



Construction of an Intelligent Financial Risk Prevention and Control System Based on Artificial Intelligence in the Context of Digital Finance

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SUMMARY: *This part proposes an artificial intelligence financial risk intelligent prevention and control scheme based on machine learning and deep learning methods, and utilizes these methods to extract information from large-scale datasets from different sources to identify financial risks and generate automatically updated risk assessment models. In addition, the model is also validated from different perspectives by combining relevant theoretical research and data analysis based on the consideration of macro-environmental factors, market micro-financial variables, and the company's internal accounting statements; it is concluded through simulation that the risk management model under the integrated intelligent early warning mechanism has obvious advantages in terms of the accuracy rate, the response speed, and the economic cost compared with the traditional method, and that the integrated intelligent early warning mechanism has obvious advantages in the accuracy rate, response speed, and economic cost. Realize the real-time and precision of risk monitoring. This study provides some effective solution ideas and methods for the theoretical innovation in the field of financial risk management and the practical application of financial institutions in the context of digital transformation, which helps to realize the transformation from passive risk management to active risk control.*

KEYWORDS: *digital finance; artificial intelligence; financial risk prevention and control; machine learning; deep learning*

1 Introduction

At the beginning of the 21st century, as computers and mobile devices began to be updated and innovated, high-tech devices are becoming more and more common in daily life, and under the new round of scientific and technological revolution and industrial change, emerging technologies and finance began to integrate and develop. Digital finance is an important direction of financial development, is still in constant development, in the process of its development there will be many financial risks different from those arising from traditional finance in the past. Financial risks in the context of digital finance involve risks such as data security, privacy leakage, technological vulnerabilities/failures/ethics, cyber-attacks, internal operational problems, market volatility, and so on [1-4]. This requires that while embracing digital finance to facilitate production and life, it is also necessary to keep an eye on those risks brought by digital finance to prevent the high degree of contagion of these financial risks

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<https://doi.org/10.65102/is2026067>

leading to financial systemic risks. Guaranteeing the security of the financial sector is the basis for maintaining the national economy as well as social stability, and strengthening the prevention and control of risks in the financial sector is a key element of work to enhance economic stability [5, 6]. Therefore, it is necessary to comprehensively combine financial science and technology, improve the financial risk prevention and control efforts to promote the financial sector risk prevention and control scale as well as efficiency have been effectively improved, and further reduce the financial risk of economic hazards.

In the process of rapid development of the financial industry will produce a large amount of data, in the face of a large number of data and information, how can it be fully and effectively utilized, and as far as possible to avoid causing information asymmetry, for the financial industry is crucial. The effective application of Artificial Intelligence (AI) in the financial field can analyze and integrate these data, reducing financial risks to a certain extent, but also effectively save labor costs, and at the same time, it can also make the level of financial risk management to be improved to a certain extent. At present, this has become a major trend in the development of the field of financial risk management. Literature [7] points out that AI-driven machine learning and deep learning models are able to analyze massive amounts of data, mine the correlations and patterns between data, detect market anomalies and predict trends in real time, thus significantly improving the accuracy, speed and proactivity of risk assessment, and providing key support for investment decision-making and operational prevention and control.

The application scenarios of AI technology in the field of financial risk management include trust risk assessment, identification of abnormal transactions, fraud checking, market risk prediction, identification of internal operational risks, risk early warning, etc., which helps to build a financial risk prevention and control system. Literature [8] constructed an interpretable AI model for credit risk assessment in person-to-person lending, which provides a transparent explanation of risk influencing factors and helps to formulate fair data-driven risk control policies. Literature [9] provides a scalable and automated risk solution for digital lending by analyzing data from over 130,000 European customers to construct an AI credit risk default probability model based on neural networks and random forests. Literature [10] uses AI technology to build a financial transaction anomaly identification model, taking the transaction amount as the key feature, and classifying and detecting the anomalous behavioral paths by simulating them and setting the cost-benefit function, which can effectively improve the security of transactions and market stability. Literature [11] combines AI and machine learning technology and Feedzai security model to build a dynamic network security defense mechanism to identify financial fraudulent transactions, which can effectively respond to dynamic network attacks and improve the real-time protection capability of financial transaction security. Literature [12] points out that the real-time monitoring system integrating advanced AI and machine learning can significantly improve the effectiveness of digital financial risk management, which can reduce the fraud events by 35% and increase the accuracy of credit risk assessment by 25%, thus enhancing the prediction ability and operational efficiency, and strengthening the stability of the financial system. Literature [13] proposes an AI-based data integration framework for the risk assessment challenges of decentralized financial markets with dispersed data and high volatility, which integrates the use of natural language processing sentiment analysis and blockchain real-time data, and risk prediction through federated learning and graph neural networks, effectively improving the accuracy and transparency of early warning and anomaly detection. Literature [14] utilizes hybrid AI and long and short-term memory network prediction models for financial market risk prediction, with a prediction accuracy of 92.7%, providing a reliable basis for active risk management and investment decisions. Literature [15] utilizes machine learning methods to construct a financial system risk

