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A Study on Predicting Career Growth Paths of Accounting Students Using AI Technology in Career Planning

Mingxiao Rao[1,2,*]

[1] School of Economics and Management, Puyang Vocational and Technical College, Puyang, Henan, 457000, China
[2] Puyang Institute of Technology, Henan University, Puyang, Henan, 457000, China

SUMMARY: *In guiding accounting undergraduates toward informed choices about their professional futures within higher education institutions, it is necessary to predict students' career growth paths. In this paper, the clustering algorithm integrated with K-Means, K-Modes and GMM is used to study the career growth path portrait of accounting students. Then the convolutional neural network model optimized by cuckoo algorithm is proposed to predict the career growth path of accounting majors. Four career trajectory profiles emerge from the analysis of accounting students' growth patterns, each representing a meaningfully distinct developmental path. The prediction accuracy of the CSO-CNN model is improved by 3.84%~8.42% compared with the comparison model, and its overall prediction accuracy of 91.33% for the groups with different career growth path portraits, and the training and testing time is smaller, which reveals the good prediction accuracy of the CSO-CNN model for the students' career growth path. Students' career growth paths with good prediction accuracy and prediction efficiency.*

KEYWORDS: *cluster analysis; prediction model; convolutional neural network; cuckoo algorithm; career planning*

1 Introduction

As the digital economy continues its rapid expansion, conventional accounting functions are under mounting pressure to evolve, and practitioners are increasingly required to acquire proficiency in a range of new technological tools, tools, and business models, and constantly update their knowledge and skills in order to have a high degree of competitiveness in the job market [1-3]. Looking at the current situation, the number of college graduates year after year set a new record, and among them, accounting graduates also continue to climb rapidly. The huge scale of graduates to seek professional positions in society, coupled with the epidemic era, graduates form a more special employment situation, the degree of competition is very great [4, 5]. If the connotation and specificity of vocational education, to give the lack of rational knowledge of the future of the students to provide targeted help, guide students to develop a reasonable career planning, and establish a correct view of the career, and timely provision of high-quality and effective vocational positions to prospective graduates of the information to improve the employability of students [6-9].

In March 2016, Deloitte & Touche launched the Deloitte Finance Robot, which can work 7×24 h without interruption, greatly improving the efficiency of accounting work and

*raomx0840@163.com
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ensuring the accuracy of accounting processing. However, there are a number of reports predicting that more than half of the accounting jobs will be replaced by Artificial Intelligence (AI) products in the future, including bookkeepers, accountants and auditors [10-12]. BBC News has reported that a considerable share of accounting positions face displacement through automation, placing a significant portion of the existing workforce at genuine risk of job loss. Building on this concern, [13] draws upon theoretical frameworks including technological unemployment to establish that AI integration within accounting practice bears a strong association with heightened workforce turnover, while simultaneously reconfiguring how decisions are made within organizations and restructuring broader socioeconomic arrangements. Literature [14] reveals that accounting professionals are generally positive about AI's ability to improve job performance and revolutionize curricular focus, with CPAs in large firms particularly emphasizing the need to develop students' skills such as data management, while educators' perceptions vary, underscoring the urgency of reforming accounting curricula. According to [15], accounting students believe that data analytics and AI will increasingly replace the entry-level positions, so they attach great importance to mastering technical skills. At the same time, their optimism is mixed with concerns about ethical issues, personal information security problems, and employment issues associated with the extensive use of technology. As [16] points out, artificial intelligence plays an important role in the development of accounting practice and directs practitioners towards analytical and strategic tasks. To perform them, accountants should form new competency clusters that include data analysis skills and digital literacy in order to adapt to the changes and be ready to capitalize on emerging opportunities in a changing environment. However, AI technology has also given rise to new positions (AI ethicist, data analyst), while helping students grow professionally and avoid being replaced by tools such as AI. Literature [17] survey shows that accounting graduates have a high demand for AI-related employment skills, and regression analysis confirms that tools such as generative AI have a significant positive impact on their employment skills, which helps to improve students' career competitiveness. However, literature [18] points out that the current accounting students' readiness for AI integration is low, and their knowledge level and opportunity perception significantly affect the readiness, revealing the criticality of improving students' AI literacy to adapt to their future careers. Therefore, AI technology must be fully utilized to provide students with support for career planning, market trend analysis and forecasting.

[19] notes some weaknesses in career counseling at universities: a uniform approach to solving the problem and insufficient resource integration. On the basis of theories of precision education management and empirical methods based on the use of big data and AI technologies, the research suggests building a personalized system of career counseling in order to increase the efficiency of assistance and improve students' competitiveness in the job market. According to [20], machine learning, reinforcement learning, and natural language processing can be used for deep data mining of multidimensional information about students, adjust decision-making strategies in real time and intelligently analyze market information, and develops a full-cycle dynamic career planning algorithm to provide scientific and personalized career guidance, and improve the effectiveness of planning and the quality of employment. With the help of techniques such as deep learning, one research article [21] proposed a personalized career planning system aimed at offering career support to college students. The study found that, using this system, the level of satisfaction of employees reached 90%, and the probability of finding a job increased by 85%, which is much higher than those of the 70% and 65% achieved through the use of other traditional methods. Literature [22] uses word frequency-inverse document frequency, word vector technology and conditional random field model to analyze online recruitment text, identifies the match

