KNOWLEDGE-AUGMENTED DYNAMIC NEURAL NETWORK MODEL AND ITS APPLICATION IN CREDIT EVALUATION

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ABSTRACT

Credit risk is the most significant risk faced by credit businesses. Currently, various approaches are widely used in credit evaluation. However, methods based on expert knowledge exhibit obvious subjective cognitive bias, while both statistical and machine learning methods require a substantial amount of historical data. In cases with limited data, the machine-learning effect is poor. Inspired by the structural similarity between neural networks (NN) and the Analytic Hierarchy Process (AHP), we propose a knowledge-augmented dynamic neural network model called KADNN to construct an effective credit evaluation model. This composite architecture will help effectively utilize existing data to alleviate the initial low-data dilemma and can be further utilized for training neural networks. Subsequent data updates can be dynamically incorporated to improve model accuracy. Additionally, this approach improves the comprehensibility and premature convergence issues of the NN model. The proposed approach is validated and evaluated through credit evaluation simulation.

KEYWORDS

Knowledge Augment, Credit Evaluation, Neural Network, Analytic Hierarchy Process, Machine Learning.

1. INTRODUCTION

With the enhancement of China's economic capabilities and modifications in financial consumption patterns, there has been a swift increase in credit requirements for small businesses and individuals. Particularly, in recent years, the emergence of Internet Plus and the big data epoch has resulted in this expansion. The substantial growth of several Internet financial platforms and microfinance institutions, which are increasingly expanding their market size, has fostered a crucial need for various lending institutions to develop appropriate credit evaluation models to expedite their credit decision-making process. This area of inquiry holds considerable significance in the academic field.

Traditional methods of credit evaluation are based on expert experience, such as 5C's**Error! Reference source not found.**, 5P's**Error! Reference source not found.**, LAPP method**Error! Reference source not found.** and so on. Those methods assess the credit scoring by credit experts' subjective judgment on relevant factors that may affect the borrower's default probability. With the popularization of statistical methods, various methods such as regression analysis, discriminant analysis, Logistic model and Probit model were introduced into credit scorings**Error! Reference source not found.**,**Error! Reference source not found.**.The Z-SCORE model proposed by Altman in 1968**Error! Reference source not found.** and Moody's

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RiskCalc model**Error! Reference source not found.**are both based on financial data. Furthermore, with the advancements in information technology, a wide array of machine learning techniques, such as artificial neural networks**Error! Reference source not found.**, support vector machines**Error! Reference source not found.**, decision trees**Error! Reference source not found.**, and genetic algorithms**Error! Reference source not found.**, have been extensively employed in credit evaluation in recent years.

Although statistical methods and machine learning approaches are objective and accurate, they require adequate training data. Unfortunately, the quantity and authenticity of data from most small and micro-enterprises cannot be guaranteed due to their small scale, weak capacity, and imperfect management systems **Error! Reference source not found.**. Moreover, the diverse nature of enterprises, encompassing their industries, locations, cultures, and business characteristics, poses a substantial challenge in acquiring relevant business information for credit assessment. This issue is equally prevalent in the domain of individual credit evaluation.

The existing credit evaluation model may not be suitable in the face of various new credit businesses or new customer groups, but there is no historical data available to initialize the new model. The use of statistical or machine learning techniques for credit evaluation encounters significant obstacles. In this case, relying on the expert experience model would be more appropriate. Therefore, the method of integrating qualitative and quantitative approaches, exemplified by the Analytic Hierarchy Process (AHP), is highly favored by studies**Error! Reference source not found.**,**Error! Reference source not found.**,**Error! Reference source not found.**. After resolving the cold start issue using AHP, the credit industry will gradually accumulate more data as it progresses. The objective analysis of default data obtained from actual losses holds immense value. Financial institutions should maximize this rare asset and avoid wasting resources by abandoning conventional experience-based approaches. It is important to note that while the AHP approach can establish a model at the beginning of a project without relying on past data through specialist expertise, it must be recognized that the AHP model is subjective due to limitations arising from human cognitive bias and experience.

Based on these characteristics, a novel knowledge-augmented dynamic neural network (KADNN) is proposed in this paper. The key contributions of our work can be summarized as follows.

