flow of young talent in the field of science and technology by applying CNN, and provide decision support for science and technology enterprises and government agencies. In order to achieve this goal, the following methods are adopted in this study: First, the academic achievements, project experience, skills and abilities of young talents are collected; Secondly, CNN is used to build a predictive model to automatically extract and learn the key factors affecting talent flow. Finally, the superiority and effectiveness of CNN in predicting the flow of young talents are verified by comparative experiments. In order to collect relevant data on young talents, the study used a variety of methods, including obtaining data from public databases, academic publications, online social platforms and other sources. In addition, we worked with a number of technology companies and institutions to obtain internal data on young talent. These data cover many aspects of young talents, such as education background, work experience, skill level, etc., providing us with rich information to build prediction models. Through this study, it is found that CNN has a significant advantage in dealing with the problem of young talent flow prediction. Compared with other traditional statistical models, CNN_S are able to automatically learn and extract the key factors affecting talent flow without relying on prior assumptions. In addition, CNN performs well in dealing with complex, non-linear flow changes and can more accurately predict the flow trend of young talent. These findings provide strong support for technology companies and government agencies to better address the challenges of youth talent mobility. It is expected that this research can provide more accurate and reliable prediction tools for the flow of young talents for scientific and technological enterprises and government agencies. At the same time, it is also hoped to further expand the application scope of CNN in the field of talent flow prediction and explore more potential influencing factors and predictive variables. In addition, the future will continue to pay attention to the dynamic changes of the phenomenon of young talent flow, and constantly improve and optimize the forecast model to adapt to the changing market environment and talent needs.

2. Related research of talent training model and CNN

With the country's emphasis on talent training, there is more and more research on talent training. Sun et al. [16] have taken into account and elaborated on the policy framework for developing technological talents and related measures. The policies cover such areas as the cultivation of talents and utilization of human resources, targeting top-tier technological talents in specific areas. Zheng et al. [17] have adopted an innovative approach to explore the unique role of personnel in promoting technological progress and economic growth from the aspect of labor factors. The research highlighted the importance of improving human capital to facilitate economic growth and narrow the income gap. Ma et al. [18] have assessed the quantity and quality of human resources by including indicators that measure the educational structure and quality of life into the original factors of human resources and incorporating indicators that measure the expenditure of public education, transfer of knowledge, and outcomes of higher education into the factors of government efficiency. Jeong [19] advocated that individual features could impose a significant impact on the brain drain of enterprises as well as job satisfaction and organizational commitment, which would in turn affect the intention of talents to quit the job. Xu et al. [20] advocated that talents constitute part of the labor resources, expertise, skills, and investment income derived from the education and training of human resources across the enterprise. Zhou et al. [21] put forward the method of bidirectional CNN. Compared with simple Recurrent Neural Networks (RNNs) that could only make use of one-way information, bidirectional RNNs are able to maximize the information flow around the current time of the sequence. Gharehbaghi and Linden [22] put forward the RNN-based language model, which is mainly based on the fact that CNNs have no restrictions on the length of text while processing longer context in the network. Quan et al. [23] put forward both long-term and short-term memory networks. To facilitate the function of preserving the state, researchers introduced a storage unit and several control gates into the basic structure of the hidden layer. Mishkin et al. [24] mainly incorporated the attention mechanism into the Long Short-Term Memory (LSTM) model for the generation of news headlines combined with RNNs. In this case, the length of the vector output from the encoder is no longer faced with constraints after the information is input to the encoder. Nezhadali and Sadeghzadeh [25] put forward an improved method to initialize the weight matrix of simple RNNs without modifying the network structure to achieve effects similar to those of the LSTM model, but with a significantly lower level of computational complexity.

CNNs are a type of feedforward neural network known for their convolutional computations and deep structure, making them a cornerstone of deep learning algorithms. CNNs excel in representation learning and hierarchical classification of input data. Both domestic and international researchers have achieved significant breakthroughs in the development of CNN algorithms. In the financial market, Mousapour et al. proposed a hybrid neural network algorithm based on meta-heuristic principles to assist investors in identifying buy and sell signals with higher accuracy. The algorithm specifically targeted false signals in the precious metal market. Through analysis, it was found that the algorithm outperformed similar deep learning algorithms in terms of recognition accuracy. This finding suggests that the algorithm can effectively address the financial and precious metals markets' uncertainties and support investor decision-making [26]. To tackle the energy crisis during mega-urbanization, Shahsavar and his team introduced an intelligent biogas energy supply framework based on artificial intelligence technologies such as random trees, random forests, and CNN algorithms. Performance tests demonstrated that this framework could address various scientific problems while reducing energy consumption in urbanization processes. By promoting sustainable green development, the framework contributes to sustainable urban growth [27]. In the context of environmental sustainability, Zhan et al. proposed a hybrid evaluation method utilizing CNN algorithms, an evaluation laboratory, correlation between standards, and decision tests. Numerical calculations verified the effectiveness of this method, demonstrating its capacity to assess the environmental impact of different activities. This approach offers valuable insights for informing policies and decision-making processes related to sustainable transportation systems [28]. For predicting residential electricity consumption, Ghadami's team developed an artificial neural network prediction model based on CNN algorithms. This model achieved a high prediction accuracy of 99.3% when applied to summer and winter electricity consumption. The practical significance of this model lies in its ability to support accurate electricity consumption forecasting [29]. Detecting illegal behaviors, crimes, and other abnormal events in video surveillance remains a challenge. To address this, Philip's team devised an automatic video anomaly detection strategy that combines deep CNNs with the Dragonfly rider optimization algorithm. Through data detection and analysis, the proposed method achieved high accuracy (0.993) and sensitivity (0.981), indicating its potential for effective anomaly detection [30]. When diagnosing respiratory diseases, CT scans are more costly and time-consuming compared to chest X-ray images. Ahmed and colleagues tackled this issue by developing a CNN-based model using f-measure, G-mean, and other methods to detect COVID-19. Sample analysis revealed the model's excellent performance, boasting an accuracy of 98.33% for precision measurement of COVID-19 [31].

To sum up, convolutional neural algorithms have been widely used by experts in various fields such as medicine, computer vision, sociology, and economics, and in-depth research experiments have been carried out, making certain contributions and values. However, few scholars have studied the relationship between it and the flow of social scientific, and technological talents. In order to better predict the flow of young talents in the field of science and technology, this study will build a new prediction model on the basis of the CNN algorithm to promote the combination of the CNN algorithm and talent flow.

3. CNN-based forecast and control ideas for the changes of flow of technological talents

In recent years, with the continuous development of Internet technology, the demand and mobility of technical talents have also shown a growing trend. In order to better cope with the change in the flow of technical personnel, it is particularly important to predict and control the flow trend of technical personnel. In this chapter, a CNN-based change prediction and control of the flow of technical talents is proposed, hoping to provide enterprises and government departments with an effective method to predict and control the flow trend of technical talents in this way, so as to better cope with the change of demand and mobility of technical talents.

3.1. CNN-based method of nonlinear combination prediction

Through the application of CNN to neural network-based portfolio prediction, academia has achieved a major breakthrough in related studies over recent years [32]. The goal of the research analysis is to achieve spatial and temporal pattern mining of talent flows among varying regions [33–35]. In addition, to predict the flow of talent, researchers aim to predict the future inter-regional talent flow based on historical data across different regions. The non-linear method of combination forecast has incorporated as many factors as possible that may impose an impact on the number of technological talents in state-owned enterprises, including social factors and technological progress, and the model is adopted to autonomously assign the extent of influence of the aforementioned factors. The impact module of the quantity of talents is illustrated in Fig. 1.