between college students' core competencies and job requirements by comparing the probability of skills, and constructs the extreme gradient enhancement model to effectively predict the jobs demanded by graduates. Literature [23] optimizes the matching process through a two-way long and short-term memory model, increasing the employment matching accuracy to 91%, increasing the matching rate by 35% within six months, and achieving a student satisfaction rate of 8.7. Literature [24] uses machine learning, deep learning, collaborative filtering, and real-time data streaming to execute the five modules of CV parsing and categorization, skills and course recommendation, and job matching to provide a personalized path of development for students the key module recommendation accuracy is more than 80%. In order to overcome the limitation associated with traditional methods in relation to huge datasets, an AI-based personalized career guidance system has been proposed [25]. The experiment performed proved the ability of its recommendation engine to make accurate career development recommendations. In another research direction, researchers proposed a novel approach involving the combination of homomorphic encryption and machine learning to forecast employment trajectories of university graduates, which provides a safe and ethical new path of prediction in the field of education and employment. Literature [27] used a plain Bayesian classifier to integrate personal data and macroeconomic indicators to predict employment trends, with an average error rate of only 2.76% on job prediction and a salary prediction accuracy of 95.68%.

In this paper, we use crawler technology to collect the career profile data of accounting majors from recruitment websites, which will be used as experimental data. In order to grasp the career growth path portraits of accounting majors, a clustering integration method is proposed, which combines the three clustering methods of K-Means, K-Modes and GMM to construct a base clustering apparatus and integrates the results of the base clustering apparatus through the voting method, thus subdividing the different career growth path portraits. With an objective to improve the ability of CNN to make predictions, the cuckoo search optimization approach is used in optimizing the weights of the convolutional and pooling layers. As a result, the CSO-CNN method becomes the main approach that will be used to forecast the career development paths of students studying accounting. The model is subjected to training analysis, comparative analysis of prediction accuracy and prediction efficiency to examine the prediction effect of CSO-CNN model.

2 Analysis of students' career growth paths

2.1 Representation of career growth paths

AI technology is used in predicting the career development paths of students in accounting. The overall structure of prediction can be depicted with the help of Figure 1 and involves a few main stages including data collection, the choice of relevant data sources, crawling to obtain data, data modeling and analysis, and determining the portrait of the career growth path of students, on the basis of which the prediction model of the career growth path can be established. The analysis of the career growth path of accounting majors is mainly to analyze the career profile information publicly available on websites such as Collage, MileagePlus, and BOSS Direct Recruitment. According to the requirements of occupational job classification, industry classification, regional classification and mobility requirements of career growth path, when conducting the analysis, the relevant personnel should generally extract the public attributes such as graduation time, employment unit, employment position, employment start time, employment end time, region where the unit is located, and the industry to which the unit belongs, etc. of the occupational profile owner (represented by encrypted codes). With these public attributes it is possible to fully express the topological properties and visualization requirements of career trajectories. In order to facilitate the analysis of the career growth paths of accounting majors, cluster analysis is introduced to subdivide the students' career growth paths.

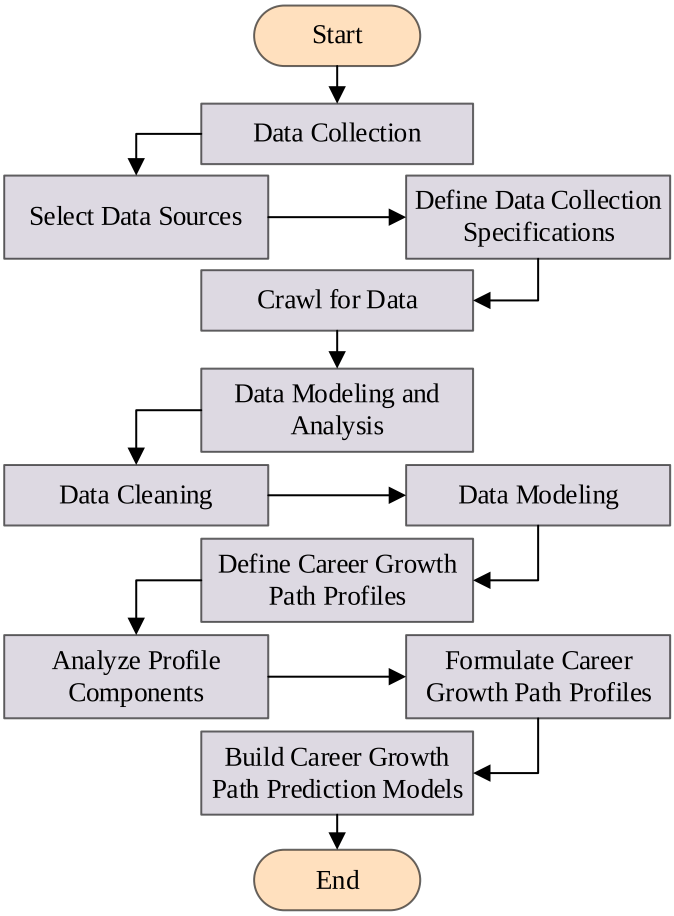

Figure 1: The prediction process of the student's career growth path

2.2 Clustering integration methods

There exist a number of different clustering techniques depending on whether they belong to the category of supervised or unsupervised learning approaches. Since the current data set is highly discrete yet quite homogeneous, density-based clustering approaches cannot provide the expected results. Therefore, in order to construct a clustering technique, there are K-Means, K-Modes, and GMM algorithms that have been selected to create a clusterization base and whose output will later be combined using the voting approach.