- We present a new credit assessment model that combines the advantages of AHP and neural networks to achieve knowledge augmentation. This model utilizes expert knowledge to initialize models in the early stages of a business, overcoming the challenge of training machine learning models. By adopting this approach, one can address the issue that machine learning models cannot be trained without historical data. Alternatively, the data derived from continuous credit operations can be leveraged to update and enrich the network within the credit assessment model through the application of machine learning techniques. As a result, the defects resulting from subjective cognitive bias in the initial stage of the model are rectified.

- The proposed neural network model we construct is inspired by the structure of the AHP model. This approach avoids the problem of determining nodes in neural network design while providing specific meaning to each node, thereby improving the comprehensibility of the model.

- Our model can easily be transformed into a non-linear model from a fundamental linear model, promoting the accuracy and objectivity of the model.

The rest of the paper is structured as follows. We begin with some background on AHP and neural networks and give a brief discussion in Section 2. We describe the design of KADNN in Section 3. In Section 4, we give specific examples to illustrate the application of the proposed method in credit evaluation and analyze the experimental results. Finally, we conclude this paper in the last section.

2. PRELIMINARIES

2.1. Analytic Hierarchy Process

AHP provides a straightforward and adaptable technique for addressing multi-criteria decision-making challenges, allowing for the quantitative analysis of qualitative issues **Error! Reference source not found.**. It utilizes the problem's logic to construct a hierarchical structure and then performs quantitative analysis on each layer under the guidance of experienced experts. Finally, it calculates the weight of each layer and aggregates them to obtain the highest index weight. The key steps of AHP are as follows.

1. Define the problem and determine its goal.
2. Structure the hierarchical framework from the top level (objective level) through the intermediate levels (criteria on which subsequent levels depend) to the lowest level, which usually contains a list of alternatives.
3. Construct a set of pairwise comparison matrices (size $n \times n$) for each of the lower levels with one matrix for each element in the level immediately above using the scale method. The pairwise comparisons are done in terms of dominance between elements.
4. Hierarchical synthesis is used to weigh eigenvectors by criteria weights, and then sum all weighted eigenvector entries corresponding to those in the next lower level of hierarchy.
5. Once all pairwise comparisons have been completed, the assessment of consistency involves calculating the Consistency Index (CI) using the eigenvalue λ_{max} as follows: $CI = (\lambda_{max} - n)/(n - 1)$, where n is matrix size. The evaluation of judgment consistency can be achieved by computing the Consistency Ratio (CR), which is derived from the calculated Consistency Index (CI) value. If CR is less than 0.1, the judgment matrix is acceptable.
   The core of AHP is the judgment matrix, but constructing it requires significant cost and effort. The restrictions inherent in human cognitive capacity often make it challenging to construct a judgment matrix that fully satisfies the consistency requirement in one attempt. It often becomes necessary to repeatedly modify the judgment matrix based on experience to achieve consistency. This complexity increases especially when there are multiple layers involved. Additionally, determining the numerical scale used for establishing the matrix structure also poses difficulties. If different numerical scales are employed, the resulting judgments often differ as well; a scale may only be applicable to one specific application and not others**Error! Reference source not found.**. In short, although AHP aims to quantify the weights of each indicator element using human experiential information, the weights of each indicator element and actual data can only be roughly similar due to humans' limited cognitive abilities and inherent ambiguity in experiences.

2.2. Bp Neural Network

The neural network (NN) is a highly nonlinear and adaptive system, which acquires knowledge from the external environment through internal neurons. Artificial neurons are typically non-linear units with multiple inputs and single outputs. The model can be mathematically represented as follows.

$$V_k = \sum_{i=1}^{n} w_{ik} x_i + b_k, \quad y_k = \phi(V_k) \quad (1)$$

Where $x_i\ (i = 1, 2, \cdots, n)$ represents the input value, w_{ik} denotes the weight of each input connection to the k-th neuron, and b_k signifies the bias level of neuron k. V_k is the weighted sum of neuron k for each input and bias. ϕrepresents the activation function, which is typically a nonlinear function. Finally, y_k indicates the output value of neuron k.

The learning of neural networks also referred to as training, aims to improve their performance through the tunning of weights and bias levels. Proposed by Rumelhart et al. in 1986, the back-propagation (BP) algorithm remains the most classical learning algorithm for neural networks. This algorithm operates in two distinct stages: the forward process calculates the output values of each node layer by layer, while the reverse process calculates the error of each hidden layer node and corrects the connection weight with the preceding layer. A BP neural network refers to a feed forward neural network that is trained by the BP algorithm. Given a network structure and initial weights, the BP algorithm repeats this process until convergence.