The main reason for dividing Fig. 1 into two groups is to show more clearly the various factors that influence the number of talents. The first group focuses on the level of talent concentration in educational and research institutions and enterprises, which is one of the important factors affecting the number of talents. Through quantitative analysis of the degree of talent concentration in these institutions and enterprises, the trend and pattern of talent flow can be better understood. The second group focuses on employment rates and the proportion of talent in public and private companies. These factors reflect the demand and supply of the talent market and are of great significance for predicting the future flow of talent. By incorporating these factors into the model, the flow of talent between different regions can be predicted more accurately. The prediction results of the model for each participating combination are adopted as the input vector of the neural network, and the actual value corresponding to each specific moment is adopted as the output of the CNN. On this basis, the paper provides a quantitative analysis of the level of aggregation of talent in education and research institutions as well as that in enterprises, the employment rate, and the proportion of talent employed in state-owned and private enterprises. In case the receiving area of a region is 20×20, then a neuron within that specific region will be able to connect 400 parameters in total. Due to the nonlinearity of the controlled objects to some extent, the majority of the predictive models currently employed are linear in the prediction and control. In addition, the model can be expressed with the use of a series of flow matrices. On this basis, the method of flow vector was included to overcome the sparsity of matrix elements, analyze the features of talent flow between varying regions, and conduct spatial and temporal analysis of talent exchanges between varying regions. On this basis, the study intends to analyze the interaction of talents between different regions from two aspects, namely, time and space, and to elaborate on the imprecision. The study has calculated the output of each neuron in the hidden and output layers of the network by using Equation (1):

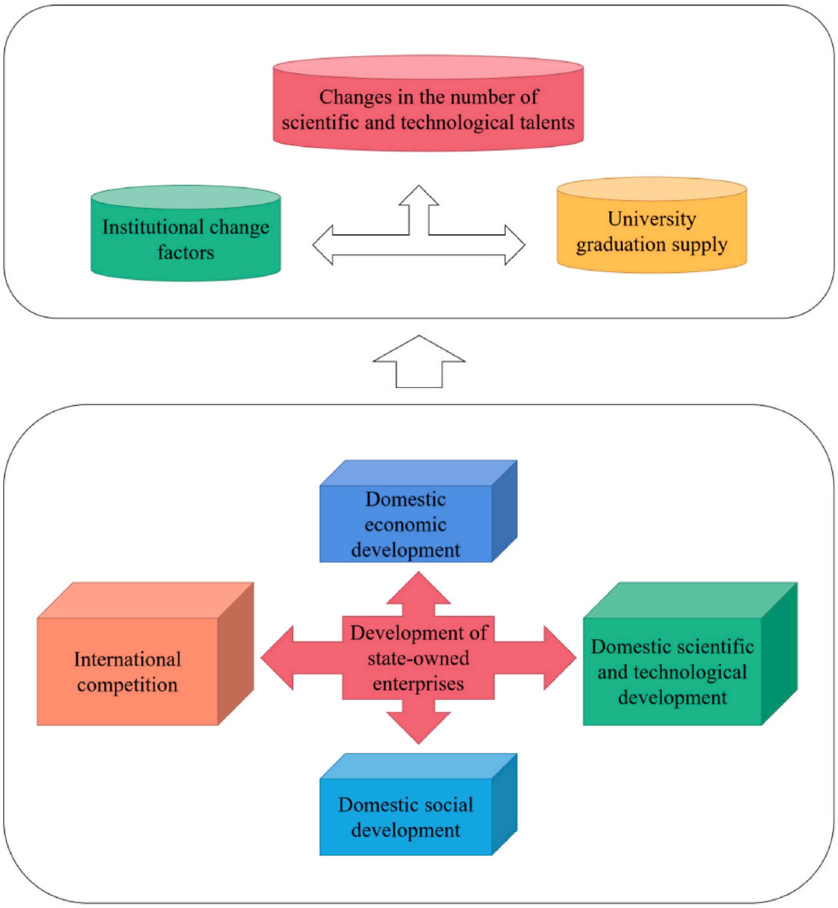


Fig. 1. Impact module of the quantity of talents.

$$O_{Pj}^{l} = f_i\left(\sum_{j} w_{ji}^{l} O_i^{l-1} - \theta_j^{1}\right) \tag{1}$$

With the use of the conventional approach, researchers aim to use a measure of proximity, which is expressed in most cases as a sum of squared errors (SSE) [36]. The SSE is specified as shown in Equation (2) and Equation (3):

$$\mathrm{SSE} = \sum\nolimits_{i=1}^{k} \sum\nolimits_{\lambda \in c_i} dis(v_i, x) \tag{2}$$

$$C_i = \frac{1}{m_i} \sum\nolimits_{\lambda \in c_i} x \tag{3}$$

k——Cluster number;
c_i——Class i;
m_i——Number of samples;
v_i——Central point;
x——Cluster sample

Second, this study leverages the CNN method to establish a nonlinear relationship between the short-term performance of individuals participating in different combinations and the predicted outcomes. Short-term efficiency of individuals refers to their output efficiency over a relatively brief period. This concept entails the total output generated by adequately skilled individuals who optimize resource allocation and leverage technological context with a unit investment. To assess the significance of each experiment's impact in a prediction assignment, the study employs Equation (4) and Equation (5) to calculate diagnostic weights:

$$X = \tan_h(H) \tag{4}$$

$$\alpha = soft_{\max}\left[\omega^T X\right] \tag{5}$$

α——Weight;
H——Hidden state sequence of layers.

This model has incorporated both previous and current information, which means that previous information is memorized and added to the current results. The nodes in the hidden layer are linked with each other. Moreover, the input of the hidden layer includes

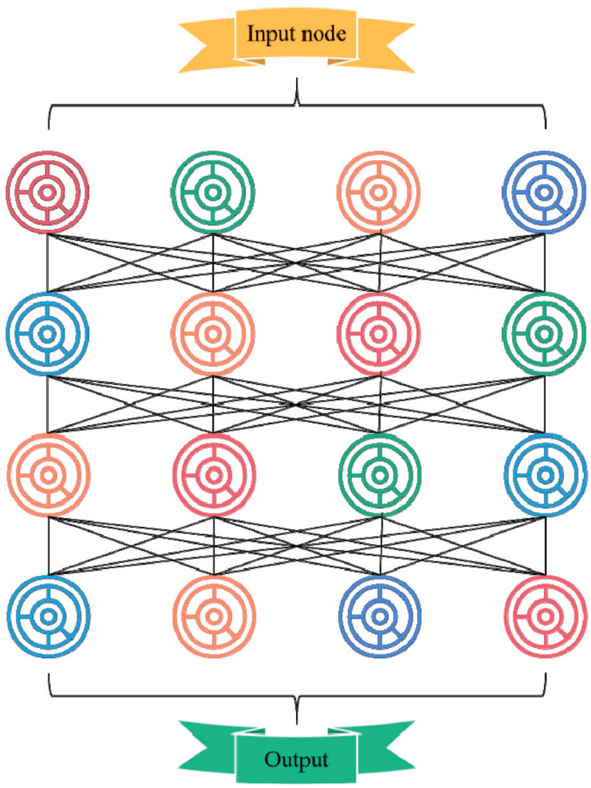


Fig. 2. Topological structure of neural network.

both the input of the input layer and the output of the hidden layer at previous times. Hence, unit neural networks are particularly suitable for continuous data. The performance of the model largely depends on the topology and learning method of the network, as illustrated in Fig. 2.

