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Investigation and application of prediction model of college students' employment sentiment index based on machine learning

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Abstract

The purpose of this research is to investigate machine learning-based prediction techniques. This study uses machine learning, which has advanced quickly in recent years and has a strong predictive function, to forecast the employment prosperity index for college students. Due to the small error between the prediction results and the actual value, and the strong generalization ability based on machine learning, the algorithm in this field has been widely studied and used by scholars in the prediction of college students' employment prosperity index in recent years. The experimental results of this paper show that in the employment prediction model of college students, the prediction accuracy of the traditional convolutional neural network (CNN) algorithm is the lowest of 0.61 and the highest of 0.70; the highest prediction accuracy is 0.84 and the lowest is 0.70 when the improved grey model (GM) algorithm is used; the prediction accuracy of the prediction model (GGNN) combined with CNN and GM is 0.97 and the lowest is 0.82. This shows that the GGNN algorithm has higher accuracy than the traditional CNN algorithm and the GM algorithm, and also shows that the machine learning-based college student employment sentiment index prediction model proposed in this paper is meaningful. At the same time, it also proves that federal learning, Internet of Things and edge computing for intelligent services can play a role in the prediction model of student employment sentiment index.

Keywords: Employment sentiment index, Machine learning, Convolutional neural network, Predictive model, Intelligent services, Edge computing

1.Introduction

The "employment rate of graduates" is a significant problem for Chinese colleges given the quick development of higher education. The actual job condition and the degree of college and university administration can be more properly and scientifically reflected in the employment rate of graduates. The prosperity degree is another name for the prosperity index. It is to process and summarize the qualitative indicators in the business prosperity survey through quantitative methods, and comprehensively reflect the state or development trend of a specific survey group or a social and economic phenomenon. In addition, it also reflects the adaptability of college education and training to the social needs related to the existence and development of colleges and universities, and has a great impact on graduates, parents and even the whole society. As a new force in China's modernization drive, effectively distributing and cultivating college students will play an extremely important role in realizing China's scientific outlook on development and building a harmonious society. Basically only by solving the employment problem of college students, social construction can be promoted more smoothly. The employment problem of college students is not only a problem between colleges and students, but also the most direct economic problem and social development problem that China urgently needs to solve.

It is possible to debate the employment prosperity index of college students from both internal and external viewpoints, and the definition of the meaning of the employment prosperity index of college students is based on an examination of the index. In this study, the employment prosperity index for college students is primarily examined and constructed from the standpoint of the external economic environment. The impact of external economic environment on college students' employment is mainly reflected in the absorption of college students' employment by economic growth. From the perspective of employment absorption, economic growth has both quantitative constraints and employment structure effects. Through quantitative and logical data, the job environment index of college students primarily shows the limitation and influence of economic growth on the

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employment volume and employment structure of college students. This study is innovative in that it provides a machine learning-based prediction algorithm and merges two separate prediction models into a hybrid model.

2. Related Work

China's college student population is growing as a result of improved educational standards, which also contributes to the country's challenging job market. Although a large number of nursing students worked during the clinical semester, Aw A contended that little was understood about the nature of employment and the connections between employment, academic achievement, and other factors. He discovered that students in the medical field had more job stress [1]. The purpose of the Desai M S study was to examine the relationship between emotions and personal achievement and employment rates. His survey of 300 college students showed that negative emotions can lead to employment pressure [2,25]. Otache I set out to investigate the connection between undergraduates' inclination to engage in both self-employment and waged work and entrepreneurship instruction. According to the study's findings, undergraduates had two opposing aspirations for their careers: self-employment and paid work. The two different kinds of employment goals interacted and tended to predominate one another [3]. Mullan K believed that mobile devices enabled people to work anytime, anywhere. Yet surprisingly little was known about employment [4]. Li X was curious as to whether a carbon fee would lessen the strain of employment losses in areas with access to coal. Using a typical coal resource-based region in China as an example, he created a dynamic computable general equilibrium model to assess the impact of different carbon tax revenue strategies on employment. The results showed that a carbon charge helped alleviate the strain of dwindling employment in coal-dependent regions [5]. Scholars have found that in modern society, although the enrollment rate and graduation rate of major colleges and universities are getting higher and higher, the employment rate has not been greatly improved. In order to study the problems in employment, it is necessary to use the employment prosperity index to analyze the problems in employment. But scholars have not mentioned how to apply it to the study of employment issues.