The neural network exhibits various strengths, including its strong robustness, fault tolerance, parallel processing capabilities, and capacity for self-learning. However, it should be noted that the network structure must be predetermined before training. This means that the level of the network and the number of network nodes in each layer need to be specified. Particularly, the lack of explicit theoretical instructions for setting the hidden layer, resulting in greatrandomness. Additionally, since the BP learning algorithm is a local optimization method when the activation function is nonlinear, it may not necessarily obtain the global optimal solution. Furthermore, due to its black-box nature, the interpretability of the neural network model is poor.

3. NOVEL METHODOLOGY IN CREDIT EVALUATION

3.1. Problem Statement

In the practice of credit evaluation, it is inappropriate to simply copy the evaluation model applicable to the A-type customer group for the B-type customer group due to their differences. Therefore, customers who have not yet developed a credit evaluation must rebuild a model that matches their characteristics. However, obtaining sufficient data samples for building credit evaluation models is difficult in reality. Especially in the initial stage of credit work where there is no information about customers, thus machine learning methods cannot be used to build models.

We attempt to combine NN with AHP to address this issue. As a result, we propose a knowledge-augmented dynamic neural network (KADNN) model based on the different characteristics of BPNN and AHP. The construction of KADNN can be summarized into three main phases: first, constructing a subjective evaluation model of credit assessment based on expert experience using the AHP method in the initial stage; then building the neural network using accumulated sample data during the credit process with regarding the structure of the AHP model and utilizing its weights as initial weights for NN; so far, an original and naive NN model has been built; after that, dynamically updating and optimizing this NN model based on continuously updated data and previous models will achieve a more accurate and objective evaluation model. This flow can be seen in Figure 1. It not only makes full use of the expert's experience but also timely utilizes credit default information generated in practice for dynamic updates and improvements.

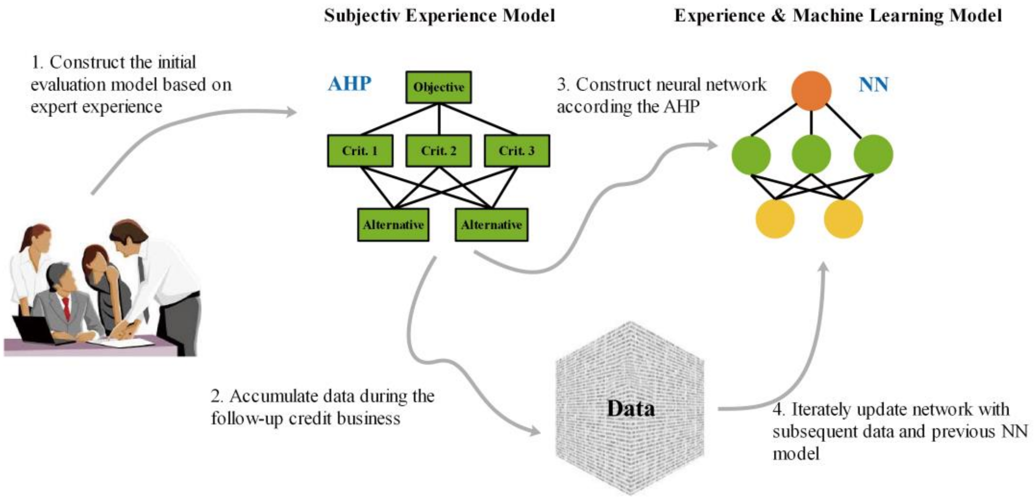

Figure 1. The basic idea of KADNN

3.2. Knowledge Augmentation using AHP and NN

To overcome the limitations of BPNN discussed earlier, we combine AHP and BPNN to complement each other and achieve better performance in credit evaluation models. However, despite being inspired by their structural similarities, we cannot simply copy the structure. The AHP model and BP neural network primarily differ in their connectivity patterns. In a general BP neural network, nodes in the previous layer are connected to all nodes in the next layer, while lower-layer nodes in AHP are only connected to some associated upper nodes. Figure 2 illustrates this comparison. Therefore, the learning algorithm needs optimization to bridge this gap.