In order to simplify the network structure representation of CNN, it is drawn that each layer has the same number of neurons, but in the actual neural network design, the number of neurons in each layer can be different. The structure of the network, including the number of neurons per layer, is designed based on specific tasks and data. Sometimes, certain layers may have more neurons in order to extract more features or make more complex transformations; Other layers may have fewer neurons to compress information or extract more advanced features. Therefore, the representation in Fig. 2 is only an example and does not represent the reality of all neural networks. In addition, the feature distribution learned in certain regions can be applied to other regions, and the feature extraction can be carried out through common parameters. Therefore, researchers regard the linear system as the research object and establish a state space equation that is easier to describe through mathematical methods. Subsequently, researchers have expanded the features in order and integrated feature words with distinct granularity at this moment, so as to obtain comprehensive features at each moment.

$$c_i = \left[c_i^1; c_i^2; \ldots c_i^k\right] \tag{6}$$

In equation (6), c_i^k——Convolution window of the i word is the characteristic representation of k.

Finally, after consistent learning and testing to reach a high level of accuracy, the network can be adopted as an effective tool for nonlinear combination prediction. Moreover, the network can be used for combination prediction so as to obtain the final prediction results. The talent flow prediction model based on the CNN algorithm employs data preprocessing, data enhancement, multi-channel input, transfer learning, and model integration to ensure its robustness to diverse data sources. These techniques improve the model's ability to adapt to different data situations and enhance predictive performance. To address moral security concerns associated with the talent flow prediction model, it is necessary to comprehensively employ privacy protection, consent acquisition, fairness guarantee, transparency, and interpretability. Through these measures, users' relevant private information is better protected while ensuring fairness to all parties involved. Furthermore, social participation and regulation play a vital role in ensuring that the use of the model is legal, reasonable, and ethical. By involving stakeholders from diverse backgrounds and regulatory bodies, potential ethical issues can be identified and addressed appropriately. Overall, this holistic approach to the talent flow prediction and control model based on the CNN algorithm promotes ethical, transparent, and responsible use of advanced machine learning techniques. The regional industrial structure is also regarded as an indicator of output efficiency, and a proper industrial structure will improve the output level and efficiency of the region to a significant extent. The industrial structure, especially the development of high-tech industries, is deemed a crucial indicator of measuring the efficiency of a region's knowledge economy. Due to the high level of randomness of the flow of technological talents in enterprises with similar business environments, such talent flow can be regarded as a form of "randomness". The study put forward a method based on multiple convolutional kernels to tackle the drawback of a single convolutional kernel that could only extract one feature and applied a fusion approach to the method. Furthermore, the study put forward the method of parameter reuse of convolution CNN to reduce the number of parameters adopted in the model, and to predict the talent flow among varying regions in the future.

3.2. Macro-regulatory control measures for the flow of technological talents based on CNN

At present, the macro-regulatory control of talent flow in China is mainly faced with the challenges of single control measures, the absence of hierarchy or type of demands of talent, and that only salary and welfare benefits serve as the incentive mechanism for managing the talent flow. Talent flow is an utterly intricate social phenomenon, and the ways of talent flow can be illustrated in Fig. 3.

The basic structure of CNN is composed of two layers. The first layer is the feature extraction layer, which is generally referred to as the convolutional layer in the structure of CNN. Activation functions introduce nonlinearity into CNN networks, enabling them to learn and model complex patterns. There are three common activation functions, among which ReLU activation function is simple to calculate, converges quickly, and effectively alleviates the problem of gradient disappearance. But when the input is negative, the output is 0, which can cause the neuron to "die." The Sigmoid activation function is suitable for binary classification problems. However, there are some problems such as disappearing gradient and large amount of calculation. The average output of Tanh activation function is 0, which has better performance than Sigmoid, but the gradient disappearance problem still exists. The basic principle of CNN architecture is as follows: the convolutional layer is responsible for extracting local features from the input data. This is achieved by applying multiple filters, or cores, that convolve over the input, detecting patterns or features that are present. The use of

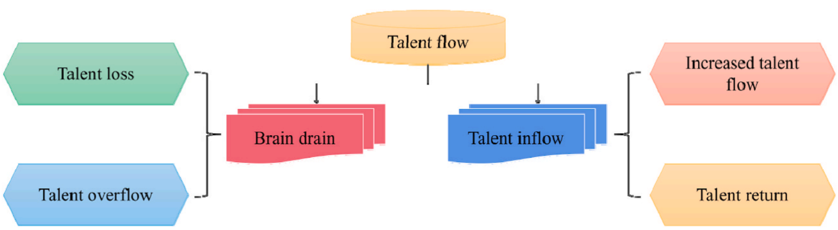


Fig. 3. Ways of talent flow.

convolution reduces the number of required parameters and facilitates the reuse of features, making CNNs very efficient in processing image and spatial data. These extracted features are then passed through the activation function, introducing the necessary nonlinearity. While the conventional feedback neural network is only able to assess the posterior probability and the weights of the network and parameters of radial basis function are determined accordingly, the output of the CNN can be expressed as Equation (7) [37].

$$y_j = \sum_{i=1}^{h} \omega_{ij} \exp\left(-\frac{\left\|x_p - c_i\right\|^2}{2\sigma^2}\right), j = 1, 2, 3, \ldots, n \tag{7}$$

ω_{ij}——Weight of hidden layer and output

Based on relevant statistics, the study has calculated the number of universities and the number of students enrolled in these universities. The regional economic adaptability of talent cultivation refers to the consistency between the methods of scientific research adopted by the education department in a certain region, the objective and orientation of talent cultivation, and the goals and requirements of regional economic growth. On this basis, by adopting the CNN composed of the sensor unit, researchers are able to complete the tasks of pattern recognition of any complexity. In other words, they are able to replicate any rational function.

Second, judging from the dynamic analysis of the proportion of talent demands in varying industries, regions, fields, areas, and levels in China, the study has clarified both positive and negative aspects of talent mobility in the country, thus laying a scientific foundation for the formulation of macro policies. On this basis, the study has applied the method of quadratic programming into the model, so as to address the issue of predictive control with mixed constraints and to obtain the optimal control performance of the system at the current time point. The study has normalized the input samples to ensure that data fall within the specified range [1,2] interval, thus facilitating the processing of data and enhancing the efficiency of networks. The procedure of normalizing input samples is given by Equation (8) [38].

$$\mathrm{X} = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \tag{8}$$

T——Unprocessed input value;
T_{max}——Maximum value of neural network input;
T_{min}——Minimum value of neural network input

Factors that may impose a decisive impact on the emergence of employee mobility intentions include the challenging nature of the job, the extent of personal autonomy and job obligations, the level of recognition of personal achievements, the prospects of career development, and the provision of training and learning opportunities by the company, and whether it is conducive to personal growth and the realization of personal values. In general, regions, where talent inflow exceeds outflow, are found to be net beneficiaries during the exchange of talents with net positive gains, and vice versa for net losers. Therefore, the study neglects the intra-regional flow of talents while calculating the value of information entropy. The information entropy of the distribution of talent outflows is defined as shown in Equation (9):

$$H\left(x_i^l\right) = -\sum_{k=1}^{\mathrm{m}} x_{ik}^l \ln\left(x_{ik}^l\right) \tag{9}$$

i——Region;
$H(x_i^l)$——Information entropy of the distribution of talent outflows.

Nevertheless, the method of increasing the number of layers of the network may require less total number of hidden nodes compared with a single hidden layer, and the method also leads to better performance. Furthermore, the method is able to improve the performance of generalization and robustness, minimize the occurrence of errors, and enhance the accuracy of the network. The reason is that under circumstances of higher dimensionality of the input data samples and that numerous identical features are extracted, a longer time will be required to train the model, which will not result in a radial basis function with an utterly desirable capacity of generalization [39]. The radial basis function with dynamic weights holds the key to CNN, and the expression of the radial basis function is specified as Equation (10):

$$\mathrm{R} = \left(x_p - c_i\right) = \exp\left(-\frac{\left\|x_p - c_i\right\|^2}{2\sigma^2}\right) \tag{10}$$

$\left\|x_p - c_i\right\|$——Norm of $x_p - c_i$;
x_p——Sample data input by the input layer; c_i and σ——Center and width of the radial basis function.