Machine learning has made significant strides in a number of sectors recently, and its capacity to anticipate outcomes in academic settings has been excellent news for society. Agent-based models (ABMs) calibration to real data, according to Lamperti F, is still a challenge. In order to directly tackle the problem of parameter space exploration and calibration of ABM and considerably minimize the computational time needed for large-scale parameter space research, he combined machine learning and intelligent iterative sampling [6]. Goodfellow I maintained that deep neural networks (DNNs) are now widely used in a variety of significant machine learning issues, including malware detection, speech recognition, self-driving car guidance, and more, as a result of advancements in deep learning. Nevertheless, it has been demonstrated that machine learning models are susceptible to hostile cases [7]. Butler K T summarized recent advances in machine learning and described machine learning techniques suitable for solving research problems in this field and future directions in this field [8]. Thrall J H analyzed the high and rapidly growing global interest in machine learning applications driven by the availability of big data, computing power, and new deep learning algorithms. In addition to developing new methods themselves, machine learning also faced many opportunities and challenges [9]. Scholars believe that machine learning has a powerful predictive function and can be applied in various fields, so it is feasible to apply it to the construction of a college student employment sentiment index prediction model. But scholars have not stated how the specific predictive model is constructed [10].

3. Hybrid Prediction Model Based On Machine Learning

In addition to quickly and efficiently understanding the job status of recent graduates, the employment guidance department should also perform pertinent analysis and forecast on the employment status of upcoming graduates [11]. Because they can better understand it, people who are going to graduate can plan ahead for future graduates' employment circumstances and establish a strong basis for directing graduates' employment. Figure 1 illustrates the factors influencing college students' employment pressures today:

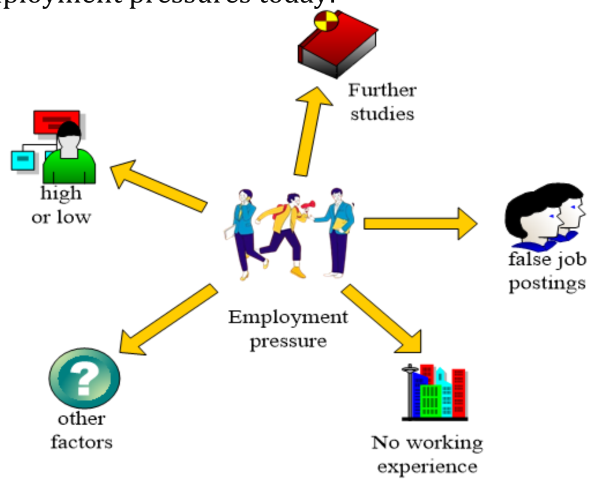

Figure 1. Factors of college students' employment pressure

As shown in Figure 1: The prosperity index is a quantitative indicator of economics, which reflects the operating conditions of different industries, such as price, transaction volume and operating rate. The common prosperity index includes the corporate prosperity index, the national housing prosperity index, and the prosperity index of various industries. Prosperity index research has a profound theoretical foundation and long-term practical tests in the fields of economics and management [12].

3.1 Convolutional Neural Network (CNN) prediction model based on machine learning

Probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory, and other disciplines are all involved in machine learning, which is a multidisciplinary subject. Many prediction algorithms that can produce excellent outcomes have been proposed by researchers in recent years as a result of the active development of machine learning and big data [13]. The main advantages of machine learning include the following: Through a large number of experiments, researchers have confirmed that machine learning has high classification accuracy, machine learning has strong fault tolerance for noisy data, machine learning adopts parallel distributed processing methods, can quickly calculate large amounts of data, and has the ability to find optimal solutions at high speed [14,24].

Since artificial feature extraction cannot extract all the effective features of time series data, the convolutional neural network has the unique characteristic of nonlinearity, and the Convolutional Neural Network (CNN) structure can understand the feature information of the data sample space through learning and training [15]. When training and processing the input data information, it can map the lower-level feature vector information in the data to the higher-level feature vector information, and do a good job of feature selection for a subsequent prediction model with higher prediction accuracy. The CNN structure diagram is shown in Figure 2:

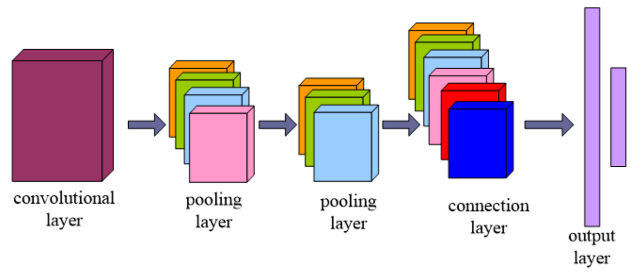

Figure 2. Structure of CNN for feature extraction

As shown in Figure 2: CNN automatically extract feature vectors through multiple iterations of feature mapping processing in the convolutional layer and downsampling processing in the pooling layer [16]. Therefore, parameters such as the size of the convolutional unit of the convolutional layer, the number of convolutional units, the number of layers of the pooling layer, and the downsampling amplitude of each pooling layer directly affect the quality of the automatic feature extraction by the convolutional neural network.

Automatic feature extraction by convolutional neural network can eliminate the subjective error formed by manual feature extraction. Data are generally input into CNN convolutional neural network in the form of matrix, as shown in formula 1:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Firstly, the information data matrix is input from the input layer into the convolutional neural network structure. The input layer generally preprocesses the data to make it conform to the input of the convolutional layer. Data preprocessing refers to some processing performed on the data before the main processing. The calculation process is as shown in formula 2:

$$a_j^l = f\left(\sum_{i \in M_j} a_j^{l-1} * k_{ij}^l + b_j^l\right) (2)$$

M_j is the input feature set of the L-the layer selected from several layers in the L-1 layer, and k_{ij}^l is the convolution kernel. Then, the result is output to the pooling layer. The pooling layer can effectively reduce the size of the data space and control the occurrence of overfitting. Its main purpose is to reduce the dimension on the premise of retaining the main features [17]. The pooling layer, also known as the down sampling layer, compresses the input feature map. On the one hand, the features are reduced, resulting in a reduction in parameters, which in turn simplifies the complexity of the convolutional network calculation; on the other hand, it maintains a certain invariance of the features. The calculation of pooling layer downsampling is as shown in formula 3:

$$a_j^l = f\left(\beta_{ij}^l down\left(a_j^{l-1}\right) + b_j^l\right) (3)$$

$down(\bullet)$ represents the downsampling function, and the convolutional and pooling layers are generated in the same way. Convolutional layers in convolutional neural networks are used to extract abstract feature vectors contained in a given dataset. The main function of the pooling layer is feature mapping. Finally, the extracted feature vector set is implanted into the GM algorithm through a fully connected layer to establish a prediction model with good prediction effect. As shown in formula 4:

$$a^l = f\left(u^l\right) = f\left(w^l a^{l-1} + b^l\right) (4)$$

The ensemble learning algorithm itself is not a separate machine learning algorithm, but completes the learning task by building and combining multiple machine learners. Through the features automatically extracted by the CNN convolutional neural network, people can use the GM ensemble algorithm to build a prediction model [18].

The feature set extracted automatically using CNN convolutional neural network is very good. It not only considers the relationship between the feature and the index, but also considers the relationship between the feature and the feature, so it can extract some features that cannot be considered in manual extraction. Because there are many features extracted by CNN convolutional neural network, people can perform feature selection to a certain extent, and remove those feature vectors that are not very important. For a learning algorithm, a good feature set is the key to training the model [19-20].

3.2 Improved Gray Model (GM) based on machine learning

Grey model (GM) is one of the most widely used grey prediction models, which uses small samples to deal with systems with uncertain and incomplete information [21]. In the presence of disturbances in the system, the model prediction results are not easy to produce great deviations. It is a fairly good prediction method [22]. The process of GM(1,1) is very simple, this paper mainly introduces its modeling process. A first-order differential formula is established as formula 5:

$$\frac{da^{(1)}(k)}{dt} + ax^{(1)}(k) = b \ (5)$$

This formula is called the whitening formula of the GM(1,1) prediction model. In the formula, $ax^{(1)}(k)$ is the parameter to be determined, the differential formula is solved, and the general solution is obtained as formula 6:

$$\hat{a}^{(1)}(k) = Ce^{-ak} + \frac{b}{a} \ (6)$$

Using the least squares method to solve, the formula 7 is obtained:

$$\hat{a} = [a,b]^T = \left(B^T B\right)^{-1} B^T Y \ (7)$$

The solution of the whitening formula is also called the time response function of the model. After performing a cumulative reduction and reduction process on A, the predicted value of the original feature sequence can be obtained as formula 8:

$$\hat{a}^{(0)}(k+1)=\hat{a}^{(1)}(k+1)-\hat{a}^{(1)}(k)\ (8)$$

The formula is the predicted value obtained by the GM(1,1) model.