2.2.1 K-Means algorithm

The K-means clustering algorithm ranks among the most widely adopted and well-established approaches within the broader family of partition-based clustering methods. Its underlying logic proceeds as follows. A value k is first designated to represent the total number of clusters into which the dataset is to be partitioned, after which k data points are selected at random to serve as the initial centroid of each cluster. The algorithm then computes the distance between every remaining data point and each of the established cluster centers. From there, the geometric centroid of each cluster is recalculated, and these updated centroids are adopted as the new cluster centers for all k groups. The distances from individual data points to the revised centers are recomputed accordingly, and each point is reassigned to the cluster whose center lies nearest to it. This iterative procedure continues until the centroid of every cluster stabilizes and no further meaningful shift occurs. At that stage, the data points residing within each cluster attain their maximum degree of internal similarity.

Consider a data sample set denoted as $X = \{X_1, X_2, X_3, \cdots, X_n\}$, comprising n samples in total. When the K-means clustering algorithm is applied to partition these samples, the procedure unfolds through the following key steps.

(a) Establish the permissible range for the clustering number k as $[1, M]$.

(b) Specify the number of clusters k.

(c) From the sample set X, randomly draw k samples and designate them as the initial cluster centers, recorded as $C_1, C_2, C_3, \cdots, C_k$.

(d) Compute the Euclidean distance separating each remaining sample from every cluster center according to the formula below:

$$d(X_i, C_j) = \sqrt{(x_{i1} - c_{j1})^2 + (x_{i2} - c_{j2})^2 + \cdots + (x_{i10} - c_{j10})^2} \tag{1}$$

In equation (2), $X_i (i = 1, 2, \cdots, n)$ denotes a sample data point, and $C_j (i = 1, 2, \cdots, k)$ refers to a cluster center.

(e) The cluster membership of each sample point is determined by comparing its distance to all cluster centers. Specifically, a sample is assigned to cluster z when the following condition holds:

$$d(X_i, C_z) = \min\{d(X_i, C_j)\} (j = 1, 2, \cdots, k) \tag{2}$$

It then follows that:

$$X_i \in C(z) \tag{3}$$

In Eq. (3), $C(z)$ refers to the cluster whose center is C_z, meaning that sample X_i is assigned membership to cluster $C(z)$.

(f) Compute the geometric centroid of each cluster to obtain the updated clustering center, as expressed below:

$$C_j = \frac{1}{n_j} \sum_{x \in C(j)} x (j = 1, 2, \cdots, k) \tag{4}$$

In Eq. (4), $C(j)$ denotes the cluster centered on C_j, and n_j represents the total number of samples contained within cluster $C(j)$.

(g) Steps (d) through (f) are repeated iteratively until the position of each clustering center stabilizes and the displacement falls within the anticipated threshold. At that point, a valid clustering outcome is obtained for the particular value of k under consideration.

(h) The clustering number is then incremented such that $k = k + 1$, and steps (c) through (g) are executed again. This process continues until $k = M$, at which point clustering results have been produced for every integer value of k within the range $[1, M]$.

2.2.2 K-Modes Algorithm

K-modes algorithm stands as a further development of the K-means model that was particularly designed for performing categorization tasks with the use of categorical data sets. The fundamental principles underlying the operation of this algorithm are similar to those followed by K-means. Initially, the number of clusters k is chosen. After that, the process of selecting the initial centers of all k clusters begins randomly. Next, the distance between each sample and each center is calculated. After the calculation is made, each sample will be assigned to the closest cluster. As soon as all samples are assigned to the corresponding clusters, a new position of centroids will be computed. This cycle of operations is repeated multiple times until there are no more changes in the positions of centroids, and thus the process ends.

In the K-modes algorithm, the distance between samples is calculated using the dissimilarity formula shown below:

$$d(X, Y) = \sum_{i=1}^{m} \delta(x_i, y_i) \tag{5}$$

where X and Y denote two samples respectively, the number of attributes of the samples is m, x_i is the ith attribute value of the sample X, y_i is the ith attribute value of the sample Y, and when $x_i = y_i$, $\sigma(x_i, y_i) = 1$. And $\sigma(x_i, y_i) = 0$ when $x_i \neq y_i$.

After all the samples are classified into the specified class, the process of recomputing the center of mass Z of the class is as follows: suppose that the class has t samples, each of which is denoted by $C_1, C_2, \cdots, C_t$, respectively. Each sample has m attributes, then the value of the jth attribute of the center of mass, Z_j, is the value of the attribute that occurs most often in the t sample attributes, $\{C_{1j}, C_{2j}, \cdots, C_{tj}\}$.

2.2.3 GMM algorithm

A Gaussian mixture model (GMM) is a probabilistic statistical model that provides a good representation of the spatial distribution and characterization of data in a parameter space.A GMM is defined as a V-linear combination of Gaussian density functions, i.e:

$$P(x|\theta) = \sum_{i=1}^{V} \alpha_i \mathcal{N}_i(x|\mu_i, C_i) \tag{6}$$

where: $\mathcal{N}_i(x|\mu_i, C_i)(i = 1, 2, \cdots, V)$ is a Gaussian distribution with a mean vector of μ_i and a covariance matrix is C_i, and x represents the p-dimensional data vector. The mixing ratio $\alpha_i(i = 1, 2, \cdots, V)$ is satisfied:

$$\sum_{i=1}^{V} \alpha_i = 1,\ 0 \le \alpha_i \le 1 \tag{7}$$

Let $X = [x_1, x_2, \cdots, x_n]^T$ be the p-dimensional sample dataset containing n independently and identically distributed samples, $Z = [z_1, z_2, \cdots, z_n]^T$ denote the hidden variables corresponding to the sample observations respectively, i.e., z_i is related to the observation x_i, then z_i denotes the hidden label of x_i.