For enterprises faced with the challenges of talent shortages and severe brain drain, senior management should carefully analyze the causes, promptly identify the underlying issues, and improve the introduction of talent. Due to the significant gap in welfare benefits and industrial development between developed and developing economies, the attraction of talent between the two economies shows a pattern of asymmetry. This would result in one country gaining “net benefits” from the talent flow and the other becoming the “net loser” of talents. Given that each model has its own strengths and drawbacks, the neural network model will be adopted in this study to process and train the vectorized data. Furthermore, high-dimensional systems are not only faced with challenges such as high computational complexity and the long time required for optimization but also numerous drawbacks. The underlying reason is that factors such as wages, housing, and children’s employment have not been fully taken into account and these policies have been implemented in the first place. However, foreign-funded high-tech companies provide higher wages and better opportunities for career development. Overall, the flow of talents is consistent with the optimal allocation of social resources and people's value orientation during career development. As for a certain region, the talent flow would carry all the necessary information for the direct exchange of talents between that specific region and other regions.

4. Application of CNN in the prediction and control of the flow of technological talents

In order to analyze the practical application effect of the CNN algorithm in predicting and controlling the flow of technical talents, this chapter firstly conducts comparative experiments on various indicators of CNN to verify its superiority in performance. Then, through empirical analysis, its superiority is verified in the practical application of forecasting and controlling the flow of technical talents.

4.1. Analysis of impact factors in the prediction of CNN

The impact factor analysis integrating the method of CNN is a general term for a category of methods in which development trends are analyzed to infer future tendencies. The basic assumption is that future movements are the result of successive developments in the past and present. The selection of an algorithm that proves to work well will lead to optimal results subsequent to the model training, which is the top priority of the work related to model training.

First, researchers collect the dynamic series of the study object and illustrate the distribution of data points, and then the best-fitting curve for the model is made based on the scattering trend, and the precision of the model fit is derived. In other words, there will be a category of indicators whose contribution to the total target increases with the improvements in the assessment results. Moreover, the results after fuzzy dimensionless processing constitute a strictly monotonic increasing function of the assessment results. To compare the performance and training time of CNN and simple RNN, researchers have conducted the following text prediction experiments through the use of LSTM. The number of nodes per layer amounts to 200, and the number of training rounds amounts to 45. The experimental results are illustrated in Fig. 4.

As can be seen from Fig. 4, the overall prediction accuracy of the CNN model is higher than that of the simple RNN model. This is due to the fact that the CNN model can extract local features from the input data through convolution operations. However, the RNN model needs to consider each input time step in turn when processing sequence data and the extraction of global features is relatively weak. In addition, the convolutional layer in the CNN model has the feature of parameter sharing, which can greatly reduce the number of parameters in the model, reduce the risk of overfitting, and improve the generalization ability of the model. However, the parameters in the RNN model are not shared, resulting in a large number of parameters and easy overfitting. Therefore, it can be concluded that the CNN model will have better performance when applied to prediction tasks. The majority of the high-tech enterprises are categorized as small and medium-sized enterprises (SMEs). In general, they do not have utterly strong technical capability and financial strength, nor do they have sound institutional settings. Instead, their system is rather arbitrary and paternalistic, and the mode of family management plays a dominant role. Although certain enterprises feature a very formal system of human resources, the personal will of leaders oftentimes overrides the corporate system, thus nullifying the system of human resource management. As such, the data of the input model is characterized by a CNN structure, which can be divided into a convolutional layer and a pooling layer. One-time exponential smoothing is adopted for direct prediction in case the actual data has a more pronounced tendency towards changes. Given that the network is globally convergent, the state of the network neurons should eventually converge to zero at any moment of sampling, and the state of the constrained neural network is illustrated in Fig. 5 when researchers have taken random sampling moments with network parameters of 10, 50 and 100, respectively.

Quadratic exponential smoothing is adopted when the change in the time series travels in a linear trend. Based on the political and

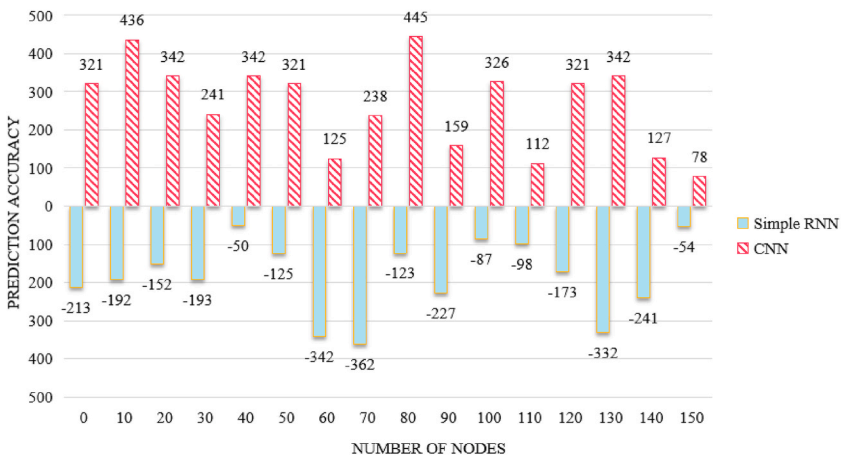


Fig. 4. Prediction results of CNN and simple RNN

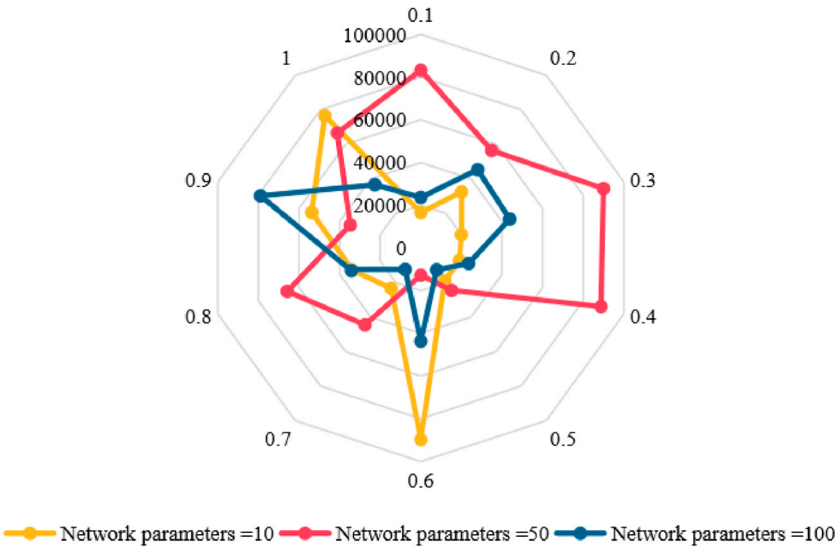


Fig. 5. Neural network state with Inequality constraints.

