DOI: 10.23977/acccm.2023.051207
ISSN 2523-5788 Vol. 5 Num. 12

Construction of Common Automation Management System for Intelligent Enterprises

Changjiang Yu[1,a], Xiao He[1,b,*], Jianjun Lin[1,c], Yuan Zhu[1,d], Changhao Zhou[1,e]

[1]*Law and Business School, Shangrao Normal University, Shangrao, Jiangxi, China*
[a]*207593@qq.com*, [b]*553174919@qq.com*, [c]*13307039915@163.com*, [d]*33111499@qq.com*,
[e]*zhouchanghao15@163.com*
[*]*Corresponding author*

Keywords: Intelligent Management System, Intelligent Employee Recruitment, Job Recommendation, SVM Algorithm

Abstract: Employee recruitment is one of the important commonalities of all enterprises. Traditional employee recruitment relies on manual communication, which has problems such as complex processes, long processing times, and low matching degree. This article aims to explore the common automation management system of intelligent enterprises, with employee recruitment as the research focus. Firstly, Microsoft Power BI is used to process and analyze employee data to identify the required positions in the company. The Survey Monkey tool is used to obtain the direction of enterprise planning through a questionnaire survey; Next, natural language processing is used to analyze the candidate information of submitted resumes, and collaborative filtering algorithms are used to find candidates who meet the company's job requirements and recommend positions to them; This article uses the Calendar tool to coordinate interview time, and finally uses support vector machines to analyze the interview results to determine whether the candidate meets the requirements. After experimental comparison, the precision rate of the system for job recommendation reached 91%, the F1 value of the system model reached 0.9, and the processing time for one piece of information was only 0.106 seconds. The quality of candidates using this system has significantly improved. This indicates that the system has the advantages of short processing time and high matching degree in employee recruitment, which is also helpful for improving employee quality. It provides ideas for the research of building an intelligent enterprise common automation management system.

1. Introduction

Modern society is an era of intelligence and digitization. With the development of technology, intelligent enterprise common automation management has become a key factor for various enterprises to improve work efficiency, reduce maintenance costs, and optimize company strategies. Employee recruitment management is an important task that every company needs to face, and effective employee recruitment strategies and processes are crucial for the long-term success of the company. Traditional employee recruitment management often faces problems such as long time costs and low matching levels.

In order to explore the common automation management system of intelligent enterprises, this article conducts research on employee recruitment. Firstly, this article explores the exploration of many scholars on the development of employee recruitment, discusses the application of artificial intelligence in the field of employee recruitment, and then designs an intelligent employee recruitment system. It analyzes company information to obtain job requirements, uses natural language processing and collaborative filtering to find suitable candidates, sets an interview time, and finally analyzes the information collected during the interview using support vector machines to obtain results. The experimental results demonstrate that the system has good matching accuracy and short processing time, which can significantly improve the quality of candidates.

2. Related Literature Review

Employee recruitment has always been one of the important common links in enterprise development, and its management has attracted widespread attention in both academic and business fields. Numerous scholars and business managers have conducted research on this topic. Jackson D [1] et al. investigated the views of graduate employers on the determinants of recruitment decisions and their preferences for recruitment channels, and discussed how to better prepare for the recruitment and selection of higher education students. Kucherov D [2] et al. investigated a sample of 449 companies in Russia and discussed the impact of electronic recruitment practices on recruitment outcomes, with the results showing a positive correlation. Köchling A [3] A et al. elucidated the current research status related to human resource recruitment and human resource development in their article, identified research gaps, and provided key future research directions. Gilch P M et al. [4] analyzed the strategic impact of digital transformation on recruitment based on human resources literature, emphasizing the role of recruitment in updating the organization's human resource foundation. Muduli A [5] et al. studied the intention of recruiters to use recruitment advertisements, online recruitment, and social media recruitment, and discussed some recruitment results. Lu Jinyi et al. [6] proposed a new perspective for studying the needs and services of minors in public libraries by analyzing and exploring the current situation and characteristics of service positions for minors in public libraries in the United States. It also provides reference for the management, support, and development of minors' service positions in public libraries. Bintoro B P K [7] et al. analyzed the impact of company reputation and service quality on headhunting service purchase decisions, and discussed the factors that candidates need to consider when choosing a headhunting company. Rodrigues D [8] et al. investigated how different digital marketing tools and strategies affect recruitment effectiveness. Numerous researchers have discussed the factors that affect employee recruitment from various aspects, but the problem of long recruitment time and insufficient intelligence has not been solved.