The multivariate Gaussian mixture model takes the form defined in Eq. (6), where $\mathcal{N}_i(x|\mu_i, C_i)(i = 1, 2, \cdots, V)$ represents the p-dimensional Gaussian density function associated with a minority class dataset, parameterized by the mean vector μ_i and the covariance matrix C_i. Each component density constitutes a Gaussian function over p variables and takes the following form:

$$f(x|\theta_i) = \frac{1}{(2\pi)^{\frac{p}{2}}} \frac{1}{|C_i|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}(x-\mu_i)^T C_i^{-1}(x-\mu_i)\right\} = \mathcal{N}_i(x|\mu_i, C_i) \tag{8}$$

where: $X \sim \mathcal{N}(\mu \in R^P, C \in R^{P\times P})$, the expectation is $E(x) = \mu$, $\mu = [\mu_1, \mu_2, \cdots, \mu_V]$. The covariance array is $E\left[(x-\bar{x})(x-\bar{x})^T\right] = C$, $C = [C_1, C_2, \cdots, C_V]$.

For the entire minority class dataset X, the joint probability density function is:

$$P(x|\alpha, \mu, C) = \prod_{j=1}^{n}\left\{\sum_{i=1}^{V}\alpha_i \mathcal{N}(x_j|\mu_i, C_i)\right\} \tag{9}$$

Therefore, the solution to the above problem is the maximum likelihood estimation of the parameters $\theta = (\alpha_1, \alpha_2, \cdots, \alpha_V, \mu_1, \mu_2, \cdots, \mu_V, C_1, C_2, \cdots, C_V)$ for maximum likelihood estimation.

2.2.4 Clustering Integration Algorithm

There are three types of algorithms used for developing base clusters, such as K-Means, K-Modes, and GMM, after which the process of data mining is performed by employing the Clustering Ensemble Algorithm (CEA). The process of CEA integration algorithm is shown in Fig. 2. The basic logic that forms the basis of CEA algorithm can be expressed as follows: all three algorithms, i.e., K-Means, K-Modes, and GMM, are applied to data objects, thus resulting in three clusters generated independently from each other; then, the voting process is performed in such a way that the label that is mentioned most often among the three clusters is considered the final one.

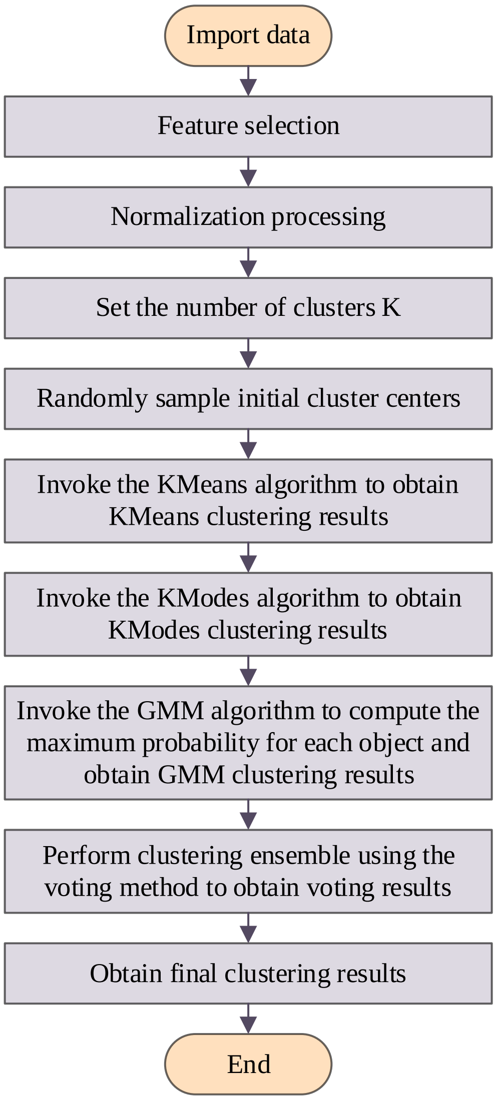

Figure 2: Flow of CEA ensemble algorithm

2.3 Breakdown of career growth paths

2.3.1 Data acquisition and processing

According to the analysis in 2.1, crawler technology is used to collect the career profile information of accounting students from job sites such as Collage, MileagePlus and BOSS Direct. The specific information collected includes: graduation institution, graduation time, employment unit, employment position, entry time, position title, region of the unit, and industry to which the unit belongs.

Given the structural complexity and considerable volume of career profile information associated with accounting undergraduates, the format and content of the fields in each table must be cleaned first to reduce the impact of noise. Data cleaning includes removing logically incorrect values and filling in missing data values, and then integrating them into a unified standard data format.

2.3.2 Feature Label Construction

Feature extraction and feature labeling based on students' attributes is another key part of profiling. The random forest classifier proves to be reliable and robust in handling outliers while serving as a feature selection technique to generate student profiles. In light of this finding, the top three feature attributes in accordance with the feature importance measure from the perspective of random forest are selected as the labels for the student profile: intended employment position (X1), intended entry time (X2), and job title (X3).

2.3.3 Analysis of clustering algorithms

To find out how many clusters there are to partition, the datasets have been tested with K-Means, K-Modes, and GMM approaches to calculate their respective silhouette coefficients. The silhouette coefficients at different numbers of centroids ranging from 2 to 9 have been shown in Figure 3. It can be seen that the best results are obtained when the number of clusters is 4, and at this time the contour coefficients of the K-Means, K-Modes and GMM algorithms are 0.554, 0.421 and 0.305, respectively.