economic situation of the country and each specific region and sector, the overall distribution of talent is well designed. On this basis, relevant leaders shall take administrative measures to improve the designation, staffing, and posting, so as to force a reasonable outflow of talent from the talent backlog units, and to enable relevant regions, units, and departments that lack talent units to introduce competent talents. Second, researchers have selected a few principal components with large contribution rates with certain criteria to simplify the original multidimensional issue and use these components as inputs. It is possible to eliminate the correlation between network inputs by reducing the number of inputs to the network and simplifying the network structure instead of reducing the number of dimensions of training samples. In the prediction of talent flow, the parameter selection of input layer is very important to the prediction accuracy of the model. According to the CNN, LSTM and IRNN algorithms adopted, input layer parameters mainly include employee personal information, including age, gender, educational background, etc., which can be obtained from employee files or human resource information system. Employment history includes positions at current and previous companies, hours worked, promotions, etc., which can also be obtained from employee files or internal company databases. Company information includes company size, market position, industry type, etc., which can be obtained from the company's public reports or internal databases. Performance evaluation includes quantitative and qualitative job performance evaluation, such as KPI achievement rate, 360-degree feedback, etc. This information is usually stored in the company's performance management system. The output parameters of the model are binary results used to predict whether an employee will quit. This can be expressed as the probability that an employee will leave or stay, which provides an important basis for decision-making. In the experiment, information on 300 mobile talents was used as a data set. This data set is divided into three parts: training set, verification set and test set. The centralized training set accounts for 70% of the total data, that is, the data of 210 employees is used for the training of the model. This data is used to adjust the weights and parameters of the model to minimize prediction errors. The validation set accounts for 15% of the total data, that is, the data of 45 employees is used to validate the model. This part of the data is used to optimize the model hyperparameters and prevent overfitting to ensure that the model has good generalization ability. The test set accounted for 15% of the total data, or 45 employees, used to test the model. This part of the data is not visible during the model training process and is used to evaluate the final performance of the model. CNN algorithm extracts local features of input data through convolution operation, which is especially suitable for processing data with spatial correlation. In the talent flow prediction, CNN can capture spatial patterns of employee information, such as similar career paths or performance trends. LSTM algorithm has memory function and can deal with long-term dependency in time series data. In talent turnover forecasting, LSTM is able to capture long-term patterns in employee historical data, such as persistent job dissatisfaction or declining performance that may indicate turnover. IRNN algorithm is a simple and efficient recurrent neural network that can process sequence data quickly and capture short-term dynamics. In talent flow forecasting, IRNN can capture short-term patterns

Table 1
Accuracy and error results of varying networks.

/	Optimal Accuracy	Optimal Error Results
IRNN Model	37.28%	0.076
LSTM Model	55.17%	0.053
CNN	76.98%	0.021
P_1	0.002	0.003
P_2	0.004	0.005
P_3	0.001	0.002

such as recent job changes or performance fluctuations of employees. By comparing the prediction accuracy, error rate and training time of these three algorithms under the same experimental conditions, we can evaluate their performance in the task of talent flow prediction. The results are specified in Table 1. P_1 is to determine whether there is a significant difference between IRNN and CNN models, P_2 is to determine whether there is a significant difference between IRNN and LSTM models, and P_3 is to determine whether there is a significant difference between CNN and LSTM models.

As can be seen from Table 1, CNN, LSTM and IRNN have performance differences in predicting young talent mobility tasks. These differences reveal the unique strengths and limitations of each model in dealing with such tasks. The CNN model achieved the best accuracy of 76.98%, which was significantly better than the IRNN and LSTM models. At the same time, the lowest error is 0.021, which is also significantly lower than the other two models. This indicates that CNN has higher predictive accuracy when processing data related to youth talent mobility. The core advantage of CNN is its local perception and weight sharing, which enables CNN to effectively extract local features from image or spatial data, while reducing the number of model parameters and improving training efficiency. These features are especially useful when working with data related to spatial distribution or images. Due to its excellent performance in tasks such as image recognition, object detection and image classification, CNN may have similar advantages when dealing with spatial patterns or image data of young talent mobility. Unlike CNN, LSTM and IRNN models are more suitable for processing sequence data. LSTM has achieved remarkable success in tasks such as speech recognition, machine translation, and text generation by effectively handling long-term dependencies through gating mechanisms. IRNN provides an efficient method of sequence modeling through simplified recursive structure. However, these models may not be as effective as CNN_S when dealing with tasks related to youth talent mobility, especially when the data contains complex spatial patterns or image information. By comparing the P-values between the three models, it can be found that the comparative P-values between the groups are all less than 0.05, indicating that these differences are statistically significant. This provides further support for CNN's strength in predicting the mobility of young talent. To sum up, the CNN model shows significant advantages in predicting the mobility of young talents, which is mainly due to its local perception and weight sharing characteristics. In contrast, LSTM and IRNN models may be less effective at handling such tasks, especially when the data contains complex spatial or image information. These findings highlight the importance of selecting appropriate models to match task and data characteristics, while also highlighting the potential of CNN_S when dealing with complex forecasting tasks. To facilitate a rapid and stable convergence of the time lag system model and to address the issue of optimizing prediction and control, researchers have compared the state variable trajectories of CNN and pairwise neural networks, and the results are illustrated in Fig. 6.

On this basis, researchers have adopted the CNN network structure to filter and synthesize features, and eventually input the results of prediction into the improved simple RNN. In the gradient descent, the result at each moment depends on both the current and the previous state of the networks. The model features the assignment of weights to historical data, indicating that recent data has a more significant weight compared to rather remote data.

Last but not least, with a cycle of two years, the results of prediction are re-added to the neural network, while the data extracted in the earliest two years are removed, and their equidimensional time history is recursively extended for continuing purposes. For an easier understanding of the initialization of the LSTM mode, only one layer is adopted in the study. For the research of the tasks related to processing natural language, researchers have adopted a simple recurrent neural network in general, which features fewer network layers and is suitable for initialization with the Gaussian method of initialization. On this basis, this study aims to adopt the least squares method to parameterize the built model prior to prediction.

4.2. *Analysis of the missing processing of CNN data in the control of talent flow*

Due to the difficulty of collecting data on certain influencing factors, there has been a rising number of missing values with the occurrence of inconsistent and non-smooth noise data. Based on the demands of varying sorts of talents to establish corresponding regression equations, the significance of each regression equation can be tested. Furthermore, the results of prediction are closer to the

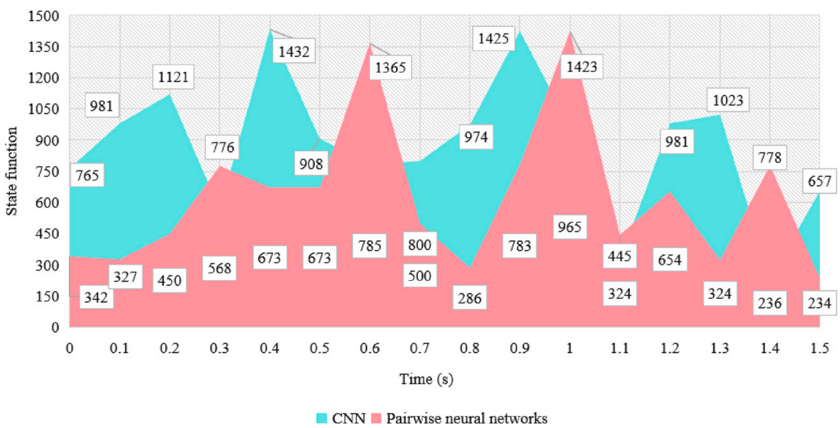


Fig. 6. State variable trajectories of CNN and dual neural network.

