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Study of Enterprise Human Resource Management Strategy Based on Hybrid Deep Learning Models

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Abstract. With the rapid development of artificial intelligence technology, enterprise management is gradually moving towards the era of intelligence. Human resource management, as one of the important areas of the enterprise, is also in urgent need of integrating AI to enhance efficiency, accurately match talent, and improve employee experience. This study aims to deeply explore the application of AI technology in enterprise human resource management and the possibility of optimizing human resource management strategies by constructing hybrid deep learning models. By analyzing the current situation in the field of AI technology and enterprise management, the current problems and bottlenecks in human resource management are excavated. Subsequently, an enterprise human resource management strategy based on a hybrid deep learning model is proposed to improve human resource allocation efficiency and employee performance through data-driven and intelligent decision-making. The study demonstrates the potential of the model in optimizing enterprise management, improving work efficiency and employee satisfaction through theoretical analysis and empirical research. This study constructs a hybrid deep learning model to provide theoretical support for enterprises to formulate intelligent management strategies and to promote the development of enterprises towards intelligent, efficient and humanized human resource management.

Keywords: Artificial Intelligence; Hybrid Deep Learning Models; Business Management; Human Resource Management; Optimization Strategies

1. Introduction

With the rapid development and popularization of science and technology, Artificial Intelligence (AI), as an important information technology and industry, has become the focus of the world's attention at present. Artificial Intelligence refers to a technical system realized by simulating and extending human intelligence, which realizes the interpretation, learning and inference of data with the help of computers, machine learning, deep learning, natural language processing and other technologies to realize the automation or semi-automation of complex tasks (Riedel et al., 2021). The rapid development of AI technology is due to several key factors. First, the arrival of the big data era has provided sufficient data support for the development of artificial intelligence, and the massive amount of data has become the basis for intelligent algorithm learning and optimization. Second, the dramatic increase in computing power, especially the efficient computing power of hardware such as graphics processors (GPUs), allows complex AI algorithms to be executed quickly and efficiently. Third, the emergence of emerging algorithms such as machine learning and deep learning, as well as the improvement of traditional algorithms have made the application of AI technology more extensive and in-depth. In the enterprise field, AI technology has shown great potential. Artificial intelligence can help enterprises solve various challenges and problems, including but not limited to marketing, product development, process optimization, risk management, customer service and other aspects (Zhu, 2021). For example, AI can analyze massive market data to discover consumer behavior patterns and preferences, thus guiding enterprises to develop more accurate marketing strategies; in product development, AI can help enterprises accelerate innovation, optimize design, reduce costs, and improve product quality; in process optimization, AI can automate many redundant and repetitive tasks to improve efficiency; in risk management, AI can reduce risk through prediction and analysis; in customer service, AI can improve service quality through intelligent customer service and intelligent reply. However, the wide application of AI technology also faces some challenges. The first is the issue of data quality and privacy protection; big data needs high-quality and diverse data to support it, while privacy leakage and data security are also issues that require close attention. Second is the transparency and interpretability of algorithms, especially in some decision-sensitive areas, such as finance and healthcare, the transparency and interpretability of AI algorithms are crucial (Ashwin et al., 2023). The last is talent and technology barriers. The application of AI technology requires the availability of appropriate technical talents and technical support, which is also an important factor that enterprises need to consider when introducing AI.

The enhancement of computing power is the basis for the rapid development of artificial intelligence. With the continuous progress of hardware technology, especially the wide application of graphics processors (GPUs), the computational power has been greatly improved, which can support the training and inference of complex models and accelerate the development of AI technology (Tian & Zhang, 2021). The wide application of big data provides valuable resources for the development of artificial intelligence. The accumulation of large amounts of data provides rich training samples for machine learning and deep learning algorithms, which makes the models more accurate and intelligent. Big data technology can also help organizations better understand the market, customers and business, and provide support for decision-making. Advanced algorithms and models are a key driver of the rapid development of AI. Continuous innovation and optimization of algorithms in the fields of deep learning, reinforcement learning, natural language processing, and computer vision have led to a wider range of AI applications, covering a wide range of fields such as healthcare, finance, transportation, security, and entertainment.

Artificial Intelligence (AI), a major technological innovation in today's technology, has had a profound impact on business management and brought new challenges. This impact covers a wide range of aspects, including organizational structure, decision making, operational management, human resources and innovation. First of all, the impact of AI technology on the organizational structure and operation mode of enterprises is significant.AI technology can automate and optimize many routine business processes, reduce the cost of business operations, and improve efficiency. Robotic Process

Automation (RPA) can automate repetitive, high-frequency, and regular tasks, freeing up manpower for more efficient operations. Second, AI has had a profound impact on business decision-making. Data-driven decision-making is increasingly valued.AI is able to analyze large amounts of data and extract valuable information from it to inform decision-making. AI applications such as predictive analytics, intelligent recommendation systems, and risk management models can help enterprises make more scientific and accurate decisions (Berhil et al., 2020). AI also has a significant impact on human resource management. ai can optimize the talent management process through recruitment intelligence, talent matching, and training recommendations. In addition, AI technology can also help companies conduct employee sentiment analysis and work efficiency assessment to better adjust management strategies. Artificial Intelligence also has a positive impact on enterprise innovation.AI technology can drive innovation through creative solutions and new business models. Technologies such as natural language processing, machine learning, and deep learning provide new opportunities for product and service innovation.

