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Risk Management Capability Prediction Model Based on Spatial Attention Mechanism Optimized Convolutional Neural Network

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Abstract. This study proposes an improved convolutional neural network model incorporating spatial attention mechanism, aiming to construct an intelligent assessment system for personal risk management ability. The model effectively synergizes local features with global semantic information by dynamically enhancing the weight allocation of key feature regions, and achieves a balanced improvement of accuracy (0.815), recall (0.815), and precision (0.802) in risk prediction tasks, which is a significant advantage over the traditional decision tree model and the Adaboost integration method (0.543). Experiments show that the spatial attention mechanism not only strengthens the model's ability to capture the spatial correlation of data, but also improves the stability of the classification decision through feature selection optimization, and its excellent performance of the three performance indicators with a difference of less than 0.015 confirms the high consistency of the model in positive and negative sample recognition. Compared with the limitations of traditional machine learning methods in feature interaction modeling, the present model demonstrates stronger noise suppression and sample imbalance adaptation, providing a two-dimensional value for the education field: learners can improve risk management literacy through dynamic assessment, and educators can optimize their practical teaching strategies relying on predictive data. The research results not only validate the technical effectiveness of the attention mechanism in risk assessment tasks, but also establish performance benchmarks for constructing more interpretable lightweight prediction models, which is of great practical significance for promoting the innovation and development of intelligent educational assessment systems.

Keywords: Spatial Attention Mechanisms, Convolutional Neural Networks, Risk Management Capacity Prediction

1. Introduction

With the acceleration of global economic integration and digital transformation, the business environment faced by enterprises has become increasingly complex, and the risk patterns are diversified, high-frequency and hidden. From the 2008 financial crisis to the global supply chain

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disruptions and geopolitical conflicts in recent years, risk management capability has become a core competitive element for enterprise survival and development [1]. Traditional risk management mainly relies on historical data analysis, statistical models and expert experience, but there are obvious limitations in dealing with nonlinear relationships, high-dimensional data and real-time dynamic risks. Traditional models are difficult to effectively integrate unstructured data and have insufficient ability to predict unexpected events. In addition, the increased correlation of risk factors further highlights the inadequacy of traditional methods. In this context, how to improve the foresight and accuracy of risk prediction has become a focus of attention for both academia and industry.

Machine learning provides a breakthrough tool for risk management by mining complex patterns from massive data [2]. Its core strengths are the ability to handle heterogeneous data from multiple sources and the flexibility to capture nonlinear relationships. Supervised learning algorithms can train models with historical risk event labels to predict default probabilities or market volatility, while unsupervised learning can identify anomalous patterns in the data to assist in fraud detection or operational risk warning.

The significance of studying risk management skills in classroom practice is mainly in its ability to enhance the predictability, adaptability and sustainability of educational activities [3]. For teachers, by systematically identifying potential cognitive conflicts, learning motivation fluctuations, or classroom interaction risks in the teaching process, resilient teaching strategies can be designed in advance. For students, the cultivation of risk identification and assessment ability helps to form a growth mindset, so that they can actively adjust their learning strategies in the face of academic challenges. This ability, when migrated to real social situations, will effectively enhance the crisis response literacy of the new generation of citizens, which is in line with the core demand for composite talents in the new era [4]. In this paper, we design a risk management ability prediction model based on spatial attention mechanism optimized convolutional neural network, which is used for rating and predicting individual's risk management ability, on the one hand, it helps students to reasonably assess their risk management ability and improve their ability in this aspect, and on the other hand, it helps teachers to improve the teaching strategy of the practical courses.

2. Introduction to the dataset

This dataset is an interdisciplinary research dataset oriented to the cultivation of management talents in engineering background, containing 269 employee sample records, focusing on the construction of multidimensional prediction model of risk management competence. The data consists of eight characteristic variables and one target variable, covering the intersection characteristics of the core competency indicators of management and the practical elements of engineering: from the perspective of data structure, the leadership scores show a normal distribution characteristic, reflecting the basic ability of managers' strategic decision-making; the technical proficiency reflects the real distribution of a small number of technological experts and the majority of ordinary developers among the practitioners in engineering; the number of years of experience in the project reflects the frequency of participation in the engineering project The number of years of project experience reflects the frequency of participation in engineering projects. In the dimension of managerial behavior, teamwork reflects the concentrated trend of collaborative ability in efficient teams. The target variable is risk management capability (categorized as high, medium, and low). The dataset contains mixed data types of continuous, discrete and categorical variables through the organic integration of management behavior indicators and engineering competence parameters,

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which is suitable for teaching and research scenarios such as competence assessment model construction of engineering managers and importance analysis of risk decision-making characteristics [5]. Part of the dataset is shownin Table 1.