GM(1,1) uses the first value of the original sequence as the first initial value of the model, but there is no theoretical basis to support this operation, and this operation may affect the fitting and prediction accuracy [23]. Based on minimizing the specified objective function, this paper proposes a GM(1,1) model with initial value correction called CGM(1,1). The CGM(1,1) process is formula 9:

$$a^{(1)}(k+1)=\left[ax^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)}\ (9)$$

The objective function is defined as formula 10:

$$W=\sum_{k=1}^{n}\left[a^{(1)}(k+1)-a^{(1)}(k)\right]^{2}\ (10)$$

There are many ways to construct background values, and the commonly used ones are homogeneous exponential function fitting method and weighted generation method. To find a fitting function, first of all, there must be a set of test or experimental data of the dependent variable and the independent variable. The higher the degree of agreement between the fitted function and the experimental data is, the higher the accuracy of the fitting is. In the traditional GM(1,1) model, the weight is usually p=0.5, and the accumulated adjacent mean is the fixed background value, and the modeling prediction is carried out on this basis. Therefore, from the perspective of error theory, PGM is formula 11:

$$z^{(1)}(k)=pa^{(1)}(k)+(1-p)a^{(1)}(k+1)\ (11)$$

p is the background generation weight, and the best value is determined to be the key to establishing the PGM(1,1) model. In the actual modeling process, p starts from 0.01 and increases by 0.01 each time. According to the prediction method of the GM(1,1) model, the average relative error of the corresponding weight is obtained until p=0.99. The obtained 99 mean absolute errors are compared, and the value with the smallest absolute mean relative error is found, and then a reasonable background value is determined according to the formula and a corresponding prediction model is established.

3.3 Employment sentiment index prediction model based on mixed forecast method (GGNN)

In this study, an enhanced hybrid prediction method (GGNN) that combines gray model (GM) and CNN techniques is proposed. CNN receives its input from the gray model's fitted value. The GGNN method combines the advantages of linear models, nonlinear models and swarm intelligence optimization.

Hybrid predictive models can also be used for data forecasting, or forecasting is a specific form of hybrid models that make better predictions on data. This paper proposes a hybrid forecasting method called GGNN, which combines different forecasting models to predict data together, firstly uses the improved grey model to predict time series, and then inputs the improved grey model prediction results into CNN. The three-layer network topology of GGNN is shown in Figure 3:

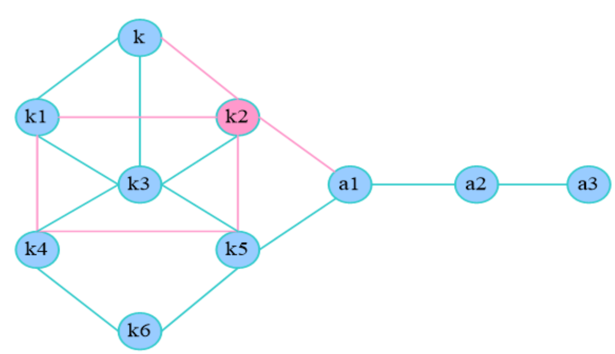

Figure 3. GGNN three-layer network topology

As shown in Figure 3: GGNN integrates the advantages of the improved gray model, and uses the function approximation characteristics of CNN to solve the problem of randomly initializing weights and thresholds of the original CNN. This enables GGNN to achieve the best prediction performance in the process of time series prediction. In addition, GGNN combines the advantages of grey model, CNN and genetic algorithm. Therefore, some trend values can be well predicted. In addition to the data applied in this paper, GGNN can also be used for prediction of other time series.

The quasi-exponential series are marked as formula 12 and formula 13:

$$0 \le p(k) = \frac{a^{(0)}(k)}{a^{(1)}(k-1)} \le 0.5 \quad (12)$$

$$1 \le \delta^{(1)}(k) = \frac{a^{(1)}(k)}{a^{(1)}(k-1)} \le 1.5 \quad (13)$$

Assuming N is the number of input neurons, d is the dimension, and m is the number of output neurons, then the generalized output function is formula 14:

$$f(a) = \sum_{i=1}^{L} \beta_i h_i(a, w_i, b_i) = h(a)\beta \quad (14)$$

L is the number of hidden layer nodes, w_i represents the parameters of the hidden layer of the network, and the goal is to keep the training error as small as possible while minimizing the output weight. The optimization model can be written as formula 15:

$$\min \frac{1}{2}\|\beta\|^2 + \frac{c}{2}\sum_{i=1}^{n} \varepsilon_i^2 \quad (15)$$