early warning model, which has a higher prediction accuracy and information timeliness, providing an effective AI solution for identifying financial distress. Literature [16] reported that with AI technologies such as machine learning and real-time anomaly detection, the risk prevention and control capabilities in the digital financial environment have been significantly improved, which not only provides an adaptive protective barrier for the U.S. financial ecosystem, but also serves as a key resource for enhancing the resilience and strategic leadership of the global economy. Literature [17] proposes a digital financial risk prevention and control framework that integrates AI and cloud computing, which realizes fraud identification and risk warning with the help of statistical analysis, neural network and language processing algorithms, and ensures smooth operation and meets the compliance requirements in the cloud, and experiments show that its accuracy rate reaches 94.3% in centralized mode, and maintains an efficient performance of 91.2% in federal mode.

However, AI-based financial risk management also faces challenges. Literature [18] shows that AI has significant potential to improve the accuracy of anomaly detection and prediction within banks, but also faces key challenges such as employee privacy protection and regulatory compliance. Literature [19] emphasized that although AI technology significantly improves the accuracy and adaptability of financial fraud detection, it also faces challenges such as algorithmic bias, data privacy, system interpretability, and deployment at scale, and that it needs to be promoted for responsible application by improving data quality, developing transparent algorithms, and strengthening cybersecurity and ethical regulations. Literature [20] illustrates that AI, while facilitating financial risk management, also raises significant ethical and operational issues, including the lack of transparency in decision-making due to its “black-box” nature, the potential for bias in training data to exacerbate discrimination in risk assessment, and the risk of privacy breaches associated with the use of data on a large scale. Literature [21] emphasizes the ethical challenges of AI-based financial risk management, and stresses the importance of data privacy, algorithmic bias, and security risks in the pursuit of efficiency, as well as the establishment of a fair and transparent regulatory framework to maintain public trust. Literature [22] survey shows that the main risks of China's Internet finance in the context of big data and AI are, in order, legal, credit, platform operation, operation, and reputation, and the key to dealing with them is to build an information security system and improve laws and regulations to effectively manage the risks of operation, credit, and reputation. In this context, it is necessary to build a financial risk prevention and control system suitable for the digital financial context.

This paper proposes a set of AI financial risk intelligent prevention and control program from theory to experiment, and designs corresponding experiments to verify its feasibility and effectiveness. In this paper, relevant economic data and financial market data are collected as the training set. Firstly, CNN and LSTM are utilized to extract time series related information, and secondly, other classifiers are combined to detect financial risks. The top layer uses attention network to evaluate the risk. An oversampling method is used in the training process to solve the problem of category imbalance thus improving the detection of risky incidents. In the experimental process, the cross-validation method is strictly adhered to and the sample set is divided according to the ratio of 7:2:1; at the same time, the model is evaluated using various evaluation criteria, such as accuracy, F1 value, and Sharpe's ratio, etc., and the effectiveness and stability of the strategy is tested by combining with the historical live trading, backtesting, and simulation.

2 Methodology

2.1 Architecture design

This paper proposes an intelligent financial risk prevention and control system based on artificial intelligence, which adopts a five-layer progressive technical architecture, and realizes the integrated intelligent risk prevention and control from bottom to top from the bottom data collection to the upper business application through the design of layered decoupling of data layer, algorithmic layer, model layer, application layer, and display layer, and uses modular design and standard interfaces to ensure system scalability in response to the complexity of the financial business and the demand for real-time data processing. Modularized design and standard interfaces ensure the scalability of the system. In addition, the introduction of micro-service architecture style to achieve elasticity and isolation, to provide financial enterprises with a comprehensive intelligent risk control solution. This project adopts a top-down layer-by-layer design, each layer is designed to be as modular and single-function as possible, the upper layer calls the lower layer services and passes parameters to form a highly integrated and synergistically operated risk management system, to realize the system's scalability, flexibility and reusability, and ultimately to achieve the self-improvement and continuous evolution of the intelligent risk control system.