Table 1: Part of the dataset

Leadership score	Tech proficiency	Project exp	Stress management	Team collab	Decision speed	Risk management_ability
82	0.33	5	5	9	5	Medium
72	0.74	6	2	7	5	Low
84	0.62	4	5	9	3	Medium
97	0.46	2	5	8	4	Medium
71	0.39	5	2	8	4	Medium
71	0.43	4	1	10	5	Low
98	0.22	3	4	9	4	High
86	0.36	4	2	7	5	Medium
67	0.41	0	3	10	2	Low

3. Method

3.1. Spatial attention mechanism

The spatial attention mechanism is a technique in deep learning that mimics selective attention in human vision, aiming to improve task performance by allowing models to automatically focus on key regions when processing images or videos. Traditional convolutional neural networks (CNNs) extract features by convolving them layer by layer, but all spatial locations are treated equally, making it difficult to distinguish the importance of information. The spatial attention mechanism directs the model to focus on regions that are more valuable to the current task by dynamically assigning weights [6]. The network structure of the spatial attention mechanism is shown in Figure 1.

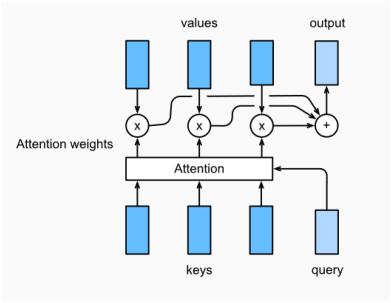

Figure 1: The network structure of the spatial attention mechanism.

Its core principle is to generate a weight matrix of the same size as the input by analyzing the spatial relationship of the feature map. Each element of this matrix represents the degree of saliency of the corresponding location, and the larger the value indicates that the region is more important. For the specific implementation, the model first extracts the input feature maps and subsequently computes the correlations in the spatial dimension through a series of operations [7]. These

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operations capture the dependencies between different locations. The final generated weight matrix is multiplied point-by-point with the original feature map to enhance the feature response in important regions and suppress the information interference in secondary regions.

3.2. Convolutional Neural Network

Convolutional neural network (CNN) is a deep learning model specialized in processing grid-like data, and its core design idea originates from the hierarchical information processing mechanism of the biological visual system.CNN effectively reduces the number of parameters of the model through the properties of local connectivity, weight sharing and spatial downsampling, while retaining the spatial structure information of the input data [8]. The structure of convolutional neural network is shown in Fig. 2.

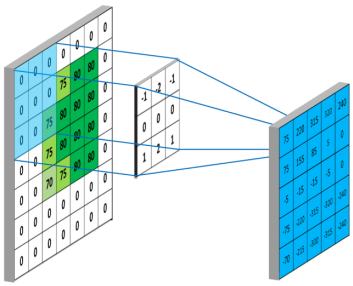

Figure 2: The structure of convolutional neural network

The core structure of CNN consists of convolutional layer, pooling layer and fully connected layer. The convolutional layer is the core module of the CNN, which slides over the input data and performs local region feature extraction through convolutional kernels. Each convolution kernel corresponds to a kind of feature detector. The mathematical essence of the convolution operation is the weighted summation of the local receptive fields with the convolution kernel, which outputs a feature map through a nonlinear activation function [9]. This locally connected and weight-sharing design drastically reduces the number of parameters while giving the model translational invariance, i.e., features are recognized by the same convolution kernel no matter where they appear in the image.

The pooling layer is usually located after the convolutional layer and is used to progressively reduce the spatial dimensionality of the feature map, thereby reducing the computational effort and enhancing the robustness of the model to small displacements [10]. Maximum pooling, which retains the maximum response value in a local region, and average pooling, which averages the values, are two common approaches. This downsampling operation allows the model to focus on more macroscopic feature combinations, resulting in a hierarchical feature abstraction structure.

3.3. Convolutional neural network optimized for spatial attention mechanism

In traditional convolutional operations, the feature extraction weights for each spatial location are fixed and uniform, while the spatial attention mechanism generates a spatial attention map using convolutional or fully connected layers by constructing a learnable weight matrix that allows the network to aggregate global information in the channel dimension. This attention map is normalized

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to weight coefficients between 0-1 by a Sigmoid function, which is multiplied with the original feature map to achieve reinforcement of important regions and suppression of non-critical regions.