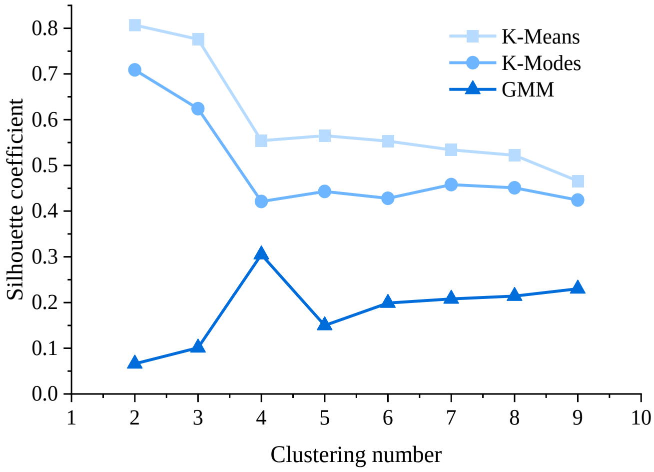

Figure 3: Silhouette Coefficient Comparison Across Multiple Clustering Algorithms

For a comparative analysis on how well the clustering algorithms have done, the error sum of squares are computed by applying K-Means, K-Modes, GMM, and CEA algorithms in order to calculate the error sum of squares in the whole data set. For robustness tests, the algorithms are compared using information entropy as the comparative tool. Since the cluster centers are randomly generated in each iteration, multiple runs will be conducted to ensure reliability. As such, 15 iterations are executed for each of the four algorithms and the information entropy of each cluster formed is recorded.

Error sum of squares and information entropy for the four algorithms are tabulated in Table 1. It can be seen that GMM has the largest error sum of squares at 104.65 while the minimum error sum of squares, 86.58, was produced by the CEA algorithm, which proves the clustering superiority of this algorithm. As for robustness, the information entropy of CEA remains the smallest among all other algorithms, at 0.834.

Table 1: Error Sum of Squares and Information Entropy Results for Four Clustering Algorithms

Algorithms	Sum of squared errors	Information entropies
K-Means	90.37	0.841
K-Modes	100.69	0.926
GMM	104.65	0.931
CEA	86.58	0.834

2.3.4 Career Growth Path Portrait

Employment position (X1), entry time (X2) and position title (X3) were selected as clustering features. Before clustering, the selected features were subjected to max-min normalization to eliminate the effect of differences in feature dimensions. The career profile data of accounting students were clustered using the CEA algorithm, Table 2 below illustrates the cluster analysis results. In order to better interpret and differentiate various career development paths followed by accounting students, we categorize students into four categories according to certain defining features, namely, the adaptation stage, the growth stage, the maturity stage, and the differentiation stage, in which most of the career growth path portraits of accounting majors are in the adaptation period and the growth period, which account for 28.65% and 37.13% of the total, and in the maturity period and the differentiation period, which account for 23.35% and 10.87% of the total.

(1) Adaptation period

It is usually 1~3 years after joining the profession. Accounting students gradually adapt to the working atmosphere of the unit and familiarize themselves with the financial internal control process. As each individual has different personality traits and work initiative, the gap gradually emerges in the process of initial growth from a newcomer to an assistant accountant. At this stage, if an individual takes the initiative to integrate into the unit's business system, exerts work initiative, improves business skills and cultivates professionalism, it will lay a good foundation for future development.

(2) Growth period

Generally 3~10 years after joining the company. The business ability and professionalism have been significantly improved, and after continuous learning, the individual usually obtains the titles of intermediate accountant, intermediate economist, etc., and gradually grows into a business backbone or assumes the responsibilities of a section head.

(3) Maturity period

Generally 11~25 years after joining the company. Most people reach new heights in their professional abilities and working methods. Titles continue to improve, and business paths are basically promoted to senior accountant or senior economist.

(4) Differentiation period

Generally between 25 years after joining the profession and retirement. Most people are more loyal to the financial work they do. There continue to be accountants who obtain senior or full senior titles and take up leadership positions, with further improvement in their work and ability to manage the overall situation.

Table 2: Cluster analysis results

Type	Indication period	Growing period	Maturation period	Differentiation period
X1	0.226	0.415	0.632	0.891
X2	0.214	0.439	0.638	0.895
X3	0.192	0.371	0.557	0.869
Number	443	574	361	168
Proportion/%	28.65%	37.13%	23.35%	10.87%

3 Prediction of students' career growth paths

3.1 Predictive modeling

Here, the Cuckoo Search (CS) optimization technique is implemented to optimize the design of the Convolution Neural Network (CNN). Subsequently, the developed Cuckoo Search Optimization Convolution Neural Network (CSO-CNN) is employed as the predictive model for predicting the future growth paths of accounting undergraduate students.

3.1.1 Convolutional Neural Networks

Convolution neural network forms part of the most representative and frequently cited models in the domain of deep learning. The architecture of the network involves three main layers: the convolution layer, pooling layer, and fully connected layer.

Convolution Layer. This particular layer serves as the feature extractor in the larger architecture of the CNN. It performs convolution operations using convolution kernels on predefined parts of the input image or other features, the features extracted from the image are mapped into the mathematical space by the activation function to form a feature map, in this layer, multiple different convolution kernels can be set up, by increasing the depth of the model to obtain multiple feature maps in order to obtain more advanced features. In the convolutional layer, a nonlinear mapping function is used to have a linear conversion of the input signal in the network to a nonlinear output signal.

(2) Pooling Layer. The main purpose of this layer in the context of CNN is the reduction and diminution of the dimension of the extracted features, thus resulting in a reduced number of parameters and reduction in the overall complexity of the network. At this layer, there are no updates required for weight parameters. There are generally two types used, which are max pooling and average pooling.