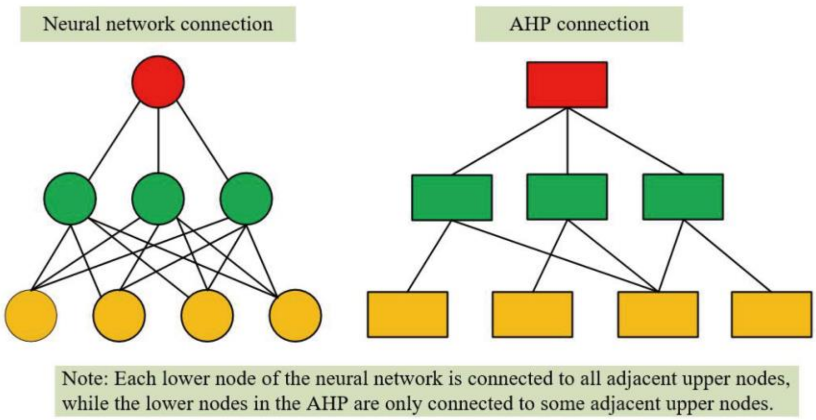

Figure 2. Comparison of network structure between NN and AHP

We first design the model structure of KADNN based on the hierarchical structure of AHP, removing the alternative layer and using the remaining index architecture as the neural network's model structure. This approach solves the problem of blindly determining the neural network's structure while providing actual meaning to each node's connection and weight, thereby improving its comprehensibility. Additionally, during KADNN's learning phase, we directly determine the connection weights between nodes according to the AHP model's weights without needing to reassign them. This extension avoids result instability caused by the random assignment of initial values.

Another optimization lies in the preservation of the activation function. In the AHP model, the output of the upper nodes is obtained by taking the weighted sum of the connected lower nodes. Therefore, the output of the upper node is only a linear transformation of the lower node. However, in the NN model, after taking the weighted sum of the lower nodes, an additional step is required to calculate through an activation function. Especially when using a nonlinear activation function, it results in a nonlinear transformation of the output from lower nodes for the upper node's output. This increases complexity but also enhances its expressive capability. The KADNN proposed in this study incorporates an activation function that inherits characteristics from neural networks and allows for nonlinearity to accurately represent relationships between upper and lower element nodes.

Last but not least, we achieve knowledge augmentation through this combination. A general neural network requires enough training samples and iterations to enable the model to learn the rules in the data and reduce its error to an acceptable level. The initial value of the KADNN model is determined based on the weighted values obtained from AHP, which is already close to the global optimum. In this scenario, the effect of insufficient samples can be mitigated, ensuring that output is not prone to significant errors. Furthermore, once new samples are acquired, they can be utilized for training and refining the model to achieve online updates of the model.

3.3. Algorithm Design

The implementation steps of the KADNN method can be divided into two phases accordingly.

Phase 1: The establishment of the AHP model. This step follows the same steps as general AHP modelling . Firstly, a hierarchical indicator system is manually constructed. Then, a judgment matrix is created for each upper-level element by comparing pairs of lower-level elements. Additionally, hierarchical ordering and consistency checks are conducted. Finally, the initial stage model of credit evaluation is constructed.

Phase 2: Constructing KADNN based on the AHP model structure, where the weights obtained from AHP are used as initial weights for the neural network model. Subsequently, the model undergoes dynamic updates using new data acquired from credit evaluation work. The overall framework of the KADNN model is illustrated in Figure 3.

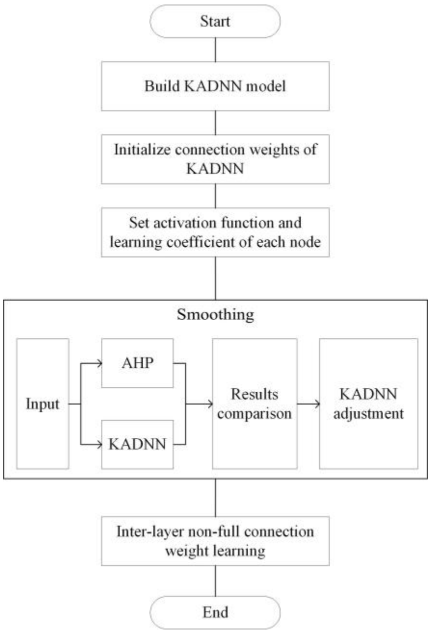

Figure 3. The algorithm framework of KADNN

The ReLu function is used as the activation function for the hidden layer to fit the linear structure of the AHP model. Meanwhile, the sigmoid function is employed as the activation function for the output layer nodes to achieve classification. Firstly, a smoothing algorithm is utilized to adjust the bias values of both hidden and output nodes to ensure that the output of the KADNN model approximates that of AHP. Then the KADNN model is trained using the training set.