Human resource management is an indispensable and important part of enterprise management, and with the development of the times, it has gone through several stages of evolution and change. The development of human resource management can be divided into several stages, as shown in Figure 1. The first is the personnel management stage, which focuses on personnel administration, including basic management tasks such as employee recruitment, training and payroll. Next is the human resource management stage, which emphasizes employee development and organizational development and involves concepts such as employee motivation and performance appraisal. This was followed by the strategic HRM stage, which emphasized the need for HRM to be closely integrated with and part of corporate strategy. The most recent development is the digital human resource management stage, which utilizes information technology for digital management, such as big data, artificial intelligence and other technologies for decision-making and management such as recruitment and performance evaluation (Chou et al., 2022). Currently, human resource management faces many challenges. The first is the demand for diversified talents, with the development of social diversity, the enterprise's demand for talents has also become diversified, requiring human resource management to meet the needs of talents at different levels, in different fields, and with different qualities. Secondly, talent recruitment and retention, with the fierce competition for talents, attracting excellent talents to join and stay in the enterprise is an important challenge for human resource management. In addition, the rapid development of technology has also put forward new requirements for human resource management, especially the use of big data, artificial intelligence and other technologies for accurate recruitment, performance management and employee development (Zhang et al., 2021). In addition, talent cultivation and development is also a challenge. In order to adapt to the rapidly changing market demand, companies need to continuously improve the skills and knowledge of their employees. Finally, corporate culture and employee engagement is also one of the current challenges in human resource management, and companies need to create an attractive culture to motivate employees to better engage in their work.

Fig.1: Human Resource Management (HRM) Definition Meaning

In recent years, deep learning, as an important branch of artificial intelligence, has made significant progress in various fields, and has gradually been noticed and applied in the field of enterprise management. Deep learning is based on a multi-level neural network structure, and acquires knowledge and experience through learning and pattern recognition of large amounts of data, thus realizing automated processing and decision-making of complex tasks. In enterprise management, the application of deep learning is mainly reflected in the following aspects: first, deep learning is widely used in the field of marketing and sales. By analyzing a large amount of market data and consumer behavior through deep learning models, enterprises can more accurately predict market trends and product popularity, and then develop corresponding marketing strategies and sales plans. Secondly, deep learning plays an important role in supply chain and logistics management. By analyzing supply chain data through deep learning models, intelligent optimization of the supply chain can be achieved, including inventory management, transportation path planning, etc., thus improving operational efficiency and reducing costs. In addition, deep learning has shown strong potential in human resource management (Nankervis et al., 2022). Enterprises can use deep learning models for employee performance evaluation, career quality analysis, as well as employee training and development planning, so as to better allocate human resources and improve employee efficiency and satisfaction. Deep learning is also widely used in risk management and decision support. Analyzing the internal and external environments of enterprises through deep learning models can help enterprises predict risks, develop corresponding risk management strategies, and assist in decision making.

Deep learning, as an important research direction in the field of artificial intelligence, has made significant progress in recent years. On the basis of deep learning, hybrid deep learning models have also gradually attracted the attention of researchers. The hybrid deep learning model combines the advantages of different deep learning models with a view to achieving more efficient and accurate learning and reasoning capabilities, as shown in Figure 2. Currently, the research on hybrid deep learning models focuses on the following aspects: first, researchers try to combine traditional machine learning methods with deep learning models in order to utilize the advantages of both. Traditional machine learning methods perform well when the data samples are small or the feature dimensions are low, while deep learning models are more advantageous when large-scale data and high-dimensional features are available. Therefore, researchers try to use traditional machine learning methods for feature selection or dimensionality reduction, and then input the processed features into deep learning models for learning and prediction to improve the accuracy of the models. Second, some research is devoted to fusing different types of deep learning models to construct hybrid deep learning models with multi-model fusion. These models can simultaneously consider multiple data types such as image, text, time series, etc. to fully explore the correlation between different data types and improve the comprehensive performance of the model. In addition, researchers are also exploring the combination of deep learning models with traditional mathematical models, with a view to constructing more explanatory and interpretable hybrid deep learning models (Cai, 2022). Such models can combine the efficient learning ability of deep learning and the interpretability of traditional mathematical models to provide clearer explanations and understanding of practical problems.