Artificial intelligence (AI) technology is a hot topic in recent years, which includes many fields such as machine learning, deep learning, natural language processing, and computer vision. In order to make employee recruitment more rapid and accurate, which is beneficial for management, scholars have tried to combine artificial intelligence technology to improve the management mode of employee recruitment. Kot S [9] et al. explored the role and impact of AI based recruitment and AI based quality to determine the mediating role of employer reputation in AI adoption. Ore O [10] et al. used qualitative research methods to conduct in-depth interviews with ten professional recruiters working in multinational corporations. The results showed that artificial intelligence promotes daily work through automation, but the use of artificial intelligence in recruitment can also lead to fear and distrust among recruiters. Koechling A [11] et al. investigated whether artificial intelligence supports and how it reduces opportunities for job applicants to perform during the entire recruitment process, and increases their emotional fear during the process. FraiJ J D [12] reviewed the application of artificial intelligence in the recruitment process of human resource management, and believed that artificial intelligence transforms tedious daily tasks into computerization, which creates a good space for humans to focus on improving performance and development. Niehueser W [13] examined the attitude of employees in a company dedicated to strategic recruitment towards introducing artificial intelligence into their workflow, and considered the impact of training and development. Kshetri N [14] discussed the application of artificial intelligence technology in human resource management in the global southern region. Numerous scholars have improved the management of employee recruitment by introducing artificial intelligence, providing reference for the recruitment management of enterprises.

3. Design of Recruitment Management System

3.1 System Process

The entire system process is shown in Figure 1:

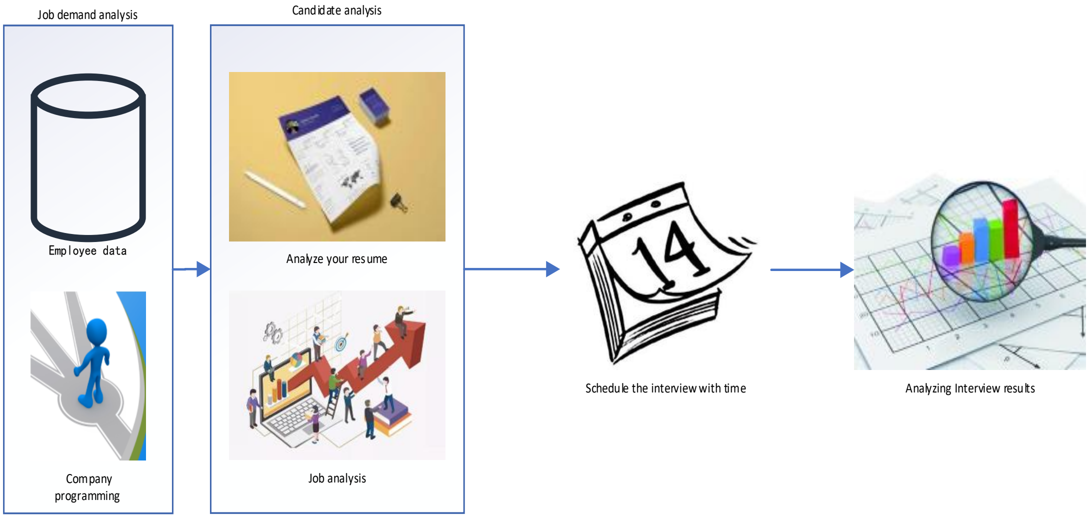

Figure 1: Recruitment Management System Flowchart

From Figure 1, it can be seen that the system first needs to analyze the data of company employees, including successfully recruited positions, employee turnover, employee salary levels, and skill data required by the employee team. Subsequently, it is necessary to analyze the company's plan, understand what kind of employees the company needs now, what kind of employees it would need in the future, and what kind of employees customers would need to provide services. After obtaining job requirements, this article analyzes and screens resumes, matches keywords and skills between positions and candidates, improves candidate screening efficiency, and generates suitable job recommendations based on candidate information. Automated tools would combine the candidate's time with the company's interviewer's time to achieve automatic scheduling of interview times. After the interview, the system would collect the interview results, evaluate the effectiveness of this recruitment, provide feedback to the system's algorithms, and continuously optimize decision-making.