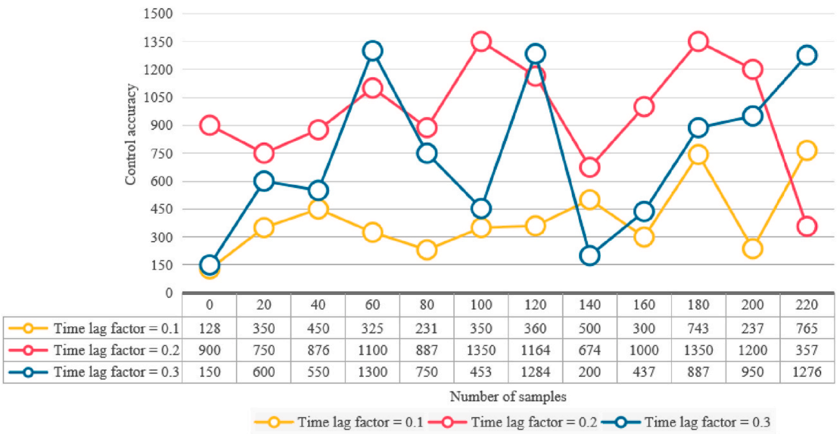
actual values, and the equations are deemed suitable given that they have formed a medium-term prediction model with higher accuracy. The existence of the time lag factor will impose a certain impact on the accuracy of control, resulting in a slower response of the system. When the time lag factor amounts to 0.1, 0.2, and 0.3, the accuracy of control of CNN is illustrated in Fig. 7.

First, researchers have adopted techniques in data mining, including but not limited to averaging and regression, to fill the gaps in the data. Numerous high-tech enterprises in China are established with individual entrepreneurship, and almost all of the senior management and core technical personnel are trained by their respective enterprises. In addition, researchers have paid closer attention to narrowing the scope of the study and placed the focus on the homogeneity and similarity of jobs to conduct targeted research. Based on the status quo and considering the influence of policy factors, researchers have opted for parameters that may reflect the actual situation for prediction. Researchers are convinced that training in business organizations is an indispensable part of the management and development of human resources, and the HR department aims to create learning opportunities for organizational members so as to improve the efficiency and performance of the organization and its internal members in a direct or indirect manner through training and learning procedures. Moreover, organizational commitment is positively correlated with age, which means that older and more senior employees have shown a higher level of organizational commitment. Therefore, for different moments, the weight from the input layer to the hidden layer always amounts to W_1, the weight from the hidden layer to the output layer always amounts to W_2, and the weight of the self-connection of the hidden layer always amounts to W_3.

Second, researchers have adopted data smoothing techniques to cope with the evident biases and burrs in the historical data. To reflect the flow of technological talents and their underlying risks in a more holistic manner, researchers shall take into account the situation of “unemployed” technological talents. The neural network can be easily implemented in the circuit, which helps to directly cope with large-scale issues of optimization and to lower the time required for computation. When the time lag constant is set to 5, the pairwise neural network is compared with CNN for period response, and the results are illustrated in Fig. 8.

Prior to the research, among high-tech enterprises across China, only a few large and medium-sized enterprises had formulated long-term development plans, while most high-tech enterprises merely focused on short-term benefits. Certain enterprises have asked employees to reduce their weekly work schedule to two to three days based on their actual situation, and then allocate the remaining work to themselves. However, there has been limited quantitative research on the underlying relations at present, and the current research in this area still assumes that the annual growth rate of enterprises remains constant, making it difficult to verify the accuracy of the research. As such, on the premise that no other residual information is accumulated, the residual information of the hidden layer would be multiplied by the identity matrix through the backward transfer algorithm. This method features a similar impact on the “forgetting gate” in the least squares method. The researchers applied BP, RPE, and CNN learning algorithms to multiple different trainer datasets to make predictions to test the generalization of different methods, and the test results are shown in Table 2.

Judging from Table 2, the average error of CNN is lowered by 0.0285 compared with the RPE learning algorithm, and the average time required is lowered by 41.6 s compared with the BP learning algorithm. By analyzing the above results, it can be found that there are several reasons why the average error and time required by the CNN model is better than that of the BP model and RPE learning algorithm. First, the CNN model has the characteristics of local connection and weight sharing. This means that the CNN model focuses only on a local region of the input data and reduces the number of parameters to be learned by sharing weights. This can reduce the complexity of the model and improve the training and reasoning efficiency of the model. Second, the CNN model uses several optimization techniques to accelerate the training process, such as batch normalization, dropout, and learning rate attenuation. These techniques can accelerate the convergence rate of the model and improve the generalization ability of the model. Finally, the structure and parameter design of the CNN model also have an influence on its performance. Reasonable model structure and parameter settings can better adapt to the characteristics of the task, so as to improve the accuracy and efficiency of the model. In addition, based on the above multi-dimensional analysis, CNN also improves the learning speed and accuracy of the model to a large extent, thus further improving the prediction speed. The changes in talent mobility in the larger society are likely to impose an impact on the changes of talent mobility in technological innovation in enterprises. Certain companies have never provided their employees with any chance to



	0	20	40	60	80	100	120	140	160	180	200	220
Time lag factor = 0.1	128	350	450	325	231	350	360	500	300	743	237	765
Time lag factor = 0.2	900	750	876	1100	887	1350	1164	674	1000	1350	1200	357
Time lag factor = 0.3	150	600	550	1300	750	453	1284	200	437	887	950	1276

Fig. 7. Accuracy of control of CNN under varying time lag factors.

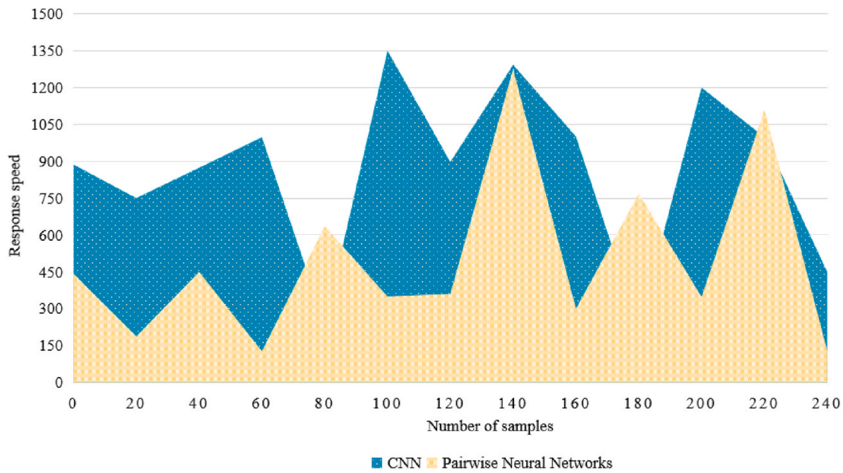


Fig. 8. Periodic response of dual neural network and CNN.

Table 2
Results of prediction.

	BP Learning Algorithm	RPE Learning Algorithm	CNN
Pre-training Steps	34990	64218	97823
Average Error	0.0672	0.0413	0.0128
Average Time Required (s)	87.3	75.2	45.7

receive further training or education, and staff members of these companies generally feel that their employer fails to make good use of their intelligence.

However, research also requires a critical review of current work to challenge the limitations of other approaches. Although the CNN model is excellent at many tasks, it has its own limitations. For example, the CNN model has strong assumptions about the local nature of the input data, which may not be suitable for more global tasks. To overcome these limitations, future studies can try to introduce more complex model structures, such as attention mechanisms, to better capture global information. In addition, the performance of the CNN model is highly dependent on the structure and parameter Settings of the model, which requires a lot of expertise and experience, and also limits its universality. At the same time, although the advantages of CNN model have been analyzed, it has not been comprehensively compared with more other models, such as recurrent neural network (RNN) model and Transformer model, etc., which also needs to be further improved in future research.