The principle of this mechanism to optimize the CNN is mainly reflected in two aspects: first, by explicitly modeling the feature correlation in the spatial dimension, it enhances the network's ability to perceive the structure of the target subject, and makes the feature extraction more relevant to the task; second, the dynamic weight adjustment provided by the attention map compensates for the limitations of the traditional convolution kernel's fixed receptive field, and achieves the feature enhancement for irregularly shaped while maintaining the translation invariance of the adaptive feature enhancement of the target.

4. Experiments

In terms of software configuration, Matlab R2024a with CUDA 11.6 is used; the hardware is an NVIDIA RTX 3090 (24GB memory) graphics card with an Intel i9-12900K processor and 64GB DDR5 RAM with NVMe SSD storage. For model parameters, the spatial attention module is added to ResNet-50 with an initial learning rate of 0.001, using the AdamW optimizer.

Output the confusion matrix of our proposed model, which is shown in Fig. 3 for the training set and Fig. 4 for the test set.

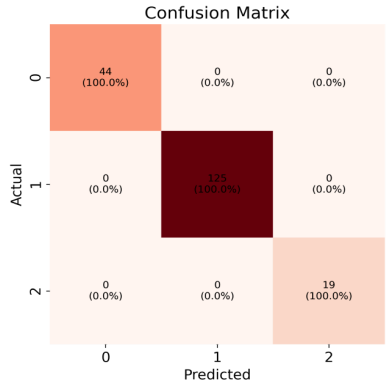

Figure 3: The confusion matrix of the training set

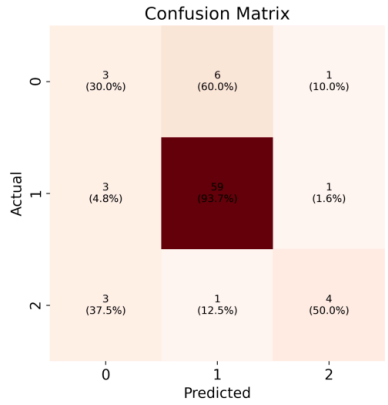

Figure 4: The confusion matrix of the test set

From the confusion matrix of the test set, it can be seen that the model proposed in this paper has an accuracy of 81.5% in predicting risk management ability, which is good enough to correctly assess the risk management ability of students.

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Classification experiments for risk capacity prediction are conducted using Decision Trees, Random Forest, Adaboost, Gradient Boosting Tree, CatBoost and Our model respectively and the output is shown in Table 2.

Table 2. Model evaluation indicators.

Model	Accuracy	Recall	Precision
Decision Trees	0.704	0.704	0.692
Random Forest	0.728	0.728	0.704
Adaboost	0.543	0.543	0.677
Gradient Boosting Tree	0.654	0.654	0.62
CatBoost	0.778	0.778	0.774
Our model	0.815	0.815	0.802

From the comparison results, the convolutional neural network model based on spatial attention optimization shows significant advantages in the classification task, with the accuracy (0.815), recall (0.815) and precision (0.802) exceeding those of the traditional machine learning models and integration methods. This indicates that the spatial attention mechanism effectively improves the feature selection ability and classification robustness of the model by dynamically focusing on key feature regions. In contrast, traditional decision tree-based models perform weakly due to the difficulty in capturing the spatial correlation of the data, while the significantly low score (0.543) of Adaboost may stem from its sensitivity to noise or sample imbalance. Notably, the difference between the three metrics of Our model is less than 0.015, indicating that its classification decision confidence is high and its ability to identify positive and negative categories is more consistent, which may be attributed to the synergistic optimization of local features and global semantics by the attention mechanism. This result validates the effectiveness of spatial attention in risk capacity prediction tasks, and also provides a performance baseline for subsequent model lightweighting or cross-domain migration.

5. Conclusion

From the comparison results, the convolutional neural network model based on spatial attention optimization shows significant advantages in the classification task, with the accuracy (0.815), recall (0.815) and precision (0.802) exceeding those of the traditional machine learning models and integration methods. This indicates that the spatial attention mechanism effectively improves the feature selection ability and classification robustness of the model by dynamically focusing on key feature regions. In contrast, traditional decision tree-based models perform weakly due to the difficulty in capturing the spatial correlation of the data, while the significantly low score (0.543) of Adaboost may stem from its sensitivity to noise or sample imbalance. Notably, the difference between the three metrics of Our model is less than 0.015, indicating that its classification decision confidence is high and its ability to identify positive and negative categories is more consistent, which may be attributed to the synergistic optimization of local features and global semantics by the attention mechanism. This result validates the effectiveness of spatial attention in risk capacity prediction tasks, and also provides a performance baseline for subsequent model lightweighting or cross-domain migration.

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