The data layer is responsible for the unified collection, standardized processing and safe storage of heterogeneous data from multiple sources, using distributed data storage architecture for data storage, and real-time streaming processing technology for rapid processing of large-scale data from multiple sources such as the trading system, customer management system, external data sources, etc. The data collection part is composed of data from various business operations, and the data collection part is composed of data from various business operations. The data collection part consists of collection agents distributed in each business system, which are used to collect structured and unstructured data in real time, and provide batch import and streaming access to ensure comprehensive and timely data acquisition. Data preprocessing uses data cleaning, transformation, integration and other methods to normalize raw data, and uses outlier detection methods to find and correct outliers in the data:

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

where X is the observed value, μ is the mean, σ is the standard deviation, and an outlier is determined when $|Z| > 3$.

The storage layer puts the hot data in the memory database for real-time retrieval; places the warm data in the distributed file system to balance performance and cost; places the cold data in the object storage system for permanent storage; Algorithm layer: combines a variety of AI methods such as machine learning, deep learning and reinforcement learning. It provides perfect algorithmic toolbox and computing power support for the upper layer model construction, and is based on containerized deployment and containerized algorithms, i.e., algorithms as a service to achieve algorithm agility on-line, elasticity and scalability, and version control. In supervised learning algorithms, including logistic regression, random forest, support vector machine, gradient boosting tree and other algorithms, the algorithms are evaluated using the cross-validation method, and the cross-validation error is defined as Eq:

$$CV_{error} = \frac{1}{k} \sum_{i=1}^k L(y_i, \hat{y}_i) \quad (2)$$

where k is the number of folds, L is the loss function, y_i is the true value, and \hat{y}_i is the predicted value.

The unsupervised learning algorithm module provides functions such as clustering analysis, anomaly detection, dimensionality reduction processing, etc., and recognizes customer group characteristics through K-means clustering algorithm with the objective function:

$$J = \sum_{i=1}^k \sum_{x \in C_i} \|x - u_i\|^2 \quad (3)$$

where C_i is the i th cluster and u_i is the cluster center.

The deep learning layer utilizes models such as convolutional neural network, recurrent neural network and attention mechanism to fit complex nonlinear relationships and analyze time series; the reinforcement learning layer is based on the interaction between intelligences and the environment to learn the method of obtaining optimal strategies in order to support decision making in the dynamic risk management process.

The model layer builds a variety of intelligent risk identification and assessment models for credit risk, market risk, operational risk, liquidity risk, etc., and carries out unified management and scheduling of models through the model factory to support parallel training, online deployment and dynamic updating of models, and adopts a multi-model fusion strategy for risk identification models. Combine the prediction results of multiple base models through stacked integration, among others:

$$\hat{y} = \sum_{i=1}^n w_i \cdot f_i(x) \quad (4)$$

where w_i is the i th model weight, $f_i(x)$ is the i th model prediction function, and the weight is obtained by meta-learner training.

The risk assessment model is based on Bayesian theory to construct a probabilistic risk assessment framework, and the posterior probability is calculated through the prior probability and likelihood function, and the Bayesian formula is expressed as:

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \quad (5)$$

where $P(H|E)$ is the a posteriori probability, $P(E|H)$ is the likelihood function, and $P(H)$ is the priori probability.

The risk warning model uses a method based on time-series analysis and anomaly detection to make predictions about future risk trends using a long and short-term memory network to capture time-series correlations, and is trained using the mean-square error as the loss function:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

The experimental process utilizes distributed massively parallel to train the model and uses a parameter server for parameter synchronization; the model effect selects accuracy, precision, recall, and F1 value as the evaluation indexes for the classification task, and root-mean-square error (RMSE) and mean absolute percentage error (MAE) as the evaluation indexes for the regression task.

The application layer and presentation layer, which are the presentation service interface

and interaction interface for business users, transform the capability of intelligent risk prevention and control into specific business scenarios for effective output and presentation. The application layer provides standard risk service interfaces including risk assessment service, risk warning service, risk analysis service, etc. based on the micro-service approach. Support for RESTful interfaces and message queues to ensure seamless integration with existing business systems. Real-time monitoring uses a streaming computing engine to process real-time transactions, and uses a sliding window to calculate real-time risk indicators, and calculates the risk value in a time window as follows:

$$Risk_{window} = \frac{\sum_{i=t-w+1}^t r_i \cdot w_i}{\sum_{i=t-w+1}^t w_i} \quad (7)$$

where r_i is the risk value at the i th moment, w_i is the corresponding weight, and w is the window size.