KADNN involves two key operations: smooth processing and inter-layer non-fully connected learning. The basic idea of the KADNN method is to first initialize the NN model with the output of the AHP model and then refine and improve the neural network model with subsequent updated data. However, when transforming from AHP to NN models, although their connection weights are exactly the same, there are differences between them in linear and nonlinear operations. Thus, there could be significant distinctions in the results produced by the AHP and KADNN models for identical input samples. To address this issue, smoothing is introduced to ensure consistency between the outputs of NN models and those of AHP for identical input data.

The smoothing process is illustrated in Figure 4. In the first step, the sample data collected is employed as input for both the AHP model and neural network. Afterward, the outputs of these models are contrasted, and the error is computed. Subsequently, we apply the error back-propagation method and use gradient descent to adjust each node's bias value to minimize output errors. This iteration cycle continues until both errors meet accuracy requirements. It should be noted that the weights of connections between nodes remain fixed throughout the smoothing process.

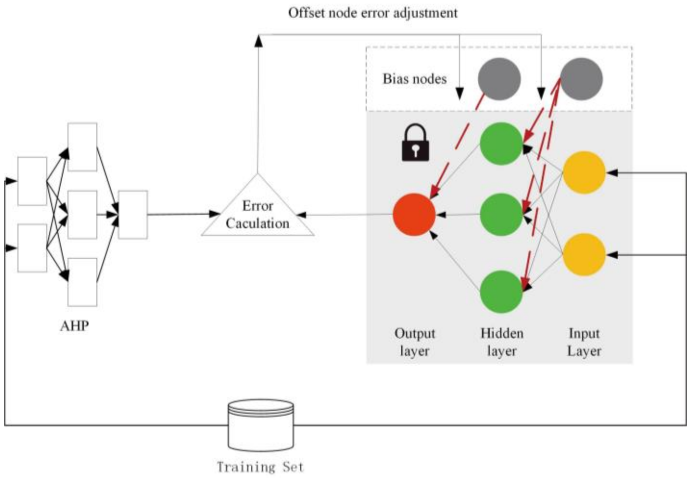

Figure 4. Schematic diagram of smoothing algorithm

In addition, since the structure of KADNN is derived from the AHP model, the upper and lower nodes of the AHP model are not fully connected, which is inconsistent with a typical neural network. To accommodate this characteristic of KADNN, we propose a modification to the network structure by introducing a connection matrix E between layers. Each element e_{ik} represents the connection between node i and node k.

$$e_{ik} = \begin{cases} 1, & \text{if } i \text{ and} k \text{have a connection} \\ 0, & \text{if } i \text{ and} k \text{have no connection} \end{cases} \quad (2)$$

Algorithm 1 demonstrates the modification of the NN algorithm, which introduces access to the connection matrix without significantly altering the time and space complexity of the model.

Algorithm 1 Modification of Neural Network Algorithm in KADNN

1: The output of each layer node is calculated from front to back.

$$v_k = \sum_i E_{ij} w_{ij} x_i + b_k$$

2: The corresponding δ_k is calculated for each node k of the output layer.

$$\delta_k = -(t_k - y_k)\phi'(v_k)$$

Where t_k is the supervisory signal (supervised output) and $\phi'(\cdot)$ is the derivative of the activation function.

3: Calculate δ_j of the hidden layer from the back to the front.

$$\delta_j = \sum_k \delta_k w_{jk} \Phi'(v_j)$$

4: Calculate and save the weight correction for each node.

$$\Delta w_{ij} = \eta \delta_j y_j$$

where η is the learning rate used to adjust the rate of learning.

5: Correct the connection weight between each node.

$$w_{ij} = w_{ij} + \Delta w_{ij}$$

4. Simulation Study

4.1. Simulation Setting And Dataset

We implemented the KADNN algorithm in Python and conducted a credit scoring simulation to demonstrate the application of the KADNN method and validate its effectiveness. In our experiments, we employed the established German credit assessment dataset from the UCI database and conducted data normalization. The German dataset contains twenty attribute variables and a single class variable, with two distinct states representing customer classification into good credit or bad credit categories. The dataset consists of a total of 1000 customer samples, wherein 700 having good credit and the remaining 300 having bad credit. During our experiment, we employed Satty's Nine-Scale to construct judgment matrices for the analytic hierarchy process (AHP). Finally, we compared the performance of AHP, BPNN, and KADNN to demonstrate the effectiveness of our algorithm. We have adopted three classical machine learning performance evaluation metrics, including precision rate, recall rate, and F1-score, as assessment criteria for this experiment.