(3) Fully Connected Layer. The purpose of this layer in CNN is the prediction and classification process of the network. Feature maps from the previous two layers are first converted to a single vector. Each neuron here is connected to every neuron from the previous layer, and the ReLU activation function is applied to its output. The output is finally sent through a Softmax function to normalize the output and get the probability value of the output corresponding to each class. So it is clear that:

$$z^l = W^l \otimes a^{l-1} + b^l \tag{10}$$

$$a^l = pool\left(a^{l-1}\right) \tag{11}$$

$$z^l = W^l a^{l-1} + b^l \tag{12}$$

$$y^l = soft\max\left(W^l x^{l-1} + b^l\right) \tag{13}$$

In these expressions, Eq. (10) corresponds to the convolutional layer, Eq. (11) to the pooling layer, Eq. (12) to the fully connected layer, and Eq. (13) to the Softmax function. The term d denotes the output of the lth layer, $\otimes$ represents the convolution operation, $pool$ indicates the pooling operation, and W^l together with b^l refer to the weight and bias parameters of the lth layer, respectively.

3.1.2 Cuckoo algorithm

The Cuckoo Search algorithm (CS) is a meta-heuristic optimization method that draws inspiration from the brood parasitism behavior of cuckoos and their characteristic Lévy flight movement patterns. The specific procedures of the algorithm are outlined as follows:

(1) The algorithm begins by randomly initializing N nest positions, expressed as

$X_0 = \left(x_1^0, x_2^0, \cdots, x_N^0\right)$, and arbitrarily designates one nest from among these as the candidate to be carried forward into the next generation.

(2) The position update of the algorithm mainly relies on Levy flights to iterate, comparing the positions of the next generation individuals in the newly acquired nests with those of the previous generation, and searching for the best-positioned individuals from them.

(3) A random number $r \in [0,1]$ is drawn and compared against the probability P_a that the host bird will detect a foreign egg in its nest. When $r > P_a$, the nest location is updated to a new position; otherwise it remains where it is. The nest positions from the current and preceding generations are then compared, and the nest occupying the more favorable location is retained, yielding $X_t = \left(x_1^t, x_2^t, \cdots, x_N^t\right)$.

(4) A check is performed to determine whether the most recently updated nest location satisfies the prescribed accuracy requirement or the termination condition for iteration. If this condition is met, that nest position is accepted as the global optimal solution of the algorithm; otherwise, the procedure returns to step (2) and continues.

Each egg housed within a nest in the cuckoo algorithm encodes a candidate solution to the optimization problem. The position update follows the expression below:

$$x_i^{t+1} = x_i^t + \alpha \otimes L\left(\lambda\right) \tag{14}$$

In this equation, x_i^{t+1} denotes the nest location of the i th bird in the t th generation, $\otimes$ represents element-wise multiplication, α is the step size parameter, and $L(\lambda)$ refers to the randomized search path governing the Lévy flight trajectory.

3.1.3 CSO-CNN Prediction Models

In the case of traditional convolutional neural networks, the weights are initially sensitive enough, and depending on how the parameters are set, a change could lead to drastically different results when running the network. It could either cause the network to have problems converging, or the rate of convergence would become exceedingly slow that training the network would take an impractical amount of time. Hence, optimizing the weight becomes important. Meta-heuristic optimization provides several benefits in achieving this goal since it doesn't need gradients to work, has fewer parameters than most techniques, and has an inherent rate of convergence that is faster. Using these facts, a novel approach using the convolutional neural network with the Cuckoo Search algorithm, which is named CSO-CNN, is proposed. The core idea is to use the Cuckoo Search algorithm to optimize the weights of the convolutional neural network during its training process, where the weights that need to be optimized are represented using vectors. Analytical approaches are then used to analyze the properties of these vectors before passing them into the convolutional and pooling layers of the convolutional neural network. Using vector encoding, every individual in the cuckoo search algorithm is represented by a vector, and every vector represents the weights that the convolutional neural network must learn and optimize during its training phase. The relation between the two can be mathematically shown as follows:

$$\begin{gathered} Bird(i) = \\ \left[\omega_{11}^{c_1}, \omega_{12}^{c_1}, \omega_{13}^{c_1}, \omega_{14}^{c_1}, \omega_{21}^{c_2}, \cdots, \omega_{KL}^{c_n}, \cdots, \omega_{11}^{p_1}, \omega_{21}^{p_1}, \omega_{32}^{p_1}, \cdots, \omega_{KL}^{p_n}\right] \end{gathered} \tag{15}$$

In Eq. (15), i identifies each individual bird within the flock, while $\omega_{KL}^{c_n}$ and $\omega_{KL}^{p_n}$

denote the weights of the convolution kernel situated in the nth convolutional layer and those within the nth pooling layer, respectively, both associated with the Kth input neuron connected to the Lth output neuron.

3.2 Predictive analysis of the model

3.2.1 Data preparation

The career profile data of accounting majors and the career growth path portrait data collected in the above chapter are used as data samples for this experiment. In order to make the predicted results of the career growth path of accounting majors more convincing, the students were divided into 5 types of universities according to their graduation institutions as the test data, and the 5 types of universities were 985 universities, 211 universities, one university, two colleges and junior colleges. The training data and the testing data are separated in a 5:1 proportion.