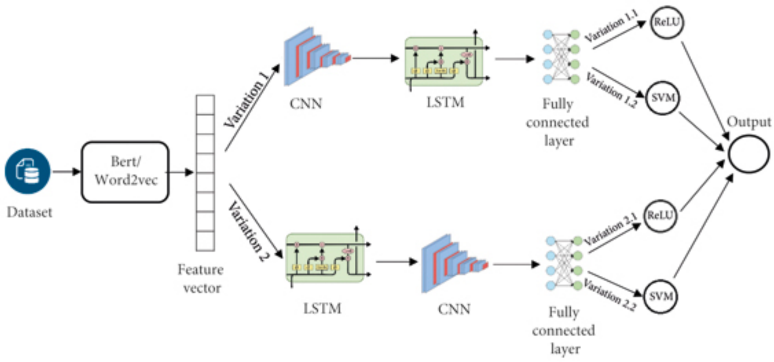

Fig.2: Hybrid Deep Learning Models for Sentiment Analysis

Artificial Intelligence (AI) is evolving and developing as a hotspot in the field of science and technology in today's world. Many research institutions, universities and enterprises at home and abroad have invested a lot of resources in researching AI technology and its application in different fields. The current status of research at home and abroad will be analyzed below. In foreign countries, especially in the United States, research and application in the field of artificial intelligence are in a leading position. Some top universities such as Stanford University, Massachusetts Institute of Technology, and University of California, Berkeley have profound research in the field of AI. In addition, some famous enterprises such as Google, Facebook, IBM, Amazon, etc. have also invested a lot of money in the field of AI, which has promoted the innovation and application of AI technology. Deep learning is an important research direction in the field of artificial intelligence. By constructing a multi-level neural network model, it simulates the information transfer process between neurons in the human brain and realizes efficient processing and analysis of large-scale data (Alqhatani et al., 2022). Deep learning has achieved remarkable results in the fields of image recognition, natural language processing, and speech recognition. Reinforcement learning is a kind of learning method based on an intelligent body learning optimal behavioral strategies through trial and error in interaction with the environment. In recent years, reinforcement learning has made breakthroughs in the field of gaming, such as AlphaGo defeating the human Go champion. (Zhou et al., 2021) Natural language processing studies how to enable computers to understand, process and generate natural human language. Significant progress has been made in translation, sentiment analysis, and semantic understanding.

Domestic research on AI has also made great strides in recent years, with governments, universities, research institutes and enterprises increasing their investment in the field of AI. The Chinese government has introduced a series of policies to support the research and development and industrialization of AI technology. The Development Plan for a New Generation of Artificial Intelligence specifies the direction and focus of development, proposing that by 2030, China's AI theories, technologies and applications will reach the world's advanced level. Domestic universities and research institutes have actively responded to the national policy, strengthened AI research, and carried out a series of research projects (Valmohammadi & Shahrashoob, 2022). Enterprises have also increased their investment in the AI field and actively cooperated with universities and research institutes, promoting the development of the combination of industry, academia and research. Domestic research focuses on applying AI technology to specific industries and fields, such as smart manufacturing, smart cities, healthcare, finance, etc. Multidisciplinary integration research oriented to applications has gradually been formed. With the continuous development of AI technology, research at home and abroad has shown a vigorous trend. Foreign countries take deep learning, reinforcement learning, and natural language processing as the main research direction; domestic research has made significant progress in government support and the combination of industry, academia and research, focusing on application-oriented AI technology. In the future, international cooperation and industrial innovation will drive the field of artificial intelligence to new heights.

There are some limitations and shortcomings in the current research on the assessment and enhancement of AI-driven enterprise innovation capacity: insufficient data quality and reliability: in the empirical analysis, there are many constraints on the acquisition and organization of data, resulting in a small sample size or poor data quality, which affects the accuracy and credibility of the results of the analysis. Completeness and complexity of models: Existing models mostly focus on the assessment of specific aspects of innovation capacity, but the comprehensive assessment of the overall innovation capacity of enterprises still needs to be improved. In addition, some models may be too complex to be easily applied or interpreted in practice. Insufficient consideration of long-term impacts: current research tends to focus on the impacts and effects of innovation in the short term, and there is insufficient research on long-term, sustained impacts and effects. Insufficient interdisciplinary integration: Since AI technology covers multiple disciplinary fields, existing research is still insufficient in integrating multidisciplinary knowledge, and deeper interdisciplinary research has not yet been fully carried out. Insufficient combination of practice and theory: research focuses more on the construction of theoretical models and frameworks, but not enough research on actual operation and practical guidance, and a lack of practical guidelines with strong operability (Zhao & Tu, 2021). Insufficient analysis of industry differentiation: there are great differences in the application and innovation of AI in different industries, and there is less analysis of differentiation and targeted research on different industries in the study. Unclear prediction of future development trend: the research on the impact, trend and direction of AI on the future development of enterprise innovation capability is not clear enough, and the outlook and prediction of the future need to be studied in depth. To solve these problems, it is necessary to strengthen data collection and analysis methods, improve assessment models, enhance practical application research, deepen interdisciplinary research, and at the same time focus on the analysis of industry differences and future trends, in order to comprehensively promote the development of the research on the assessment and enhancement of AI-driven enterprise innovation capacity.