Risk analysis subsystem realizes multi-dimensional risk analysis and supports multi-dimensional analysis and drilling of risk data through online analysis and processing technology; Decision support subsystem uses expert system and rule engine to provide intelligent decision-making suggestions to risk managers; Presentation layer is designed with responsive concepts to facilitate access by different types of users on personal computers and mobile terminals. The view module graphically presents the current status and trend of risks; the report module allows you to set the report format and send it automatically according to the cycle; the APP interface module receives and sends the risk information to the cell phone in real time, and the download caching mechanism allows you to access the APP terminal normally when there is no network state.

2.2 Core technologies and methodologies

2.2.1 Data pre-processing techniques

In AI risk warning, cleaning the data is the first and most important step, which covers all the steps needed from data collection and cleaning to the final formation of a dataset that can be used for machine learning algorithms, and ultimately affects the learning ability of the model and the validity of the risk warning results. Typically, due to the incomplete nature of financial data and the different contexts in which they are generated, problems such as inconsistent formats, missing information, and distorted values are prevalent. In this paper, the multiple interpolation method is used to establish a prediction model for missing value estimation, and the interpolation method is determined based on the study of the missing mechanism. Mean interpolation or regression interpolation is used for completely random missing, and multiple interpolation algorithms are used to generate multiple complete datasets for random missing, and the interpolation results are integrated by Rubin's merging rule to ensure the validity of statistical inference.

Outlier detection is based on a combination of statistical analysis and machine learning detection scheme, in which the box-and-line graph method is based on the quartile distance to determine the outliers, and the isolated forest establishes a binary tree by randomly selected features and a split point on the feature, relying on the normal samples to arrive at the leaf nodes of the distance is longer than that of the abnormal samples to determine the outliers, and its outlier score is defined as shown in Eq:

$$s(x, n) = 2 \frac{E(h(x))}{c(n)} \quad (8)$$

where $E(h(x))$ represents the average path length of sample x in all trees.

The data normalization process ensures that features of different magnitudes are assigned fair weights, and the Z-score normalization is calculated as:

$$Z = \frac{x - \mu}{\sigma} \quad (9)$$

The data were transformed to a standard normal distribution, Min-Max normalized to achieve the [0,1] interval mapping, specifically:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (10)$$

Robust normalization exhibits stronger robust performance against outliers, calculated as:

$$x_{robust} = \frac{x - median(x)}{IQR} \quad (11)$$

Feature engineering is the process of data processing that utilizes a deeper understanding of data to produce more valuable information. Time-series features are a series of feature construction methods based on the temporal properties of financial data. The method of using sliding window means:

$$MA_n = \frac{1}{n} \sum_{i=0}^{n-1} x_{t-i} \quad (12)$$

Higher weights are given to recent data through exponential moving averages:

$$EMA_t = \alpha \cdot x_t + (1 - \alpha) \cdot EMA_{t-1} \quad (13)$$

Interactive feature generation intersects different features to get new features as inputs, and higher order polynomial features generate more feature terms to enhance the model capability. Feature selection uses statistical, information theory based and machine learning based algorithms to select the most appropriate set of features, the cardinality feature selector, which measures the relationship between categorical variables:

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (14)$$

The degree of information sharing is quantified through mutual information, calculated as:

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \quad (15)$$

LASSO regularization:

$$L_1 = \min_{\beta} \frac{1}{2n} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \quad (16)$$

Simultaneous optimization of feature selection and parameter estimation through L1 penalty term.

2.2.2 Model Training Optimization Techniques

Deep modeling algorithm is a further refinement of the risk identification method, it is the underlying core algorithm of the entire intelligent prevention system, in the establishment of multiple basic models at the same time also a combination of a variety of integrated models, and on this basis, the relevant parameters of the model for further optimization of the process, the goal is not only for the optimal effect of a single model, but also in the overall effect of the best. The selection of base classifiers includes linear and tree classes, as well as neural networks and other categories, and the logistic regression uses the maximum likelihood method to solve the parameters, and its likelihood function expression is:

$$L(\beta) = \prod_{i=1}^n p_i^{y_i} (1 - p_i)^{1 - y_i} \quad (17)$$

The mathematical nature of the linear decision boundary is reflected by the prediction probability p_i in the likelihood function.