3.2.2 Training analysis of the model

The evaluation system used to measure the CSO-CNN prediction model established in this study involves using two indicators: namely, the accuracy indicator (Acc), as well as the Loss function, which are used to evaluate the training process of the prediction model. In order to investigate the optimization effect generated by the CSO algorithm, the CNN and the CSO-CNN models are trained separately for comparison purposes. Fig. 4 shows the Acc curve of the CNN prediction model, where the Acc of the test set under the CNN prediction model approaches 0.740, while the Acc of the training set converges to approximately 0.865. Fig. 5 shows the Loss curve, where the Loss of the test set declines to 4.87 and then converges to approximately 0.30. The Loss of the training set declines from 4.50 and finally converges to approximately 0.28.

Fig. 6 and Fig. 7 respectively display the Acc curve and Loss curve of the CSO-CNN prediction model. In terms of this model, the Acc of the test set and the training set converges to approximately 0.88. The Loss of the test set converges to approximately 0.2, declining from its original value of nearly 2.55, while the Loss of the training set is decreased from 4.25 and finally converges to a similar level. Considering both the Acc and Loss performance, there is enough evidence to prove that the CSO algorithm is significantly optimized for CNN and the CSO-CNN model.

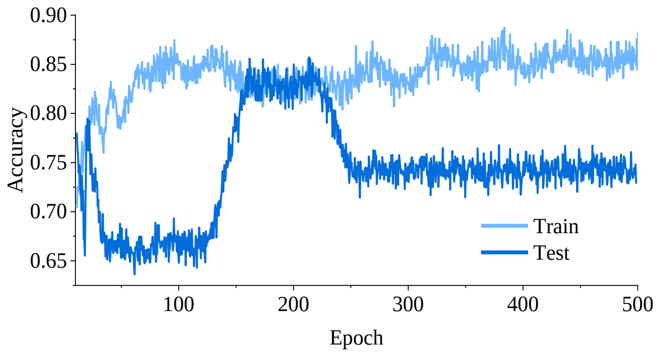

Figure 4: Acc curve of the CNN prediction model

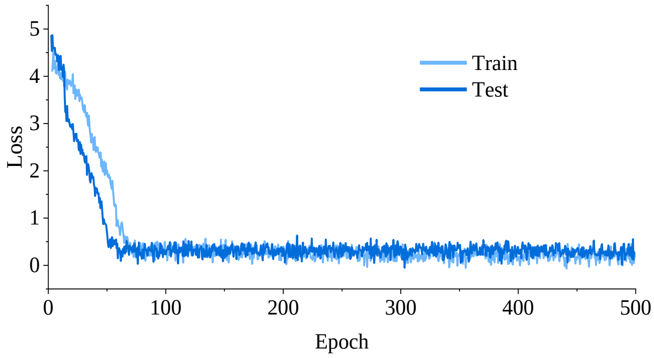

Figure 5: Loss curve of the CNN prediction model

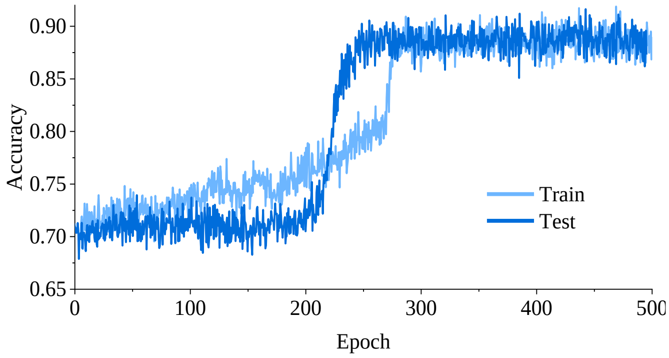

Figure 6: Acc curve of the CSO-CNN prediction model

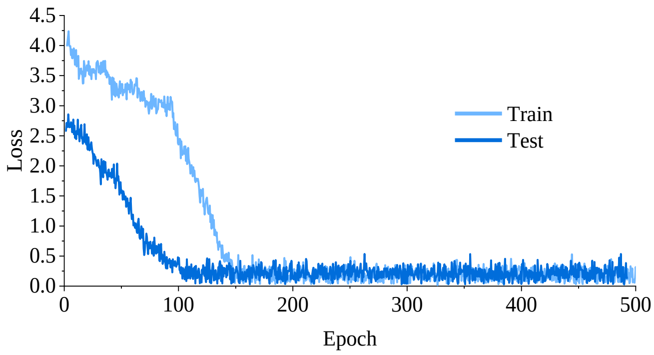

Figure 7: Loss curve of the CSO-CNN prediction model

3.2.3 Comparison of prediction accuracy

Five benchmark models are chosen for comparison, including the traditional CNN, SVM, BP Neural Network, ANN, and RF. All six models for predicting career development paths for accountants are tested on the experimental data collected from accounting students with different backgrounds of institutions for graduation, and the accuracy rates for predicting the five categories of institutions of graduation are depicted in Figure 8.

(1) ANN and BP neural network have the lowest accuracy of career growth path prediction, and the average value of the accuracy of prediction for accounting students of five types of graduating schools is 82.09% and 82.48%, respectively, which indicates that ANN and BP neural network can not accurately characterize the changes in the career growth path of accounting students, which results in the largest analytical error.

(2) The prediction accuracy rate of the SVM model exceeds that of the ANN and BP

Neural Network model, with an average accuracy rate of 84.35%, due to its strong generalization ability, while no such limitations are imposed on either the ANN and BP Neural Network models. Therefore, the accuracy rate in prediction for career development paths for accounting students is improved. The prediction accuracy rate of the Random Forest model is slightly lower than that of the SVM model, with an average accuracy rate of 84.18%.

(3) The prediction accuracy of CNN is better than SVM as well as random forest model, with an accuracy mean of 86.67%, because it belongs to the current popular deep learning algorithms with better fitting and modeling ability, but its prediction effect is also worse than that of CSO-CNN, which is due to the fact that there is also a parameter optimization problem in CNN.