4.3. Discussion

With the rapid development of science and technology and the advancement of globalization, the flow of young talents in science and technology has a profound impact on the development of countries, regions and enterprises. This mobility involves not only geographical migration, but also shifts in industries, fields of study, and career development. Traditional forecasting methods often struggle to capture this complex dynamic change, so a more intelligent and precise method is needed to predict and control the flow of young talent in science and technology. As a deep learning algorithm, CNN has achieved remarkable results in image recognition, natural language processing and other fields. CNN has strong feature extraction and pattern recognition capabilities, which can mine useful information from a large amount of data. Therefore, the application of CNN to the prediction and control of the change of the flow of young talents in science and technology is expected to improve the accuracy of prediction and the effectiveness of control. By constructing the prediction model based on CNN, we can analyze the potential rules in the historical data, and then predict the future flow trend of young talents in science and technology. At the same time, combined with the control theory, the corresponding control strategy can be designed to guide and optimize the flow of young talents in science and technology, so as to better meet the needs of social, economic and scientific development. Such research not only helps enterprises and organizations to formulate more scientific human resource management strategies, but also provides decision-making support for government departments' science and technology talent policies.

The results of this study show that the CNN model is superior to the simple RNN model in the prediction task, because it can extract local features through convolution operation and realize parameter sharing, reducing the risk of overfitting. When RNN model deals with sequence data, global feature extraction is weak, and unshared parameters can easily lead to overfitting. This result is consistent with the results obtained by the Kattenborn team in the study of CNN model in 2021 [40]. The reason for this result may be that the CNN model can effectively extract local features through convolution operation, realize parameter sharing, reduce overfitting risk, and thus perform well in prediction tasks. However, RNN model is weak in global feature extraction and parameter sharing, which can easily lead to overfitting. In addition, the results showed that the best accuracy of the CNN model is 76.98%, which is significantly better than 37.28% of the IRNN model and 55.17% of the LSTM model. In addition, which is significantly better than 37.28% of the IRNN model and 55.17% of the LSTM model. The best error result of the CNN model is 0.021, which is also significantly lower than 0.076 of the IRNN model and 0.053 of the LSTM model. By comparing the P-values among the three models, it can be found that the P-values of the comparison between the groups are all less than 0.05, indicating that they are statistically significant. The results of the above research are similar to those obtained by Liu et al., in 2022 [41]. This study shows that the superior performance of CNN model in accuracy and error is mainly attributed to the local perception and weight sharing characteristics of CNN, which enables CNN to effectively capture local features of data, reduce the number of parameters, and improve training efficiency, so as to significantly outperform IRNN and LSTM models in prediction tasks. And finally, the study also found that the average error of CNN is lowered by 0.0285 compared with the RPE learning algorithm, and the average time required is lowered by 41.6 s compared with the BP learning algorithm. This is similar to the results obtained by Holden et al. in their research on phase-functional neural networks [42]. The reason for the above results is that CNN model can effectively extract features through convolution operation and reduce errors. Compared with RPE and BP algorithms, CNN is more efficient and takes less time, which significantly improves the prediction performance.

In conclusion, this study demonstrates the superior performance of the CNN model in predicting the flow of young talents in science and technology compared to traditional RNN models. The key advantages of the CNN model lie in its ability to extract local features through convolution operations and achieve parameter sharing, which not only reduces the risk of overfitting but also enhances the model's generalization ability. Moreover, the CNN model exhibits higher computational efficiency, resulting in a significant reduction of both prediction error and required time compared to other algorithms such as RPE and BP. Further validating the effectiveness of CNN in talent flow prediction. Overall, this study highlights the potential of CNN in accurate talent flow prediction, paving the way for more effective human resource management strategies in a rapidly evolving scientific and technological landscape.

5. Conclusion

The advancement of technology in various cities has had a profound impact on the quantity, quality, and dynamics of local talent, making it an integral component of the urban industrial value chain. Predicting talent flow is a critical task in talent retention; however, current methods for talent flow prediction are limited. To address this gap and enhance talent retention on a global scale, this study investigates the evolving trend of young talent flow in the science and technology field using a CNN model. Furthermore, a comprehensive prediction and control method is proposed. The performance evaluation of the CNN-based talent flow prediction model in this study demonstrates its superiority over models based on the BP learning algorithm and the RPE learning algorithm. The average error and average processing time of the proposed model were 0.0128 and 45.7 s, respectively. In contrast, the BP-based model yielded 0.0672 average error and 87.3 s processing time, while the RPE-based model produced 0.0413 average error and 75.2 s processing time. These results highlighted the high accuracy and feasibility of the proposed method in predicting and controlling changes in young talent flow within the science and technology sector. The implications of this research extend to the development and innovation of the science and technology field. The findings provide decision-makers with a scientific basis and valuable references for facilitating the flow and retention of young talent. Nevertheless, the study has several limitations. Firstly, the relatively small size of the dataset used restricts its ability to generalize across all regions and industries, thereby potentially affecting the prediction model's effectiveness. Secondly, the lengthy training and testing time of the model necessitates further optimization and acceleration. Future research endeavors should focus on expanding the dataset by incorporating samples from diverse regions and industries. This expansion will contribute to improving the accuracy and predictive power of the model. Additionally, exploring the integration of alternative machine learning algorithms or the combination of multiple algorithms may further enhance the model's performance and stability. In summary, this study introduces a talent flow prediction model based on CNN, which demonstrates high accuracy and feasibility in forecasting and managing young talent flow within the science and technology field. Addressing the study's limitations through the incorporation of larger and more diverse datasets, as well as the exploration of alternative algorithms, will contribute to bolstering its applicability. The insights and recommendations provided in this research can pave the way for valuable advancements in talent management and retention, fostering development and innovation in the science and technology sector.

Ethics approval

Not applicable.

Informed consent

Not applicable.

Funding statement

This study received no funding.

Data availability statement

Question: Has data associated with your study been deposited into a publicly available repository?

Response: No.
Question: Please select why. Please note that this statement will be available alongside your article upon publication.
Response: Data will be made available on request.