With the continuous development of artificial intelligence technology, enterprises are gradually recognizing that AI is not only a technical tool, but also a strategic element for the future development of the enterprise. AI's intelligent decision-making, data analysis, automated processes, and other characteristics can provide unprecedented efficiency and precision for enterprise management.AI can help enterprises to analyze massive amounts of data quickly and accurately, provide data-supported decision-making, and reduce the risk of decision-making AI can be used in production, supply chain, logistics, etc. to improve operational efficiency and reduce costs.AI can improve customer satisfaction and enhance brand loyalty through intelligent customer service systems, personalized recommendations, etc.AI can accelerate the R&D process of new products, optimize the path of innovation, and promote the continuous updating and iteration of enterprises. Enterprises need intelligent decision-making systems supported by AI capabilities, which can predict the direction of the market, customer demand, and adjust strategies in advance. Enterprises need to realize automation and intelligence in production, warehousing and logistics through AI to improve operational efficiency. Enterprises need AI technology to improve customer experience and achieve personalized recommendations, intelligent customer service, etc. Enterprises need AI to enhance network and data security, prevent and deal with potential risks. The application of AI technology requires enterprises to fully understand the AI principles, technical capabilities, and customized development of AI applications for different business scenarios. Enterprises need to have talents with AI technology knowledge and capabilities, and to adjust their organizational structure to adapt to the application of new technologies. Enterprises need to pay more attention to the privacy protection of user data, and at the same time should pay attention to the impact of AI on the social and ethical levels. The investment cost of AI technology is high, and enterprises need to weigh the pros and cons and formulate appropriate investment strategies.

The purpose of this study is to deeply explore the impact of artificial intelligence on enterprise innovation capability. First, this paper will analyze the mechanism of the impact of AI on enterprise innovation capability, and analyze how AI technology changes enterprise innovation mode, process, organizational structure and other aspects. Second, this paper will establish a comprehensive and objective assessment model to provide a basis for quantitative assessment of enterprise innovation capability based on AI technology and innovation-related factors. Finally, this paper aims to discover the problems in enterprise innovation through research and propose innovation strategies based on artificial intelligence to promote the improvement of enterprise innovation capability. The importance of this research cannot be ignored. First of all, artificial intelligence, as a new generation of core technology, has a great role in promoting enterprise innovation. Through in-depth research on the application of artificial intelligence in innovation, it can provide innovative ideas and methods for enterprises, and then promote enterprise innovation-driven development. Secondly, innovation ability is one of the key factors of enterprise competitiveness. With the help of artificial intelligence technology, enterprises can respond to market changes more quickly and accurately and improve their competitive advantages. In addition, as an emerging industry, the application of artificial intelligence has a positive role in promoting the upgrading and transformation of traditional industries. Research on the application of AI in innovation capability can help guide traditional enterprises to utilize AI for transformation. Finally, the research results can also provide decision support and reference for the government to formulate innovation policies and promote scientific and technological innovation, and promote academic research and practical innovation. Therefore, this study has important practical significance and theoretical value for promoting enterprise innovation-driven development, enhancing competitiveness, and promoting industrial upgrading and transformation.

2. Method

2.1. Overview of Hybrid Deep Learning Models

A hybrid deep learning model is a deep learning architecture that combines a multilayer perceptron (MLP) and an auto-encoder (AE) model. An MLP is a forward-feedback artificial neural network that consists of multiple layers of neurons, with each neuron layer being fully connected to the neurons in the previous and subsequent layers. Self-encoder is an unsupervised learning model designed to reconstruct input data by learning feature representations. Combining these two models allows for optimization of feature learning and representation, which in turn improves the generalization ability and accuracy of the model. The hybrid deep learning model consists of multiple layers, each containing multiple neurons. The whole model combines two parts, MLP and AE, where: the MLP part: includes an input layer, multiple hidden layers and an output layer. Each hidden layer is connected to neurons in the previous and next layers through weights. MLP is responsible for supervised learning and can be used for tasks such as classification, regression, etc.AE part: consists of encoder and decoder. The encoder maps the input data to the latent space and the decoder maps the latent representation back to the original data space. the AE can unsupervised learn the feature representation of the data. This structure is designed to fully utilize the supervised learning capability of MLP and the feature learning capability of AE, combining the advantages of unsupervised and supervised learning to achieve better performance.