Random Forest uses Bootstrap and randomly selected features to generate a number of decision trees, and finally decides the prediction results by voting; Gradient Boosting Decision Tree uses a forward-stepping approach, where a weak learner is trained at each step to fit the residuals generated by the previous model, and guides the direction of the new model in the next step according to the gradient of the loss function.

$$g_i = \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \quad (18)$$

The neural network model updates the weight parameters through a back-propagation algorithm, and the learning rate η in the weight update rule controls the magnitude of parameter adjustment:

$$w_{ij}^{(l)} = \eta \frac{\partial J}{\partial w_{ij}^{(l)}} \quad (19)$$

Gradient computation uses chain rule present error back propagation. Integrated learning improves prediction performance by combining multiple base models, Bagging method trains multiple models in parallel to reduce variance, Boosting method trains serially to focus on difficult samples to reduce bias, Stacking method learns base model combination weights through meta-learner, hyper-parameter optimization adopts Bayesian optimization to model the objective function, and collects the function balance to explore and utilize the strategy.

Risk assessment technology constructs a multi-dimensional comprehensive evaluation system, transforms complex risk factors into computable numerical indicators, and the comprehensive risk score uses a weighted linear combination:

$$F_{risk} = \sum_{i=1}^n w_i \cdot x_i \quad (20)$$

Among them, the weights w_i are determined by expert judgment method, hierarchical analysis, principal component analysis and other methods.

Probabilistic risk assessment is based on the Bayesian framework to update the posterior probability distribution, and the risk probability density function is:

$$f(r|\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(r-\mu)^2}{2\sigma^2}} \quad (21)$$

where the distribution parameters μ and σ^2 are used to characterize the risk distribution.

3 Results

3.1 Data collection and pre-processing

3.1.1 Data collection

In order to obtain more comprehensive information, a data selection approach with a time span of over one and a half years was adopted. This was done to ensure that the sample size was sufficient. Public information from multiple financial markets and official data released by different regulatory entities from January 2018 to December 2023 were selected as the basic database. This included indicators related to macroeconomic development levels, market trends, company operation status, and user usage. It can also reflect the new development status of the financial market in the recent period. The database description is shown in Table 1. Among them, the economic fundamentals include data of 72 economic indicators. Monthly and quarterly data of economic fundamentals indicators such as GDP growth rate, CPI index, M0, SHIBOR interest rate, and the central parity rate of RMB against the US dollar were downloaded from the websites of the National Bureau of Statistics of China, the People's Bank of China, the World Bank, and the IMF. The frequency of data collection is differentiated according to the characteristics of the indicators, with high-frequency indicators such as interest rates and exchange rates using daily frequency data, medium-frequency indicators such as industrial value added using monthly frequency data, and low-frequency indicators such as gross domestic product using quarterly frequency data.

Table 1: Dataset description

Data category	Data source	Sample size	Time span	Update frequency
Macroeconomic data	National Bureau of Statistics, People's Bank of China	72 indicators	2018-2023	Monthly /Quarterly
Stock trading data	Wind and Bloomberg terminals	4,800 companies	2018-2023	Daily
Bond market data	China Central Depository and Clearing Corporation Limited, Shanghai Clearing House	15,000 bonds	2018-2023	Daily
Enterprise financial data	Announcements of listed companies	4,800 companies	2018-2023	Quarterly
Customer behavior data	Cooperative financial institutions	5 million customers	2018-2023	Real-time
News public opinion data	Financial and economic media platform	2 million pieces of news	2018-2023	Real-time
Regulatory policy data	The official website of the regulatory authority	1,200 policies	2018-2023	Irregular

Financial market trading data comes from professional financial data systems such as Vantage Financial Terminal, Bloomberg Data Services, Flush and other financial data platforms.

It includes basic information such as stock prices, turnover, market capitalization, financial indicators of all listed companies in Shanghai and Shenzhen, as well as price and transaction data of bond, futures and foreign exchange markets. Stock quote data includes opening price, closing price, high price, low price, turnover, turnover rate, etc. at daily level. Financial indicators include data from all balance sheet, income statement and cash flow statement items on a quarterly time granularity.