Lagrangian method is one of two methods to describe fluid motion, also known as satellite method and tracking method. c is a parameter set by the user for the trade-off between the output layer weights and the training error. The optimization model can be transformed into a solved unconstrained optimization problem by the Lagrangian method, as formula 16:

$$f(a) = h(a)\beta = h(a)\left(\frac{1}{c} + H^T H\right)^{-1} H^T T \quad (16)$$

To make it linearly separable in this space, the most commonly used kernel function is the RBF kernel function, whose form is formula 17:

$$K(u,v) = \exp\left(-\gamma\|u - v\|^2\right) \quad (17)$$

The layers other than the input and output layers are called hidden layers. The hidden layer does not directly receive signals from the outside world, nor does it directly send signals to the outside world. The feature maps of the hidden layers remain unknown and are replaced by their corresponding kernel functions. The number of hidden layer nodes (dimension of the hidden layer feature space) also does not need to be set.

Forecasting is a hot topic of concern. Traditional forecasting methods and machine learning-based forecasting models have limitations, and these methods often cannot fully capture all the characteristics of time series. Hybrid forecasting methods and compound forecasting methods combine their respective single forecasting methods in various ways, and can effectively utilize the strengths of each model.

4. Experiment Of Employment Sentiment Index Prediction Model Based On Mixed Forecast Algorithm

One of the main concerns of China's higher education system, and indeed of the entire country, has always been the employment of college students. College student employment in higher education research has grown to be a significant issue, and the issue of inadequate employment in higher education has steadily gained attention, particularly since the start of the year due to China's increase in the number of people enrolled in higher education. The goal of the employment research for college students has been steadily broadened in recent years, as have the research findings and the research talent team. The employment and graduation rates for 2019 and 2020 are shown in Figure 4:

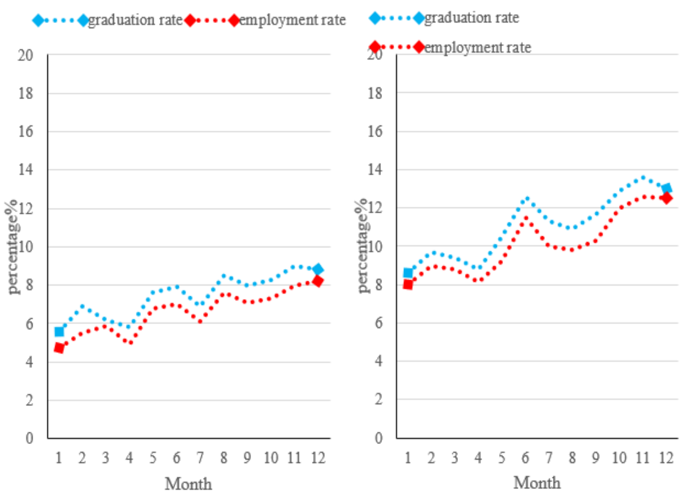

Figure 4. Employment and graduation rates in 2019 and 2020
(a).Employment and graduation rates in 2019
(b).Employment and graduation rates in 2020

As shown in Figure 4: It can be seen from Figure 4(a) that the employment rate in 2019 is lower than the graduation rate, and in Figure 4(b), it can be seen that the employment rate in 2020 is also lower than the graduation rate. On the other hand, it can be found that China's higher education is far behind developed countries and has just reached the limit of popularization, and college students are still in short supply of high-level talents. Another hot spot that continues to be concerned in the employment research of college students is the employment environment. China's economic system has changed from a planned economy to a market economy, and the employment of college students has also changed from distribution to employment, and the employment environment has always attracted much attention.

4.1 Influence of contracted salary on employment sentiment index

Because college students are relatively disconnected from social life on college campuses, most of their understanding of salary comes from news media, family environment and historical information of previous graduates. The historical information itself is relatively lagging, thus causing the lag of college students' salary expectations.