The hybrid deep learning model performs level-by-level feature extraction and learning through a multilayer structure. The working principle of the whole model can be briefly described as follows: initial input: raw data first enters the input layer of the model. MLP part processing: the data passes through multiple hidden layers in the MLP part, each of which is connected to the previous and the next layer by weights. The MLP is trained by supervised learning methods such as back propagation, and progressively extracts more advanced features. Potential space representation: the output of the last layer of the MLP can be used as the input of the AE. In this way, the data passes through the MLP section and then enters the AE section, where it is mapped into the potential space by the encoder. Feature learning: the encoder of the AE is responsible for learning the feature representation of the data. The representation of the latent space should be able to preserve the features and information of the original data as much as possible. Reconstructing data: the representation of the potential space is mapped back to the original data space through the decoder of the AE to realize reconstruction. By minimizing the reconstruction error, AE learns a better feature representation. The whole model's combines the processing of MLP and AE, both supervised learning by MLP and unsupervised learning by AE, which improves the efficiency and quality of feature learning.

The hybrid deep learning model fully combines the supervised learning capability of MLP and the unsupervised learning capability of AE, which makes the model able to learn on both limited labeled data and a large amount of unlabeled data; extracting features step by step through the multilayer structure, which is able to obtain a more abstract and higher-level feature expression, which helps to improve the performance of the model; and combining the supervised and unsupervised learning facilitates the model's generalization of new data and improves the model's robustness. generalization, which improves the robustness of the model.

Suppose the input to layer l is $Z^{(l)}$, weight is $W^{(l)}$, bias voltage is $b^{(l)}$, activation function is σ, then the forward propagation equation is as follows:

$$Z^{(l+1)} = \sigma(W^{(l)}Z^{(l)} + b^{(l)}) \tag{1}$$

The loss function of the self-encoder includes the reconstruction error and the regularization term:

$$L(X,\hat{X}) = \frac{1}{N}\sum_{i=1}^{N}\left\|X_i - \hat{X}_i\right\|^2 + R(W) \tag{2}$$

Among them, $X\ is$ input data, $\hat{X}$ is reconstructing data, N is sample size, W is parameters of the self-encoder, $R(W)$ is regularization term.

The forward propagation of a hybrid deep learning model can be expressed as:

$$MLP\_output = \sigma(W_{MLP}Z_{in} + b_{MLP}) \tag{3}$$

$$AE\_output = Decoder(Encoder(Z_{in})) \tag{4}$$

Among them, Z_{in} is input data, W_{MLP} and b_{MLP} are the weights and biases of the MLP, Encoder and Decoder represent the encoder and decoder of the self-encoder, separately.

2.2. Data preprocessing

Data preprocessing is a crucial step in machine learning and deep learning. Its purpose is to organize raw data into datasets that can be directly applied to model training to improve model accuracy and performance. Data preprocessing includes processes such as data cleaning, data transformation, and normalization to make the data more analyzable and usable, as shown in Figure 3. In the initial stage of data preprocessing, this paper performs data cleaning. This step looks at dealing with data that may have errors, inconsistencies or incompleteness in the dataset. First, this paper needs to identify missing values, i.e., detect missing values in the dataset and determine their location and number. Next, this paper can take various approaches to deal with missing values, such as filling the missing values, which can be done using suitable filling methods such as mean, median, and plurality. Another way to deal with it is to delete the samples or features that contain missing values. Detection and processing of outliers is also an important part of data cleaning. By using statistical methods or visualization techniques, this paper can identify outliers in the data and can select appropriate processing methods based on the nature of the outliers. Finally, in order to reduce the noise in the data, this paper takes noise reduction measures such as smoothing or filtering techniques.

Next, this paper performs data transformation and normalization to ensure data consistency and adaptation to the model. This includes steps such as data coding and feature scaling. First, this paper performs data encoding to convert the categorized data into a numerical format that can be handled by the model, and commonly used encoding methods include unique heat encoding and label encoding. Then, feature scaling is necessary because features may have different units of measure and ranges. Feature scaling is able to map the values of features to similar numerical ranges, avoiding certain features from overly influencing the model. Normalization is a method of feature scaling that scales the data to a standard range, usually [0, 1] or [-1, 1], to eliminate the differences in magnitude between features and to ensure that the model can fit the data better. These data preprocessing steps not only improve the quality of the data, but also set the stage for the modeling and analysis that follows.