3.2 Job Requirements

Firstly, it is necessary to collect and organize employee data of the company, establish a database, and the data channels are shown in Figure 2:

Figure 2: Data Source Channel Diagram

From Figure 2, it can be seen that there are various channels for obtaining data. Firstly, it is the recording of internal system data of the company, which includes human resource management systems, recruitment management systems, and so on. The interview records of employed employees can reflect the existing types of employees in the company. Employee relations include the relationships between employees and the relationship between employees and the company, including training records, employee promotion records, etc. Social media can capture employees' interests and hobbies outside of work, which is more helpful in analyzing employee types. Finally, there is a questionnaire survey, which obtains information by asking questions about company satisfaction and reasons for resignation.

The data analysis tool has chosen Microsoft Power BI, which is a powerful business intelligence tool used to collect, organize, and analyze data from various data sources, and generate interactive reports and dashboards. It has the ability to connect multiple sources of data, including databases, Excel files, online services, etc. And it comes with data organization and cleaning tools to ensure the accuracy and consistency of data. Meanwhile, Microsoft Power BI provides powerful security and compliance features, including data encryption, access control, auditing, etc., to ensure data security and privacy compliance.

The company's corporate planning can be addressed through the SurveyMonkey tool, which is a commonly used online survey questionnaire tool suitable for various research purposes, including analyzing the company's needs. The questionnaire not only needs to conduct research on all employees of the company, but also requires more non company practitioners to participate and analyze the overall trend of the industry in order to better draw conclusions.

3.3 Selecting Candidates

NLP, also known as Natural Language Processing, is an important branch of computer science and artificial intelligence, dedicated to enabling computers to understand, interpret, generate, and interact with human natural language. It uses NLP to screen a large number of resumes and identify candidates with high job matching. When NLP processes resumes, it first removes meaningless characters, stop words, etc., from the text to improve processing efficiency. Next, this article would identify key information, such as the candidate's name, contact information, education background, work experience, and so on. After obtaining the information, the matching degree with the position would be calculated based on the candidate's skills, experience and abilities, and finally transmitted to the manager in order of matching degree from high to low. Although automatic screening can improve efficiency, the final decision-making power still lies in the hands of managers, and increasing the accuracy of manual review can further match.

NPL only analyzes the information of candidates who have already submitted resumes, and more importantly, it needs to search from a large number of internet job seekers. This system uses collaborative filtering algorithms to find groups with the same goals as the target user. If the target user has not browsed the position information of company, they would recommend the position of company.

Collaborative filtering algorithms are a widely used technology in recommendation systems, used to predict users' preferences or ratings for items. It is classified into two types: user based collaborative filtering and item based collaborative filtering. Figure 3 is a simple schematic diagram of user similarity matrix and item similarity matrix.