(4) The predictive accuracy attained by the CSO-CNN model surpasses that of all comparison models by a considerable margin, with an average accuracy of 90.51%, and an overall improvement of 3.84%~8.42%, which indicates that the CSO-CNN model better overcomes the problem of large prediction error of the current model, and well describes the changing characteristics of the career growth path of the accounting students, which verifies the superiority of the CSO-CNN model. CNN model's superiority.

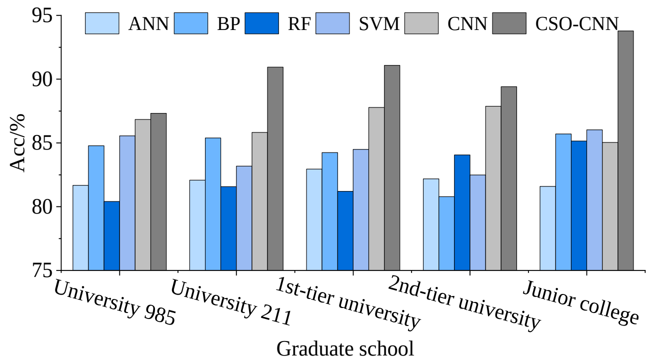

Figure 8: Comparison of prediction accuracy of different models

3.2.4 Comparison of forecasting efficiency

The training time and testing time of CSO-CNN prediction model and comparison model are shown in Table 3. The model with the highest prediction efficiency is CSO-CNN, and the mean values of training time and testing time of CSO-CNN model are 5.18s and 7.87s, respectively, which are smaller than the other five prediction models.

Table 3: The comparison of the training and test time of prediction models

Models		University 985	University 211	1st-tier university	2nd-tier university	Junior college
ANN	Training time/s	2.72	4.99	8.08	9.36	10.92
	Test time/s	3.31	5.56	10.91	12.97	14.51
BP	Training time/s	2.83	6.69	7.29	10.96	13.72
	Test time/s	3.25	6.65	11.16	14.58	16.39
RF	Training time/s	4.65	3.74	9.29	10.73	11.14
	Test time/s	2.71	7.68	10.09	13.96	15.15
SVM	Training time/s	3.84	5.26	10.23	11.25	12.07
	Test time/s	3.73	7.89	9.53	14.29	16.83
CNN	Training time/s	3.22	4.46	8.14	10.87	13.83
	Test time/s	3.29	6.29	8.69	12.74	14.15
CSO-CNN	Training time/s	2.28	3.27	5.28	6.27	8.79
	Test time/s	1.24	4.48	8.27	11.61	13.73

3.2.5 Model predictions

After employing the CSO-CNN model to forecast the career growth trajectory development of accounting students in various developmental stages, a comparison of all the predictions made versus the actual career growth path developments leads to the following overall results: 1,412 predictions are accurate, leading to an overall accuracy of 91.33% with an associated error rate of 8.67%. On the other hand, individual predictions are categorized based on the individual career growth path development stages to determine the single-category accuracies, which are shown in Table 4 below. Each of the career growth paths' prediction accuracy is determined by the ratio of accurate predictions divided by the total number of observations within each category. The four career growth path development stages, namely the adaptation stage, growth stage, maturity stage, and differentiation stage, have individual prediction accuracies of 93.23%, 91.99%, 89.75%, and 87.50%, respectively.

Table 4: The prediction results of the individual growth path

Career growth path	Forecast sample	Actual sample	Acc%
Indication period	413	443	93.23%
Growing period	528	574	91.99%
Maturation period	324	361	89.75%
Differentiation period	147	168	87.50%
Total	1412	1546	91.33%

4 Conclusion

The research methodology employed for this paper encompasses AI techniques such as cluster analysis and convolutional neural network, where the career growth paths of accounting undergraduate students have been segmented and profiled, followed by building a prediction model on a career growth path using cuckoo search optimization algorithm-based convolutional neural network. The key conclusions from this research can be highlighted as follows:

(1) The proposed clustering integration algorithm obtains the smallest error sum of squares and information entropy results in the test, which are 86.58 and 0.834, respectively, reflecting its better accuracy and robustness. The career growth path portrait of accounting students was divided into the adaptation period, growth period, maturity period and differentiation period, in which the number of people in the adaptation period and the growth period accounted for the largest proportion, more than 65%.

(2) As shown, among all five models selected for comparison, the average prediction accuracy is lower than 87% in all cases, while the prediction accuracy of CSO-CNN model can reach up to 90.51%, significantly better than all five models used in this experiment. It indicates that the improvement rate of prediction accuracy of the model is between 3.84% and 8.42%, and the overall prediction accuracy of CSO-CNN model can reach 91.33%. Moreover, when compared with all five models selected for comparison, it is evident that the computational costs of CSO-CNN model are relatively lower, because it only requires 5.18 seconds for model training and 7.87 seconds for testing. Based on these results, it can be concluded that the CSO-CNN model proposed in this paper has a good balance of prediction accuracy and computational costs.

While the prediction results achieved through this experiment have proven themselves reliable, there are some drawbacks associated with the findings. The generalization capability of the proposed prediction model needs to be further enhanced in the future. This could be done by extending the field of disciplines in which the research participants have studied and increasing the quantity of sample data used for analysis.

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About the Author

Mingxiao Rao (born April 1983), female, Han nationality, Associate Professor, China Certified Public Accountant (CPA), Director of the Accounting Teaching and Research Office at Puyang Vocational and Technical College.

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