CRediT authorship contribution statement

Lianfeng Xia: Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fanshuai Meng:** Writing – review & editing, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A. Rosado-Cubero, A. Hernandez, F.J.B. Jimenez, T. Freire-Rubio, Promotion of entrepreneurship through business in cubators: regional analysis in Spain, Technological Forecasting and Social Change 190 (2023) 122419.
[2] G. Li, Y. Jin, X. Gao, Digital transformation and pollution emission of enterprises: evidence from China's micro-enterprises, Energy Reports 9 (2023) 552–567.
[3] A. Malik, V. Pereira, P. Budhwar, A. Varma, M.D. Giudice, Sustainable innovations in an indigenous Indian Ayurvedic MNE, Journal of Business Research 145 (2022) 402–413.
[4] I. MacLachlan, Y. Gong, China's new age floating population: talent workers and drifting elders, Cities 131 (2022) 103960.
[5] G.P. Mahapatra, S. Dash, Round table: talent development in a changing world of work, IIMB Management Review 34 (1) (2022) 83–91.
[6] Y. Zhang, F. Zhang, H. Yu, N. Yang, Y. Zhao, J. Yang, H. Yu, Performance evaluation of the practical application of cleaner production management system: a case study of steel enterprise, Journal of Cleaner Production 379 (13) (2022) 134468.
[7] P. Abreu, D. Santos, A. Barbosa-Povoa, Data-driven forecasting for operational planning of emergency medical services, Socio-Economic Planning Sciences 86 (2023) 101492.
[8] Y. Shang, J. Xu, X. Zhao, Urban intensive land use and enterprise emission reduction: new micro-evidence from China towards COP26 targets, Resources Policy 79 (2022) 103158.
[9] S.S. Gill, M. Xu, C. Ottaviani, P. Patros, R. Bahsoon, A. Shaghaghi, M. Golec, V. Stankovski, H. Wu, A. Abraham, M. Singh, H. Mehta, S.K. Ghosh, T. Baker, A. K. Parlikad, H. Lutfiyya, S.S. Kanhere, R. Sakellariou, S. Dustdar, O. Rana, I. Brandic, S. Uhlig, AI for next generation computing: Emerging trends and future directions, Internet of Things 19 (2022) 100514.
[10] L.Y. Adadimova, G.P. Yu, Modeling of scientific and technological development of agriculture in the region, IOP Conference Series Materials Science and Engineering 753 (2020) 062017.
[11] S. Golubev, A. Efremov, A. Gorokhova, V. Gayduk, E. Kravets, Development of the scientific and technological forecasting methodology based on using TIPS instruments, Economic Annals-XXI 187 (1–2) (2021) 223–231.
[12] V.N. Opanasenko, S.L. Kryvyi, Synthesis of neural-like networks on the basis of conversion of cyclic hamming codes, Cybernetics & Systems Analysis 53 (4) (2017) 627–635.
[13] M. Kahng, P.Y. Andrews, A. Kalro, D.H. Chau, ActiVis: visual exploration of industry-scale deep neural network models, IEEE Transactions on Visualization & Computer Graphics 24 (1) (2018) 88–97.
[14] O. Inik, M. Altiok, E. Ulker, B. Kocer, MODE-CNN: a fast converging multi-objective optimization algorithm for CNN-based models, Applied Soft Computing 109 (2021) 107582.
[15] C.Y. Zhang, D.H. Kim, Analysis of impact position based on deep learning CNN algorithm, Transactions of the Korean Society of Mechanical Engineers A 44 (6) (2020) 405–412.
[16] W.Z. Sun, J.S. Wang, S.Z. Gao, Soft-sensor modeling of PVC polymerizing process based on F-GMDH-type neural network algorithm, Journal of Sensors 2017 (2017) 7872030.
[17] W. Zheng, W. Bo, C. Liu, W.S. Wang, Improved BP neural network algorithm to wind power forecast, The Journal of Engineering 2017 (13) (2017) 940–943.
[18] X. Ma, Z. Dai, Z. He, J. Na, Y. Wang, Y. Wang, Learning traffic as images: a deep convolutional neural network for large-scale transportation network speed prediction, Sensors 17 (4) (2017) 818.
[19] T. Jeong, Deep neural network algorithm feedback model with behavioral intelligence and forecast accuracy, Symmetry 12 (9) (2020) 1465.
[20] H. Xu, Z. Yu, J. Yang, H. Xiong, H. Zhu, Dynamic talent flow analysis with deep sequence prediction modeling, IEEE Transactions on Knowledge & Data Engineering 31 (10) (2019) 1926–1939.
[21] Y. Zhou, Y. Guo, Y. Liu, High-level talent flow and its influence on regional unbalanced development in China, Applied Geography 91 (2018) 89–98.
[22] A. Gharehbaghi, M. Linden, A deep machine learning method for classifying cyclic time series of biological signals using time-growing neural network, IEEE Transactions on Neural Networks and Learning Systems 29 (9) (2018) 4102–4115.
[23] T.M. Quan, T. Nguyen-Duc, W.K. Jeong, Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss, IEEE Transactions on Medical Imaging 37 (6) (2018) 1488–1497.
[24] D. Mishkin, N. Sergievskiy, J. Matas, Systematic evaluation of convolution neural network advances on the Imagenet, Computer Vision and Image Understanding 161 (2017) 11–19.
[25] A. Nezhadali, S. Sadeghzadeh, Experimental design-artificial neural network-genetic algorithm optimization and computer-assisted design of celecoxib molecularly imprinted polymer/carbon nanotube sensor, Journal of Electroanalytical Chemistry 795 (2017) 32–40.
[26] M. Mousapour Mamoudan, A. Ostadi, N. Pourkhodabakhsh, A.M. Fathollahi-Fard, F. Soleimani, Hybrid neural network-based metaheuristics for prediction of financial markets: a case study on global gold market, Journal of Computational Design and Engineering 10 (3) (2023) 1110–1125.
[27] M.M. Shahsavar, M. Akrami, M. Gheibi, B. Kavianpour, A.M. Fathollahi-Fard, K. Behzadian, Constructing a smart framework for supplying the biogas energy in green buildings using an integration of response surface methodology, artificial intelligence and petri net modelling, Energy Conversion and Management 248 (5) (2021) 114794–114803.
[28] C. Zhan, X. Zhang, J. Yuan, X. Chen, X. Zhang, A.M. Fathollahi-Fard, G. Tian, A hybrid approach for low-carbon transportation system analysis: integrating CRITIC-DEMATEL and deep learning features, International Journal of Environmental Science and Technology 7 (3) (2023) 1–14.
[29] N. Ghadami, M. Gheibi, Z. Kian, M.G. Faramarz, R. Naghedi, M. Eftekhari, G. Tian, Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods, Sustain. Cities Soc. 74 (2) (2021) 103149–103162.
[30] F.M. Philip, V. Jayakrishnan, F. Ajesh, F. Ajesh, P. Haseena, Video anomaly detection using the optimization-enabled deep convolutional neural network, The Computer Journal 65 (5) (2021) 1272–1292.
[31] E.H. Ahmed, M.R.M. Alsemawi, M.H. Mutar, Hanhoosh Ho, M. Albadr, Convolutional neural network for the detection of coronavirus (COVID-19) based on x-ray images, Solid State Technology 63 (4) (2020) 8730–8739.
[32] A. Bate, Bayesian confidence propagation neural network, Drug Safety 30 (7) (2018) 623–625.

[33] X. Li, Y. Sun, Stock intelligent investment strategy based on support vector machine parameter optimization algorithm, Neural Computing and Applications 32 (6) (2020) 1765–1775.
[34] R. Liu, J. Tan, A review of talent management research at home and abroad, Journal of Chinese Human Resources Management 13 (1) (2022) 39–58.
[35] S. Zhang, The establishment and application of talent evaluation system: a quantitative model of individual human capital, Journal of Chinese Human Resources Management 12 (1) (2021) 18–33.
[36] X. Li, Y. Sun, Application of RBF neural network optimal segmentation algorithm in credit rating, Neural Computing and Applications 33 (14) (2021) 8227–8235.
[37] B. Hu, S. Yue, Z. Zhang, A rotational motion perception neural network based on asymmetric spatiotemporal visual information processing, IEEE Transactions on Neural Networks and Learning Systems 28 (11) (2017) 2803–2821.
[38] Z. Zhang, Y. Oh, S.D. Adams, K.E. Bennet, A.Z. Kouzani, An FSCV deep neural network: development, miniaturization, and acceleration on an FPGA, IEEE Journal of Biomedical and Health Informatics 25 (6) (2021) 2248–2259.
[39] S.Y. Zhang, G.U. Ye, Y.I. Guo-Dong, Z.L. Wang, A knowledge matching approach based on multi-classification radial basis function neural network for knowledge push system, Frontiers of Information Technology & Electronic Engineering 21 (7) (2020) 981–994.
[40] T. Kattenborn, J. Leitloff, F. Schiefer, S. Hinz, Review on convolutional neural networks (CNN) in vegetation remote sensing, ISPRS Journal of Photogrammetry and remote Sensing 173 (5) (2021) 24–49.
[41] D. Liu, H. Yang, K.I. Elkhodary, S. Tang, W.K. Liu, X. Guo, Mechanistically informed data-driven modeling of cyclic plasticity via artificial neural networks, Computer Methods in Applied Mechanics and Engineering 393 (5) (2022) 114766–114778.
[42] D. Holden, T. Komura, J. Saito, Phase-functioned neural networks for character control, ACM Transactions on Graphics 36 (4) (2017) 1–13.