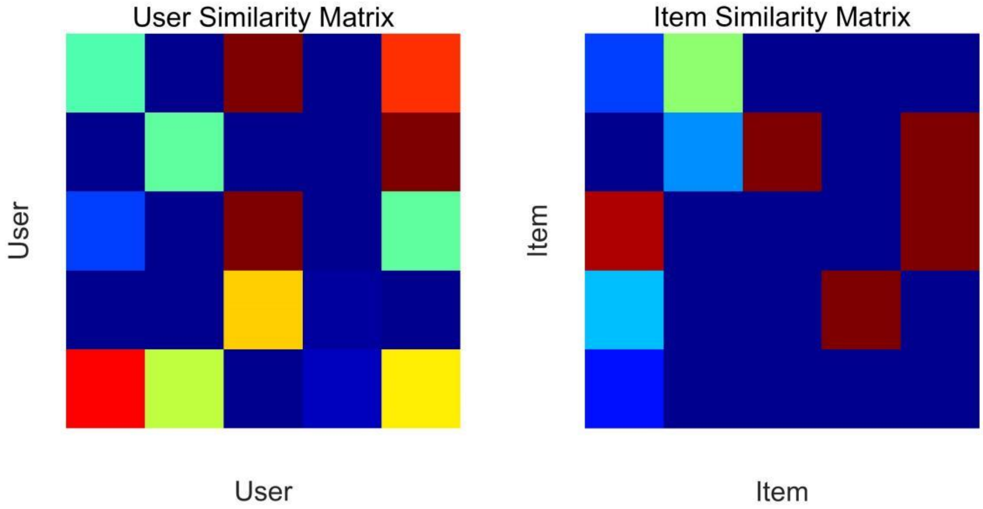

Figure 3: Schematic diagram of similarity matrix

This system adopts user based collaborative filtering, whose principle is to calculate the similarity between users, usually using the Pearson correlation coefficient method. The Pearson correlation coefficient is used to represent the strength of the linear correlation between two variables. Assuming there are two feature sets $\{A_1, A_2, ... A_L\}$ and $\{B_1, B_2, ... B_L\}$ with length L, the calculation formula for the Pearson correlation coefficient H is:

$$H = \frac{\sum_{i=1}^{L}(A_i - \bar{A})(B_i - \bar{B})}{\sqrt{[\sum_{i=1}^{L}(A_i - \bar{A})(B_i - \bar{B})]^2}} \tag{1}$$

Among them, $\bar{A}$ and $\bar{B}$ represent the average size of each sample within the two features, and the value range of H is between [1-, 1].

The collaborative filtering algorithm calculates a similarity matrix based on the user's similarity level, which is expressed as:

$$S_{x,y} = \frac{|N(x) \cap N(y)|}{\sqrt{N(y)}} \tag{2}$$

$N(x)$ represents a collection of users who have browsed company's information, while $N(y)$ represents a collection of users who have browsed the same type of position but have not browsed company's information. The larger the value of $S_{x,y}$, the higher the degree of overlap between the two user sets, the more similar the information of the positions, and the greater the probability that the user set matches the positions of the company.

3.4 Coordinate Interview Time

After determining the interview position and interviewees, it is necessary to determine the interview time. This model utilizes the Calendar tool for scheduling. Firstly, the interviewer needs to set their available time, including working days, non working days, or lunch breaks, etc. Subsequently, Calendly would generate a link independently, such as Calendly.com ABC, and send the link to the interviewee. Interviewers can click on the link to see available time periods and select their available time. The system would automatically select the appropriate time to schedule the interview. If there is a change in the itinerary of both parties, Calendar can also automatically plan a new interview time and send text messages to notify both parties, reducing telephone communication and improving communication efficiency.

3.5 Interview Results

During the interview, it is necessary to simultaneously assess the comprehensive qualities of the interviewee. The overall information to be collected is classified as shown in Table 1:

Table 1: Classification of Inspection Information

Survey information	Basic information	Traits of character	Knowledge and skill	Comprehensive quality
	Education background	Responsibility	Professional knowledge	Professional ethics
	Foreign language level	Self-confidence	Non-professional knowledge	Time management
	Scholarship and prize	Leadership	Learning ability	Emergency capacity
	Family background	Ability to communicate	Scientific payoffs	Interpersonal relationship

According to the information in Table 1, basic information can be obtained through resume information and inquiries. Personality traits are evaluated during interviews. Knowledge and skills can be determined by their school's ranking scores or patent works. The comprehensive quality can be determined through past work experience and performance during the interview process.

This model uses Support Vector Machine (SVM) for judgment.

Convert the collected interviewee information into model features and input them into SVM. Use the MinMaxScaler method to scale the features within a reasonable numerical range. The expression is:

$$M = \frac{T - T_{min}}{\Delta T} \tag{3}$$

Among them, T represents the original feature, T_{min} represents the minimum value of the feature, and ΔT represents the maximum absolute difference among all features.

The configuration of SVM needs to consider the selection of kernel function and regularization parameter C.