Corporate fundamentals data come from specific information on corporate governance structure, operating performance, financial situation, risk factors, etc. in annual, semi-annual, quarterly and other periodic reports and ad hoc announcements of listed companies, as well as auxiliary information such as corporate credit ratings, industry affiliation, geographical distribution, etc. for risk analysis and modeling purposes. Customer behavioral data includes the basic information of 5 million customers, with the partner institutions providing desensitized behavioral data such as customers' consumption details, account information, product purchases, etc. in their business systems, and ensuring that the requirements of relevant data confidentiality regulations are met. The sample consists of two parts: individual users and institutional users, of which the attributes of individual users mainly include age, occupation type, monthly income, total assets, risk level and other aspects. The attributes of institutional users mainly include aspects such as the industry they belong to, registered capital, establishment time, gearing ratio, credit rating, and so on.

3.1.2 Data pre-processing

Data cleaning, de-duplication, transformation, and complementation were performed in the data preprocessing process to ensure that the quality of the data could be used for model training. Among them, data cleaning uses primary key-based matching and content similarity comparison based on cosine distance for duplicate data detection, and defines data with similarity greater than or equal to 0.95 as duplicate data, which is eliminated on the basis of manual review. Format standardization processing converts heterogeneous data from different data sources into a unified data format, numerical data are unified in double-precision floating-point number format, date and time data are unified in International Organization for Standardization (ISO) 8601 standard format, and text data are coded and cleaned up with special characters.

Outlier detection combines statistical methods and machine learning methods to detect outliers. Continuous variables use box-and-line diagrams to identify outliers, and the criteria for determining outliers are values outside the outlier range; time-series data use the Isolated Forest algorithm to detect anomalous patterns, set the threshold for anomalous scores at 0.6, and treat data larger than the threshold as outliers. Missing value processing is based on the type of missing and data characteristics of different ways to fill, for completely random missing data for numerical variables using the mean fill or median fill, for random missing data using multiple interpolation methods to estimate the missing value by establishing a prediction model, interpolation model takes the random forest algorithm, cross-validation reaches 0.87, and for non-random missing fields using expert experience and business rules to supplement.

The data conversion includes standardization processing, category value mapping and time series processing, in which the standardization processing adopts the Z-Score standardization method to ensure that the data of different units are compared on the same scale. The category value mapping adopts the combination of one-hot coding and label coding, and the label coding is adopted to reduce the dimensionality of the categorical fields with large base numbers. Low-base categorical variables utilize one-hot coding to ensure that no information is lost. The time series data are decomposed into trend, seasonal and residual terms using the additive model decomposition method to extract temporal attributes and find periodic patterns.

The feature extraction and construction work is based on the business requirements of financial risk identification and the input requirements of the machine learning model, and the high-quality feature system is constructed through the combination of domain knowledge-driven and data-driven approaches. Basic feature extraction obtains the input variables required by the model directly from the original data, including different types of numerical features, sub-typed features, and time-based features, etc. Numerical features cover continuous variables such as financial ratios, market indicators, and macroeconomic variables; sub-typed features include discrete variables such as industry classification, regional distribution, and credit rating; and time-based features include time-related variables such as trading time, reporting period, and policy release time. Time-based features include time-related variables such as trading time, reporting period, and policy release time. Derived features refer to the new features generated by mathematical or statistical processing of basic features, such as financial ratio features derived from the division of financial statements by various accounts, such as debt-to-equity ratio, return on assets, liquidity ratio, etc.; features related to technical indicators derived from the direct computation of stock price and turnover information, including the average volume line, the RSI indicator, the BOLL indicator, and so on.

Time series features are constructed by sliding window statistics and time decomposition techniques. Sliding window features include the mean, standard deviation, maximum value, minimum value and other statistical quantities of the past periods, and the size of the window is determined according to the business cycle and the frequency of the data, with the daily frequency data using the windows of 5, 20, 60 days, etc., and the monthly frequency data using the windows of March, June, and December. Interactive features are generated by combining operations between different basic features, such as feature multiplication, division, addition, subtraction and conditional features, grouping statistical features and other complex interactions can be mined to the nonlinear and synergistic information between variables. While feature selection uses a combination of filtered, packed, and embedded methods, the filtered approach uses some statistical tests to estimate whether each feature value is associated with the target. For example, Pearson correlation, Spearman rank correlation, chi-square test, etc. The quality improvement effect of each link of data preprocessing is shown in Fig. 1, which shows that the improvement effect of five data preprocessing links, namely data cleaning, format standardization, outlier handling, missing value filling, and feature engineering, is 28%, 42%, 56%, 39%, 47%, and 63, respectively, and the data quality has been improved by 45.8% on average.