4.2. Training KADNN With Baseline Credit Evaluation Index Model

The network structure of KADNN needs to be initialized by constructing a nascent AHP model first. Based on the specific meaning of the variables provided by the data set and drawing inspiration from the well-known FICO credit scoring index system in the United States**Error! Reference source not found.**, Figure 5 shows the personal credit scoring system established for the German data set in this paper.

Based on the index system, we obtain the relative weights of three hierarchies in the AHP model shown in Table 1. Subsequently, the KADNN model is initialized using these weights from the AHP model. Finally, a non-fully connected neural network model based on the AHP model is depicted in Figure 6. Since the output of those three models is a continuous number of [0, 1] intervals, while the result of the German data set is binary, it is necessary to set a threshold to convert the continuous output value into binary data.

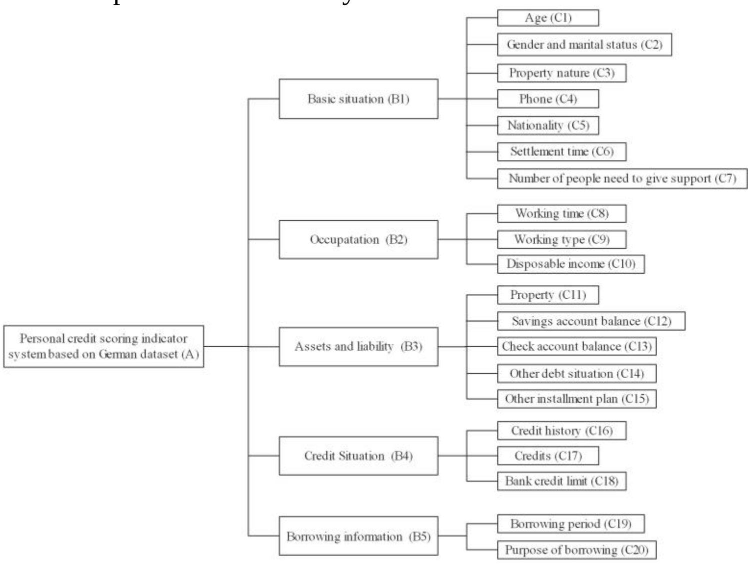

Figure 5. German credit scoring index system

The Youden Index, alternatively referred to as the adopted to determine the optimal threshold value. It serves as a measure for assessing reliability of screening tests and is calculated as follows.

$$Youden\ index = (sensitivity + specificity) - 1 \quad (3)$$

Table 1. Relative weights of three hierarchies

1st Hierarchy	Relative weights	2st Hierarchy	Relative weights
B1	0.048	C1	0.0755
		C2	0.1415
		C3	0.1656
		C4	0.0492
		C5	0.0744
		C6	0.1966
		C7	0.2971
B2	0.1014	C8	0.11
		C9	0.58
		C10	0.31
B3	0.2888	C11	0.2601
		C12	0.2601
		C13	0.2601
		C14	0.0819
		C15	0.1378
B4	0.4829	C16	0.69
		C17	0.19
		C18	0.13
B5	0.0789	C19	0.6667
		C20	0.3333

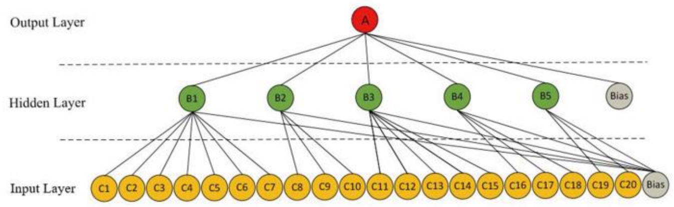

Figure 6. A simulation example of KADNN

Among them, sensitivity represents the probability of correctly identifying positive samples, while specificity represents the probability of correctly identifying negative samples. The Youden index reflects the overall ability of the screening method to detect both positive and negative samples. The magnitude of this index is directly proportional to the effectiveness and reliability of the screening experiment. In our experiment, we calculate the Youden index for each model based on training set data and use the maximum value as the classification threshold for each model. The threshold values for AHP, BPNN, and KADNN are 0.47, 0.375, and 0.406 respectively. Taking AHP as an example, if a sample's credit score is greater than 0.406, it is classified as a good customer; otherwise, it is classified vice versa.