Kernel functions are mainly divided into three types: linear kernel, Gaussian kernel, and polynomial kernel. This model selected Gaussian kernel function, which is a highly localized kernel function that has good performance in both linear and nonlinear situations. The expression is as follows:

$$K(x, x^{'}) = \exp(-\frac{x, x^{'}}{\sigma^2}) \tag{4}$$

x and $x^{'}$ represent the feature vectors of the sample, while σ is the bandwidth parameter of the Gaussian kernel function. It controls the width of the Gaussian function, which in turn affects the complexity of the model. The relationship between σ and $K(x, x^{'})$ is shown in Figure 4:

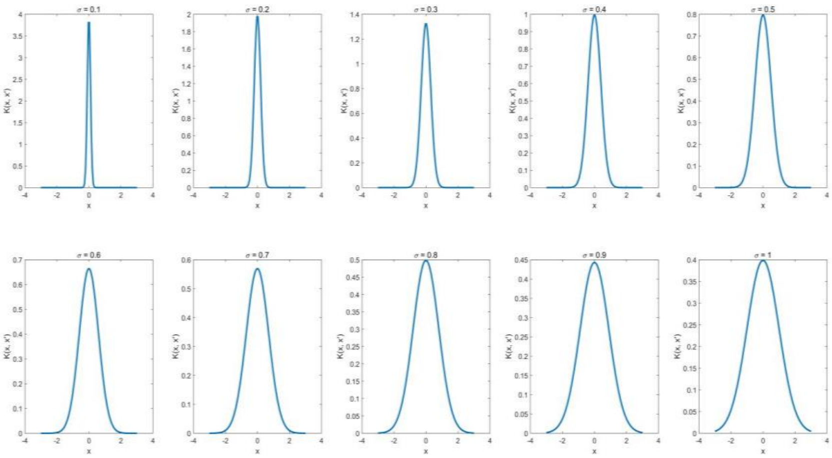

Figure 4: Effect of different σ on Gaussian kernel function

Figure 4 shows the image changes of the Gaussian kernel function when σ increases from 0.1 to 1 each time. As σ gradually increases, the Gaussian distribution curve would gradually widen, and the curve would become smoother, reducing fluctuations. Due to the relatively consistent feature scales of this data, it is not advisable to choose σ too large, as excessive σ values may cause the model to underfit.

The regularization parameter C is a key hyperparameter in support vector machines, which controls the complexity of the model and the degree of fitting to the training data. The value of C is usually a positive real number, and the larger the value, the better the model fits during training. Figure 5 shows the relationship between the change in C-value and the degree of model fitting:

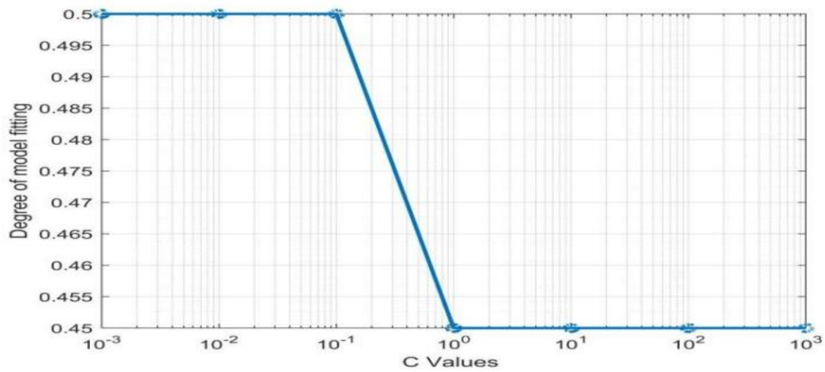

Figure 5: Relationship between C-value and model fitting degree

For the sake of convenience, Figure 5 represents the relationship between the C value and the degree of model fitting in a dataset containing only two features. The range of C values includes [0.001, 0.01, 0.1, 1, 10, 100, 1000]. The C value in the graph rapidly decreases the fitting degree of the model within the range of [0.1,1], so theoretically, the optimal C value for this dataset is between [0.1,1].

4. Experiment on Recruitment Management System

4.1 Datasets

Due to privacy concerns, it is not possible to obtain resume information from recruitment websites. Therefore, this study used the Faker library in Python to simulate the generation of recruitment data. It includes the candidate's name, contact information, educational background, work experience, personality, job requirements, work location, etc. The number of simulations is 1000.

4.2 System Evaluation Indicators

The confusion matrix is usually used to evaluate the performance characteristics of a system, and Table 2 shows the confusion matrix:

Table 2: Confusion Matrix

type		Sample real classification	
		Ture	False
Prediction model classification	Ture	TP	FP
	False	FN	TN

The indicators used in this experiment are P (Precision), recall rate R (Recall), and F1 score.