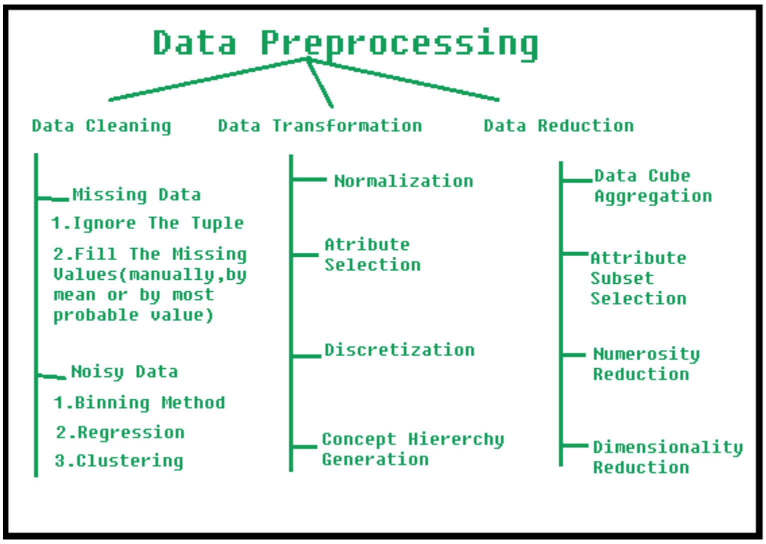

Fig.3: Data Preprocessing in Data Mining

2.3. Data preprocessing

The construction of deep learning models is one of the most important tasks in the field of modern artificial intelligence based on the fact that it directly affects the performance and predictive ability of the models. In this section, we will discuss several important approaches for building deep learning models, including recurrent neural network (RNN) models, convolutional neural network (CNN) models, and long short-term memory network (LSTM) models, as well as model integration methods.

RNNs are a special class of neural networks that have the ability to process sequential data by introducing a recurrent structure in the network to convey information. This structure makes RNNs suitable for many domains involving time series, text processing, etc. The core idea of RNNs is to use the output of the previous time step as the input of the current time step, thus allowing the network to capture dependencies in the sequence. However, the training of traditional RNNs often encounters problems such as gradient vanishing or gradient explosion, and in order to overcome these problems, improved structures such as Long Short-Term Memory Networks (LSTMs) have been subsequently developed.

CNN is a deep learning model specialized for processing gridded data (e.g., images, videos) with shared weights and local connectivity. These properties enable CNNs to effectively extract local features of data with translation invariance. CNNs have achieved remarkable results in tasks such as image recognition, target detection, etc., and have become an important technique in the field of deep learning.

LSTM is a special kind of RNN designed to solve the problems of gradient vanishing and gradient explosion encountered in traditional RNN models. LSTM effectively controls the flow and forgetting of information by introducing gating structures, i.e., forgetting gates, input gates, and output gates, which enable the network to capture long-term dependencies. LSTM is widely used in the fields of text generation, speech recognition, and so on. Model Integration is a technique that combines multiple models for better predictive power. It can be done by weighted averaging, voting or otherwise to get the final prediction from the predictions of multiple models. Model integration reduces the risk of overfitting and improves the stability and generalization of the model.

2.4. Assessment indicators and methodology

Evaluating the performance of deep learning models is one of the key parts of the research, which can help us understand the strengths and weaknesses of the models and their scope of application. In this section, this paper will introduce the commonly used evaluation metrics and evaluation methods for deep learning models, including accuracy rate, precision rate, recall rate, F1 value, ROC curve and AUC value. In binary classification problems, this paper usually focuses on the metrics of accuracy, precision, recall and F1 value. Accuracy rate is the ratio of the number of samples correctly predicted by the model to the total number of samples, precision rate is the proportion of the samples predicted positive by the model that are really positive, recall rate is the proportion of the samples that are really positive that are predicted positive by the model, and the F1 value combines the precision rate and the recall rate, and it is the reconciled average of the precision rate and the recall rate. The ROC curve is a kind of graph showing the performance of a classification model, and the horizontal axis is the False Positive Rate (FPR) and the vertical axis is the False Positive Rate (FPR). The ROC curve is a graph showing the performance of a classification model, with the False Positive Rate on the horizontal axis and the True Positive Rate on the vertical axis. The AUC value is the area under the ROC curve, which is used to measure the model's ability to discriminate between positive and negative samples. The larger the AUC value, the better the model's performance. The AUC value is the area under the ROC curve.

In addition, for multicategorization problems, there are other evaluation metrics, such as Multicategorization Accuracy, Confusion Matrix, etc., which can more comprehensively evaluate the performance of the model in multicategorization tasks. Evaluation methods not only include the computation of single metrics, but also can use cross-validation, leave-out method, self-help method and other methods to evaluate the performance of the model. Cross-validation can fully utilize the limited dataset and improve the reliability of the assessment. The leave-out method is simple and fast, and is suitable for large datasets. The self-help method fully utilizes the data, but has a high computational overhead. These evaluation metrics and methods constitute an important tool for evaluating the performance of deep learning models, which can help researchers comprehensively and accurately assess the strengths and weaknesses of the models and provide guidance for model improvement and optimization.