In addition, salary news that can be widely disseminated among college students often comes from graduates with strong employability with demonstration effect. Therefore, to a certain extent, the salary expectations of college students often exceed their own ability. In order to prove the existence of this problem, this paper aims to understand the contracted salary of college students in 2020 and the satisfaction degree of contracted salary. This paper surveys 180 college students who have signed contracts, as shown in Tables 1 and 2:

Table 1. Contracted salary of 180 students

Salary(yuan)	number of people	Percentage%	Effective %
Below 3000	15	8%	8%
3001-4000	48	27%	27%
4001-5000	65	36%	36%
5001-6000	40	22%	22%
Above 6000	12	7%	7%

Table 2. 180 students contracted salary satisfaction

satisfaction level	number of people	Percentage%	Effective %
Very satisfied	10	6%	6%
more satisfied	16	9%	9%
basically satisfied	39	22%	22%
more dissatisfied	87	48%	48%
very dissatisfied	28	15%	15%

As shown in Table 1 and Table 2: There are 15 people whose contracted salary is less than 3,000, accounting for 8%, which is similar to the number of people whose contracted salary is greater than 6,000; there are 48 people in 3001-4000, accounting for 27%, and 65 people in 4001-5000, accounting for 36%. It can be seen that the salary of most students is between 3000-6000, and the salary of more than 6000 is rare.

And their satisfaction with salary is not high, only 6% are very satisfied, but 485% are very dissatisfied, accounting for almost half of them. It can be seen that one of the reasons for the low employment prosperity index of college students is that college students' expectations of their own salary are too high, which leads to their low employment rate.

This paper investigates the employment sentiment index from 2017 to 2019, as shown in Figure 5:

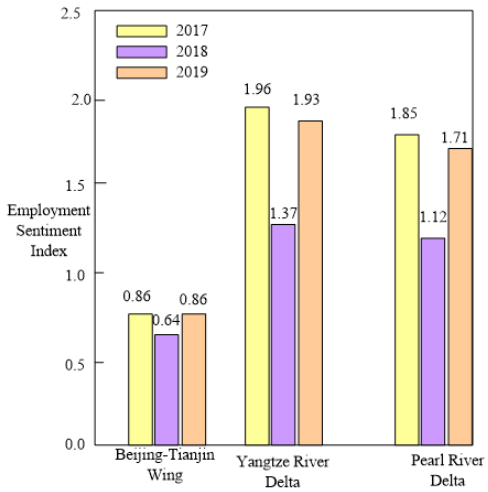

Figure 5. Employment sentiment index from 2017 to 2019

As shown in Figure 5: It can be seen that the Beijing-Tianjin wing of China's employment sentiment synchronization index has remained basically stable from 2017 to 2019. From the perspective of the leading composite index of employment prosperity, due to the slowdown of China's economic growth, from 2017, China's employment pressure is increasing. The employment sentiment leading index has shown a clear downward trend in recent years. This is mainly due to the slowdown in China's economic growth and the increase in employment pressure. The decline of the index indicates that the employment situation of college students is not optimistic.

The process of college students seeking a job is also a process of proving themselves, so it is inevitable that they will be compared in terms of salary, and they cannot objectively seek companies and salaries that match their own strengths. College students generally believe that their salary level should be higher than that of their parents, but they ignore the lack of their own work experience. College students generally believe that high education is a powerful capital for themselves to seek high wages, but in the talent market, wages need to be matched with work experience, which further causes graduates' salary expectations to be seriously inconsistent with reality. Therefore, it is imperative to help college students establish a correct employment outlook, a correct understanding of university education, and an objective and practical employment idea through salary expectations.

4.2 Prediction effect experiments of three prediction models

The simulation platform built on Matlab in this research validates the accuracy of the employment prediction model for college students based on the GGNN algorithm.

This research compares the prediction results based on the GGNN algorithm with the prediction results of the CNN convolutional neural network and the GM algorithm alone in order to more thoroughly assess the prediction effect of the three approaches. The outcomes are displayed in Figure 6 using 500 data samples.

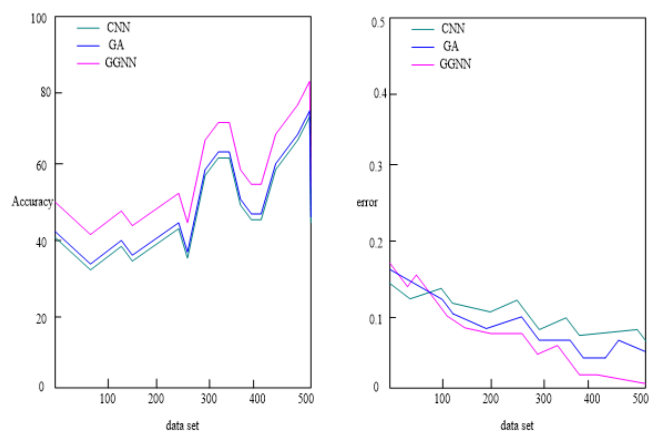

Figure 6. Comparison of prediction accuracy and error of the three methods
(a) Comparison of the prediction accuracy of the three methods
(b) Comparison of the error of the three methods