The precision rate reflects the percentage of correct classification in the classification results of the model, and its expression is:

$$P = \frac{TP}{TP+FP} \times 100\% \tag{5}$$

The recall rate reflects the percentage of correctly classified positive samples in the total positive samples, and its expression is:

$$R = \frac{TP}{TP+FN} \times 100\% \tag{6}$$

The F1 value, defined as the harmonic mean of P and R, is used to reflect the stability of the system, and its expression is:

$$F = \frac{2 \times R \times P}{R+P} \tag{7}$$

4.3 Experimental Results

Table 3: Experimental Results of Each Model

	P(%)	R(%)	F1	Time(s)
DT	87	81	0.81	0.179
LR	85	79	0.79	0.187
LightGBM	89	83	0.85	0.164
SVM	91	89	0.90	0.106

This article categorizes positions based on four aspects: job hierarchy, job nature, skill types, and job roles, and proposes a total of 25 job information as the required positions for the company. This article would input 1000 pieces of information into the model for testing, set to 0.3, and set the regularization parameter C to 0.1. At the same time, it uses Decision Tree (DT), Logistic Regression (LR), and LightGBM (Light Gradient Boosting Machine) models for comparison. In addition to calculating the above test indicators, this article also records the time taken by the model to process individual candidate information. The results are shown in Table 3:

From the results in Table 3, it can be seen that in this study, the F1 value of the model in this experiment reached 0.90, indicating that the model has good balance. The precision rate is 91%, which is 6% higher than the logistic regression model, and the recall rate also reaches 89%. Observing the processing time, the SVM based model only took 0.106 seconds to process one piece of information, which is much lower than the other three models, reflecting the high efficiency of model processing. Overall, the experimental data indicates that the model used in this experiment has good performance.

In order to verify the quality of candidates before and after using the system, the experiment evaluated the quality of candidates, and the specific data is shown in Figure 6:

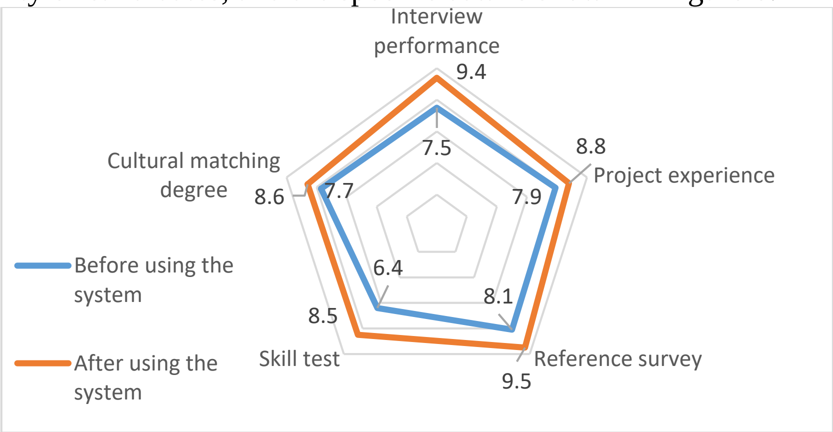

Figure 6: Comparison of Candidate Quality

Evaluate five data items: interview performance, project experience, cultural fit, skill testing, and reference survey, with a maximum score of 10. From Figure 6, it can be seen that employee candidates have significantly improved in all five data items after using this system, indicating that the system has improved the quality of candidates and thus the overall quality of employees in the company.

5. Conclusions

Intelligence is a product of social development, and it is a huge change for all industries. In this intelligent enterprise common automation management system, the paper focused on the design and research of intelligent employee recruitment. This system improves the efficiency of the company in processing resume information, simplifies the recruitment process, and improves the quality of candidate employees. A slight deficiency is that the system has not established effective emergency measures, and if a technical failure occurs in the system, it may have an impact on the recruitment process. It is hoped to conduct more research in the future and make effective improvements to emergency measures.

Acknowledgement

This work was supported by Soft Science Project of Shangrao Science and Technology Bureau "Research on Optimizing Regional Innovation Mechanism of Enterprise General Technology Platform" (2020L015).

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