3. Empirical Analysis and Case Study

Empirical analysis and case study is an important part of this research, which can verify the hypothesis, model or theory of the research through actual data and cases. Data is the foundation of empirical analysis, and good data collection and pre-processing can ensure the credibility and validity of empirical analysis. In this paper, we will discuss the two aspects of enterprise internal data collection and external data integration. In terms of internal data collection, this paper will introduce how to obtain key data within the enterprise, including human resource management, product development, marketing, finance and other aspects of the data. These data can help us gain a deeper understanding of an organization's operations and innovation capabilities. In terms of external data integration, this paper will introduce how to integrate external data resources, including industry reports, market research data, public data and so on. By integrating external data, this paper can obtain broader and more comprehensive information and provide more dimensional data support for empirical analysis. Then, this paper will introduce the selection of empirical analysis methods. Empirical analysis methods refer to the methods of statistical analysis of data and modeling to verify research hypotheses or solve research problems. This paper will introduce the commonly used empirical analysis methods, including statistical analysis methods (e.g., regression analysis, t-test), machine learning methods (e.g., decision tree, support vector machine), and deep learning methods. It is very important to choose appropriate empirical analysis methods for different research questions. In the process of empirical analysis, this paper will make full use of the collected data and apply the selected empirical analysis methods to carry out an in-depth study of the research problem. Through empirical analysis, this paper can verify the research hypotheses, discover the potential laws, and provide scientific basis for the conclusions of the study.

Enterprise X faces multifaceted challenges in human resource management that affect its operations and growth. The following are some of the HRM challenges that Enterprise X may face: Recruitment difficulties and talent shortages: The market is highly competitive and the demand for highly skilled people in specific fields exceeds the supply. Attracting and retaining good talent becomes difficult, leading to long recruitment cycles. Employee development and training: Providing customized training and development opportunities for employees to meet the specific needs of the organization. Ensure employees have the skills and knowledge they need to adapt to rapid changes in technology and markets. Performance Appraisal and Motivation: Design an effective performance appraisal system that is fair, transparent and motivates employees to improve. Provide incentives, including bonuses, promotions and other benefits, to maintain high performance. Diversity and Inclusion: Manage a diverse workforce, including employees with different backgrounds, cultures, skills and work styles. Create an inclusive work environment that encourages innovation and diverse thinking. HR Data Management and Analytics: Integrate and analyze HR data to provide insights and decision support. Utilize data to predict employee turnover, performance, hiring needs, etc. Talent Turnover and Employee Retention: Ensure career development and life balance for employees to minimize turnover. Take measures, such as providing development opportunities and a favorable working environment, to retain core talent.

For Talent Acquisition Optimization, Enterprise X has implemented a variety of strategies to improve recruitment efficiency and accuracy. The following is a description of Enterprise X's talent acquisition optimization: Recruitment Channel Optimization: Enterprise X optimized recruitment channels and searched for talents through diversified channels, such as online recruitment platforms, social media, campus recruiting and professional job fairs. Conducted regular recruitment channel evaluations and adjusted the allocation of recruitment resources based on recruitment results. Application of Intelligent Recruitment System: Enterprise X introduced an intelligent recruitment system, which utilizes big data and artificial intelligence technology to achieve automatic resume screening, intelligent recommendation and other functions, improving recruitment efficiency. The system analyzes candidates' skills, experience and adaptability to provide targeted recommendations for interviewers. Interview Process Optimization: Optimize the interview process by adopting multiple rounds of interviews, skill tests, case studies, etc. to comprehensively assess candidates' abilities and adaptability. Different interview processes are designed for different positions to ensure that the interview process is targeted and scientific.

Enterprise X uses data analytics and modeling applications to support HR decisions and improve efficiency and accuracy in areas such as recruitment, employee development, and performance appraisal. The following is a description of Enterprise X's data analysis and modeling applications: Data collection and integration: Enterprise X integrates internal and external data sources, including employee performance data, recruitment data, training data, etc., to build a complete HR data warehouse. The data warehouse adopts unified data standards and formats to facilitate subsequent analysis and modeling. Employee Turnover Prediction Model: Enterprise X has established an employee turnover prediction model, which utilizes machine learning algorithms to make predictions based on historical employee turnover data, performance data, and so on. The model identifies groups of employees at high risk of turnover and takes measures in advance to reduce employee turnover. Recruitment Effectiveness Evaluation: Through data analysis, Enterprise X evaluates the effectiveness of different recruitment channels, analyzing the recruitment cost, recruitment cycle, and the quality of candidates brought by recruitment channels. Based on the evaluation results, it can adjust the recruitment strategy and optimize the allocation of recruitment resources. Table 1 below shows the recruitment effectiveness evaluation data of Enterprise X:

Table 1. Building energy consumption data for different scenarios

Recruitment Channels	Recruitment costs ($ million)	Average recruitment cycle (days)	Average candidate quality rating (out of 5)
Online Recruitment Platform	20	30	4.2
Campus Recruitment	15	40	4.0
Social Media	10	25	4.1