As shown in Figure 6: the prediction accuracy of the CNN model in Figure 6(a) is the lowest, and the prediction accuracy of the GGNN is the highest; the CNN model in Figure 6(b) has the highest error, and the GGNN has the lowest error. The worst prediction result is the CNN model, which fluctuates little. The predicted curve is too smooth, which leads to inaccurate prediction of some mutation cases. Therefore, the predicted value is quite different from the actual value. This leads to a large error in the prediction results of the final prediction model, and the final prediction error is about 0.1. The prediction results based on the GGNN prediction model are the best, and it shows that GGNN can achieve very good results in prediction.

4.3 Comparison of the effects of three prediction models on the employment sentiment index of college students

The dataset in this paper is the employment sentiment index of college students from 2015 to 2020. In the experiment, the CNN algorithm, the GM algorithm and the GGNN combination algorithm in this paper are used as the prediction models respectively, in order to compare the prediction effects of the three algorithms and select the algorithm with the best performance as the final prediction model. Since the prediction results of the CNN algorithm and the GM algorithm will vary depending on the selection of samples, the error comparisons of the three algorithms are shown in Table 3, Table 4 and Table 5:

Table 3. Prediction accuracy and error of CNN algorithm

years	Accuracy	Absolute error
2015	0.65	0.39
2016	0.69	0.42
2017	0.61	0.79
2018	0.70	0.36
2019	0.66	0.42
2020	0.68	0.35

Table 4. Prediction accuracy and error of GM algorithm

Years	Accuracy	Absolute error
2015	0.84	0.27
2016	0.76	0.30
2017	0.80	0.38
2018	0.70	0.32
2019	0.81	0.37
2020	0.75	0.31

Table 5. Prediction accuracy and error of GGNN algorithm

Years	Accuracy	Absolute Error
2015	0.82	0.02
2016	0.88	0.05
2017	0.95	0.06
2018	0.97	0.03
2019	0.93	0.04
2020	0.92	0.01

As may be seen in Tables 3, 4, and 5, the highest forecast accuracy for college students' employment is 0.97. This clearly demonstrates how the GGNN combined prediction model put forward in this paper can more accurately forecast college students' employment.

On the other hand, it can also be seen that compared with CNN algorithm and GM algorithm, GGNN combined prediction model not only avoids the process of manual selection of K value, but also has higher accuracy in this model.

After proving the accuracy of the GGNN combined prediction model, this paper applies it to the prediction of the employment index of college students, as shown in Figure 7:

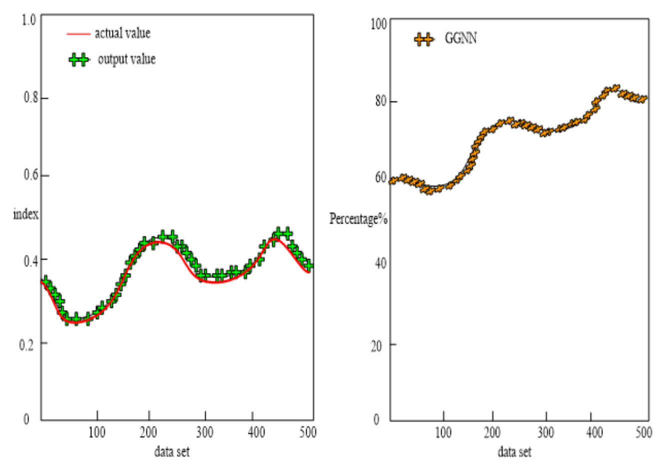

Figure 7. The prediction effect of the GGNN method on the employment sentiment index
Prediction error of GGNN method for employment sentiment index
(b) Prediction accuracy of GGNN method for employment sentiment index

According to Figure 7: Figure 7(a) shows that the output value of the GGNN combined prediction model is nearly identical to the real value, showing that the error is minimal; Figure 7(b) shows that the prediction accuracy of the prediction model, when the GGNN method is applied, typically reaches 80%. This can clearly demonstrate that the forecasting model put out in this study can successfully accomplish the employment forecasting. The combination algorithm based on GGNN can also well capture a small amount of mutation information in the fluctuation of employment prosperity index, and can better predict the trend of these mutations, which reflects the robustness of the GGNN combination algorithm. Overall, the error of GGNN prediction results is very small.