4.3. Results and Discussion

In Figure 7, we present the receiver operating characteristic (ROC) curve and area under the curve (AUC) values of three models using both the training set and the test set. The ROC curve is a graphical representation that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold varies. The AUC curve is defined as the area under this ROC curve, with its value limited to not exceed 1. Since a typical ROC curve lies above the y = x line, AUC ranges between 0.5 and 1, serving as an evaluation criterion for assessing classifiers' classification performance. The larger its value, indicating better the classification effect.

The results based on the training set, as depicted in Figure 7, show that the BPNN model demonstrates a high level of fitting with an AUC value of 0.831. Similarly, KADNN exhibits a comparable degree of fitting to AHP, achieving an AUC value of approximately 0.711. However, it is crucial to focus on the results obtained from the test set. The AUC values for AHP, BPNN, and KADNN are 0.771, 0.795, and 0.804 respectively. It can be observed that KADNN exhibits the best-fitting degree.

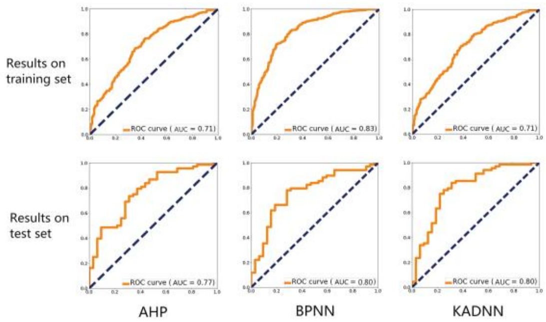

Figure 7. ROC curve and AUC values of three models.

The performance comparison of the three models is presented in Table 2. It can be observed that among these models, the AHP model exhibits the lowest accuracy rate, recall rate, and *F1* score. This suggests that a model based solely on subjective experience lacks discriminative power compared to a machine learning model that leverages objective data. However, it is worth noting that the AHP model consistently achieves values close to 0.7, indicating its good judgment capabilities. On the other hand, when sample data is limited, the KADNN model consistently performs well across different customer types - good, bad, or average - with its value being the highest among all three models. This demonstrates the advantages of incorporating both expert experience data and objective information for building robust models. Furthermore, in credit evaluation scenarios, particular importance lies in accurately identifying bad customers (recall rate). Although slightly lower than BPNN's recall rate, KADNN significantly outperforms the AHP model in this aspect as well. Thus highlighting not only the substantial improvement achieved by our proposed method for detecting default customers but also emphasizing how the integration of new data has played a pivotal role in enhancing our model.

Table 2. The comparison of the three model’s evaluation performance

Model	Customer types	Precision	Recall	F1-score
AHP	Good	0.51	0.69	0.59
	Bad	0.82	0.69	0.75
	Average	0.72	0.69	0.70
BPNN	Good	0.78	0.24	0.37
	Bad	0.76	0.97	0.85
	Average	0.76	0.76	0.71
KADNN	Good	0.71	0.58	0.64
	Bad	0.86	0.92	0.89
	Average	0.82	0.83	0.82

5. Conclusions

The credit evaluation model is important to promote the rapid development of the financial credit business. In the era of continuous innovation in Internet Plus and financial services, the existing credit evaluation models may not be appropriate in the face of various new credit businesses or new customer groups. Nevertheless, constructing a credit evaluation model based on machine learning and statistical methods is unrealistic without sufficient historical data, particularly default data. To address this challenge, we develop the KADNN model in this study by amalgamating the benefits of the neural network and AHP. The findings of this study demonstrate that KADNN outperforms both AHP and neural network models in terms of accuracy.

However, further research is still required in this field. Initially, it is notable that the weight adjustment algorithm implemented in KADNN is the gradient descent method. Advancements to neural networks can include more globally optimized weight adjustment algorithms for neural networks. Moreover, the expansion of network layers can prove useful in practical applications. Still, it is crucial to note that deep networks can lead to serious issues, such as the worsening gradient vanish**Error! Reference source not found.**. Therefore, investigating the implementation of a deep learning mechanism and identifying the suitable activation function to address this challenge represents a potential area for future research.

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