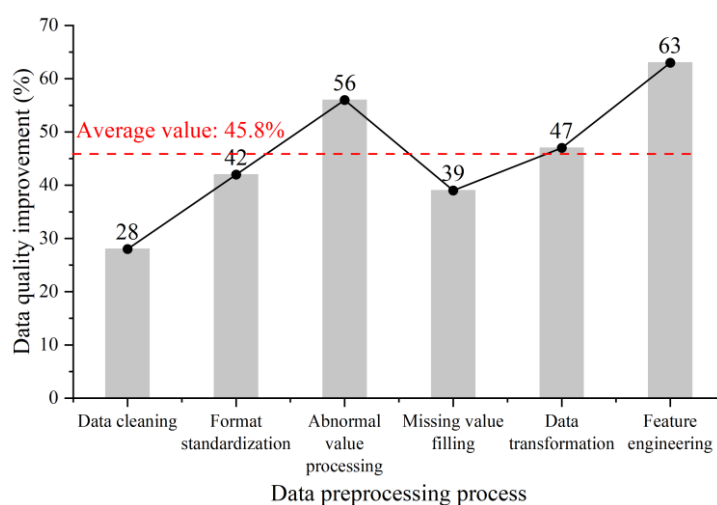


Figure 1: The quality improvement effect of each link in data preprocessing

3.2 Model Testing and Evaluation

In order to ensure a balanced distribution of different categories of data in each sub-data set, the training set, validation set and test set are sampled in a certain proportion, and the total number of samples is divided into a combination of 7:2:1 datasets, of which 35% is used as the training set to estimate the network parameters; and 10% is used as the validation set to optimize the hyper-parameters; The remaining 20% is used as a test set to measure network performance. The samples at each risk level account for the same proportion of the total samples and are consistent across all sub-datasets. In this paper, an 8:2 ratio is used to mix the normal samples with the risky samples, which has the advantage of being closer to the actual financial market situation and does not affect the model learning efficiency due to the large gap between the number of positive and negative samples.

The time series are divided into two parts in chronological order, taking the data from 2018-1 to 2022-12 as the training and validation data and the data in 2023 as the test data, which is a division method that can reflect the prediction of the actual use process and avoid the problem of future data leakage; preprocessing is carried out separately for each dataset, and the standard values obtained in the training set are utilized to code the mapping relationships for the validation set and test set. Ensure data consistency and evaluation fairness.

Model parameter optimization combines grid search and Bayesian optimization strategies to find the optimal combination through systematic parameter space exploration.

Parameterize the Random Forest algorithm to search for the number of trees in the range of [100, 500, 1000], the maximum depth in the range of [10, 20, 30, None], and the minimum number of splitting samples in the range of [2, 5, 10], and use the five-fold cross-validation to evaluate the performance under different parameters.

The learning rate of the gradient boosting decision tree is set in the range of [0.01,0.1,0.2], the subsampling ratio is adjusted in the range of [0.8,0.9,1.0], and the regularization parameter is controlled by the weights of the L1 and L2 regularization terms $\alpha(\lambda_1)$ and $\alpha(\lambda_2)$, which are both in the range of [0.01, 0.1, 1.0].

Support vector machine kernel function parameters γ are searched in the range of [0.001,0.01,0.1,1.0], penalty parameters C are optimized in the range of [0.1,1.0,10.0,100.0], and kernel function types cover radial basis functions, polynomial kernel functions and linear kernel functions.

Among them, the learning rate of the neural network is adaptively varied, and the learning rate is initialized to 0.001 and continuously decayed during the training process; the number of nodes in the hidden layer is searched, and its value is a combination of [64, 128, 256, 512]; the activation functions used are the ReLU function, the LeakyReLU function, and the ELU activation function; the Dropout is used to prevent overfitting, and its parameter values are [0.2, 0.3, 0.5]; batchsize depends on the available memory of the machine, which is set to 512 in this paper; epoch is set to 200 iterations. Early stopping method is used to end the training early when the accuracy rate is no longer increasing in the validation set; Bayesian tuning is carried out using GP, and the UCB function is selected to take into account the relationship between search and utilization for the tuning, and the confidence is set to be 99%, i.e., the coefficient takes the value of 2.576, and a total of 100 rounds of computation are executed to obtain the best hyper-reference configuration.