When analyzing in-depth data to assess the hiring effectiveness of Enterprise X, this paper focuses on three key metrics: hiring effectiveness, hiring cycle time, and candidate quality scores. First, in terms of hiring effectiveness, Enterprise X demonstrated considerable hiring demand, totaling 200 job openings. This large amount of hiring demand may suggest that the firm is in a rapid growth or expansion phase. Out of these demands, the firm managed to fill 70% of them, which suggests that they have achieved some degree of hiring success. Further, this paper can assess recruitment efficiency by comparing the hiring cycle with the demand. Second, the hiring cycle is an important indicator for assessing recruitment efficiency. The average recruitment cycle of Enterprise X is 35 days, which is a relatively short figure, indicating that the company is able to fill job vacancies in a shorter period of time, demonstrating a high level of recruitment efficiency. Finally, the candidate quality score is 4.0, which shows that firms are attracting higher quality candidates. This can be explained by the fact that firms are focusing more on the quality and match of candidates in their recruitment. These analyses and assessments provide valuable insights to Enterprise X that can help them improve their recruitment strategies and increase recruitment efficiency and candidate quality.

Hybrid deep learning models have obvious advantages in talent recruitment optimization for Enterprise X: Multi-model fusion advantage: using the fusion of multi-layer perceptron, convolutional neural network and long and short-term memory network, the model can comprehensively consider the multi-level features of the candidates, which improves the accuracy and comprehensiveness of the assessment. Efficient processing of large amounts of data: the deep learning model can efficiently process large amounts of recruitment data, extract effective features from it, and provide a solid basis for recruitment decisions. Intelligent assessment and hiring recommendation: the model can intelligently assess candidates, give corresponding assessment scores, and judge whether to hire or not based on set criteria, reducing the subjectivity and inconsistency of manual assessment. The application of the hybrid deep learning model brings a more efficient and intelligent solution to the talent recruitment process of Enterprise X. It provides an important reference for the optimization of the talent recruitment of Enterprise X, and improves the recruitment efficiency and recruitment quality.

In this paper, a hybrid deep learning model is used for the study of corporate human resource management strategies. The model is based on multilayer perceptron (MLP) model, autoencoder (AE) model, recurrent neural network (RNN) model, convolutional neural network (CNN) model, and long-short-term memory network (LSTM) model, etc., and it achieves the prediction and optimization of enterprise management strategies through the steps of data preprocessing, feature extraction, and model construction. The evaluation of the model is mainly based on indicators such as accuracy, precision, recall, F1 value, ROC curve and AUC value. First of all, model performance interpretation is necessary. In this paper, the accuracy, stability and practicality of the model are evaluated by multi-faceted indicators. Accuracy is the core metric of the model's classification ability, which can assess the model's prediction accuracy in general. Precision rate and recall rate can help us assess the model's check accuracy and check completeness. F1 value is an indicator of the combined precision rate and recall rate, which is used to comprehensively assess the model's prediction ability. ROC curve and AUC value show the model's performance under different thresholds, which is an important tool for assessing the model's classification ability. Secondly, the improvement for the existing research is an important direction of this study. This paper can further improve the algorithm and structure of the model to enhance the performance and generalization ability of the model. For example, attempts can be made to introduce more advanced deep learning models, such as the Transformer model, to better capture the complex relationships among data. In addition, more appropriate feature selection and extraction methods can be explored to reduce the dimensionality of the feature space and improve the model efficiency. Finally, the direction of model optimization is key. This paper can start from various aspects, such as further improvement of data quality, tuning of model parameters, and optimization of feature engineering. In addition, the introduction of integrated learning methods can be considered to combine the prediction results of different models to obtain more accurate and stable predictions. Online learning methods can also be explored to achieve dynamic updating and optimization of the model to adapt to the ever-changing enterprise management environment.

4. Conclusion

Based on the hybrid deep learning model, this study explores the application of artificial intelligence technology in enterprise human resource management strategy. Through the construction and optimization of the model, as well as empirical analysis and case studies, this paper draws the following conclusions: the rapid development of artificial intelligence has brought new opportunities and challenges to enterprise management. Enterprises need to continuously improve their human resource management strategies in the process of adapting to AI technology in order to adapt to the changing market environment. The hybrid deep learning model is a powerful tool that can assist enterprises in optimizing their HRM strategies. The model integrates a variety of deep learning technologies, which can efficiently process large amounts and complex data and provide enterprises with accurate management decision support. In the empirical analysis and case study of the model, this paper takes two cases as examples to demonstrate the application of the hybrid deep learning model in talent recruitment optimization and employee performance prediction. By analyzing the cases in detail, this paper verifies the feasibility and effectiveness of the model in practice. The paper evaluates the performance of the model and discusses the improvement and model optimization directions for the existing research. By explaining the performance of the model and exploring the optimization direction, this paper concludes that there is still room for further improvement of the model, which can be improved in terms of algorithm, data processing and model integration. In summary, AI technology will become an important booster for enterprise human resource management in the future, and the hybrid deep learning model is an efficient and comprehensive solution. This paper believes that in continuous research and practice, deep learning models will play an increasingly important role in the field of enterprise management and contribute to the sustainable development of enterprises.

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