4.4 Strategies and suggestions for improving the employment policy of college students

In promoting the employment of college students, the state has an irreplaceable and irreplaceable responsibility. The efficient implementation of the policy of strengthening the nation through science and education as well as strengthening the nation through only ability is related to the smooth growth of college students' employment and is a crucial component of creating a harmonious socialist society. The government should intensify and broaden its reforms of the economic and educational systems, enhance the many programs that support employment, and aid college students in finding jobs.

(1) Encourage college students to start their own businesses and broaden their employment channels

The state should give certain policy support to encourage college students to start their own businesses. Firstly, the state should give certain financial support. Difficulty in obtaining start-up funds is one of the biggest difficulties faced by college students when starting a business. The state can designate banks to provide small-scale loans for college students to start their own businesses, and encourage college students to start businesses with discount, interest reduction and interest-free policies. Secondly, the state should develop corresponding psychological and skill training institutions to provide free services for college students who are interested in starting a business, help them avoid detours. The third is to reduce or exempt taxes. For enterprises founded by college students, the government can reduce or exempt taxes for a certain period of time. Finally, information support is provided.

(2) Reform the traditional talent-training model

At present, the society is highly developed, and the society's requirements for talents are constantly increasing. Coupled with the factor of enrollment expansion, the employment pressure of college students is increasing, and the degree of competition accumulation is evident. The current competition can be described as white-hot, which is not only the competition of professional knowledge, but more importantly, the inspection of comprehensive quality. Employers not only have requirements and inspections for college students' morality, but also focus on inspecting college students' computer proficiency, English application level, social communication ability and so on. Therefore, schools should conform to the trend of social development, focus on the improvement of the comprehensive quality of college students, effectively change the current talent evaluation and assessment mechanism, eliminate backward methods and methods of talent training, and break the rules and regulations, thus improving the ability of college students to adapt to the society and developing market competitiveness.

(3) Actively improve their comprehensive quality and enhance their employability

From the overall trend, college students are increasingly cultivating their own comprehensive quality. Employers not only consider professional counterparts in the recruitment process, but also pay more attention to the comprehensive quality of college students. Employers generally believe that the lack of technology for enterprises is not fatal, because technology can be acquired through training. But the creativity of job seekers and the ability to respond to new things should be one of the motivations and compulsory outcomes of their extensive study. This has also become a quality that employers attach great importance to. It can be seen from the survey that personal ability has become the second largest factor affecting employment. Therefore, efforts are made to cultivate their own comprehensive quality in order to play an important role in the job search process. Hence, college students not only pay attention to the study of professional knowledge, but also pay more and more attention to participating in various extracurricular activities. Active participation in social practice activities helps to improve college students' organizational and leadership abilities, as well as their ability to think and judge independently, and enhance their employability and competitiveness.

Conclusions

Federal learning, Internet of Things and edge computing for intelligent services are being applied to more fields. With the advent of the information age, information technology continues to affect and change all aspects of economy, society, culture and life. The field of education has also been profoundly affected by the changes in information technology. The difficulty of finding employment for Chinese college students is closely related to the imbalance between the overall talent supply and demand. Therefore, the capacity of educational information database has become larger and larger. The field of education urgently needs an effective information technology to forecast college students' employment and promptly suggest appropriate remedies in light of these massive amounts of data. In light of this, this study offered a CNN prediction model and a gray prediction model based on machine learning, and it outlined how the two prediction models might be combined to create a GGNN mixed prediction model. Compared to just the GM prediction model and the CNN prediction model, this model's predictive power was greater. The three approaches were simply tested in the experiment and used to forecast the employment prosperity index for college students in order to demonstrate the efficacy of the hybrid model described in this study. Finally, it was found that the error of the employment sentiment index prediction model based on GGNN was very small and the prediction accuracy was very high, so the model was suitable for real life. Because only two methods were considered for mixed prediction in the construction of the model, the effect was only stronger than that of a single prediction model. In the future work, it should be tried to mix more than two prediction methods, and it is believed that such a prediction model will have a stronger prediction effect. More importantly, in the follow-up research, more technologies will be used to improve the prediction model of college students' employment sentiment index, such as federated learning for intelligent services, the Internet of Things and edge computing.

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