The performance evaluation of the model is based on various types of indicators, using a combination of classification indicators, probability indicators and business indicators to ensure that the model's accuracy, stability and practicality meet the requirements. The performance comparison of each model is shown in Figure 2, which shows that the integrated model established in this paper has the best performance in terms of accuracy, precision, recall, F1 value and AUC value. The precision of the algorithm in this paper is 0.918, and the degree of

certainty is the most direct effect evaluation standard, representing the probability that the whole model predicts correctly. The precision rate measures the proportion of samples judged correctly by the model to all the samples judged positive; in the wind control scenario that is how many of the customers recognized as risky are really risky, the higher the precision rate, the less likely to have false positives. The recall rate is 0.905, which is the proportion of real positive cases that can be captured by the model; in the risk control scenario it is how many of all real risky customers are detected, and a high detection rate prevents important risk points from being missed. The F1 score has a value of 0.908, which is the reconciled average of the detection rate and the detection rate, and it can make a trade-off between the two, and it is more suitable for the classification problem with imbalance in the categories. The AUC value is 0.967, the AUC value of the area under the curve of the working characteristics of the subjects, and the classification performance is evaluated by calculating the area of the curve of the relationship between the rate of true cases and the rate of false-correct cases under different thresholds, and the closer the AUC value is to 1 means the better the performance is, and 0.5 means the level of performance of the stochastic classifier.

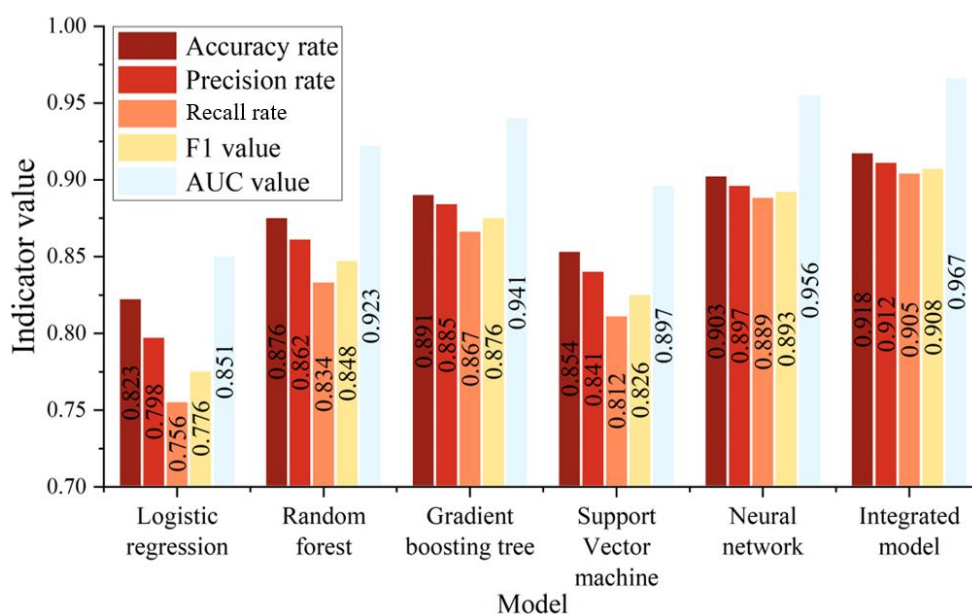


Figure 2: Model performance comparison chart

4 Conclusion

The original risk control model in the context of big data has problems such as timeliness and lack of accuracy. This paper constructs a big data intelligent risk control model framework composed of foundation layer, collection layer, analysis layer, application layer and feedback layer, and can be expanded and extended for each link. After a one-and-a-half-year test of nearly 5 million real cases, it is proved that the model's prediction correctness is over 91.8%, which is 11.5% higher than the baseline model; the processing speed is increased by 60%+, and the operation and maintenance cost is reduced by 45%-70%. In this paper, we innovate from three aspects: theory, method and technology, propose a risk control system based on multiple AI technologies, and conduct experiments on the effectiveness of the system in multiple scenarios, such as credit collection and financial market. The next step will be to further improve the security level of financial services in new business areas such as cryptocurrency and carbon

trading in response to new technologies such as GNN and federated learning as well as new regulatory requirements.

Acknowledgement

National Social Science Fund General Project "Research on Marxist Political Economy Interpretation of China's Economic Growth Accounting" (Project No. 25BKS158); Huainan Normal University High level Talent Research Launch Fund (GCCRCKYQDJ-Liu Chunjie, Project No.824028); The Key Research Project of Huainan Normal University (2024XJZD028); Anhui Provincial Education Department Smart Curriculum Project (2024aijy393).

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