# Research on Internet Financial Risk Control Based on Deep Learning Algorithms with Human-Computer Interaction

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**Abstract.** To improve the effect of Internet financial risk control, this paper combines the deep learning algorithm to construct the Internet financial risk control system. Moreover, this paper identifies Internet financial risks, formulates control strategies through the system, and calculates the option price and implied volatility embedded in financial products. In addition, this paper further discusses the effect of the issuer's delta dynamic hedging and hedging operations under different scenarios under implied volatility. Finally, this paper uses the deep learning model to predict the volatility of stock returns during the duration and constructs the corresponding deep learning model framework. The simulation results show that the Internet financial risk control system based on the deep learning algorithm proposed in this paper has sound effects and can be applied to Internet financial risk control.

**Keywords:** deep learning; internet; finance; Human-Computer Interaction; risk control;
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## 1 INTRODUCTION

With the continuous development of AI machine learning, natural language processing, knowledge graph, and other technologies, as well as the constant improvement of algorithms, data, and hardware processing capabilities, financial risk control has gradually entered the stage of intelligence. The system design of advanced technology at home and abroad not only has the characteristics of modularization, parameterization, and standardization, but also the system after construction, the advantages of normative, advanced, forward-looking, security, high efficiency, practicability, reliable, flexible, and expandability after construction. Integrating stream computing technology, machine learning, graph analysis, natural language processing, biometric identification technology, etc., can improve the existing decision-making engine's computing power level and processing time in a higher-level intelligent risk control decision-making system. With the innovation of technology, the future risk control decision-making system will evolve towards a more thoughtful, complete, and efficient omnichannel, all-scenario, and all-time risk control real-time intelligent decision-making system.

As a customer-oriented, cross-channel, cross-product, and full-process bank-level risk control platform, intelligent risk control realizes customer access control beforehand, transaction warning and interception during the event, batch detection, and risk analysis after the event. Multi-level, all-scenario intelligent risk control is realized through terminal risk identification capability, indicator platform, and thoughtful decision-making functions. Terminal risk identification mainly collects non-sensitive information such as device hardware, environment, and network through technologies such as device fingerprints and produces a unique ID for each device. In addition, it can identify the abnormal environment of the device, generate a device risk label, and mark the potential fraud risk of the device for analysis and decision-making. At the same time, various security measures such as anti-cracking, anti-debugging, and anti-replay are adopted to dynamically and continuously fight against fraudulent behaviors. Practical risk prevention and control benefits from data, and rapid data collection is the first step in dealing with dishonest behavior. The indicator platform innovatively applies technologies such as streaming computing, big data, artificial intelligence technology, device fingerprint technology, and behavioral feature learning to realize the extraction, storage, and calculation of real-time and batch transaction data, unify standards and calibers, and realize the commercialization of data assets. It meets the service and policy model requirements of different timelines and scenarios. It provides essential support for recognizing the effect of the decision-making engine on the decision-making process. The intelligent decision-making layer is the center of various data, rules, and model summarization calculations.

Therefore, building a global intelligent risk control decision-making center is necessary to realize intelligent risk control of echelon defense. The risk control platform builds an echelon defense system with pre-event customer access control, mid-event transaction warning and interception, post-event batch detection, and risk analysis [1]. Through the integration of internal and external list data, equipment environment data, real-time transaction data, and customer behavior data, cross-channel and cross-business user behavior tracking is realized [7]. Moreover, the decision engine, risk control strategy, and Model comprehensively evaluate the user behavior risk, carry out different risk disposal, and realize the overall intelligent risk control decision [2]. The rise of internet-based financial services has introduced new risks, such as fraud and data breaches. Traditional risk control methods need help to keep pace with these challenges. Deep learning algorithms offer promise for analyzing complex financial data to detect and prevent risks. Effective Human-Computer Interaction (HCI) is also crucial for ensuring user trust and usability. Integrating E-commerce into these financial services adds another layer of complexity and opportunity, as E-commerce platforms require robust security measures to protect transactions and user data. This research aims to integrate deep learning algorithms with HCI principles and E-commerce strategies to enhance internet financial risk control and the user experience. The study addresses the specific needs of online marketplaces and financial transactions by incorporating E-commerce elements. Through this study, we aim to develop secure, user-friendly, and efficient online financial systems where E-commerce and HCI work together to provide users with a seamless and trustworthy experience. This paper combines the deep learning algorithm to build an Internet financial risk control system, identify Internet financial risks, and formulate control strategies to improve Internet finance's anti-risk ability.

## 2 RELATED WORK

Consumer finance loans, particularly Internet-based consumer finance loans, are prone to credit risks such as default and fraud, which bring many challenges to the credit risk management of Internet financial institutions and commercial banks [19], especially for groups with insufficient credit records such as consumer loans. The traditional central bank credit information makes it challenging to identify the credit risk of borrowers effectively. The introduction of more high-frequency data on e-commerce consumption behavior and the help of big data technology can effectively reduce information asymmetry and improve the credit risk identification of people with insufficient traditional credit information [8]. Therefore, establishing a scientific and practical risk control system based on big data, especially a consumer personal credit scoring system to accurately predict the default probability of borrowing customers, is essential for commercial banks and Internet finance companies to manage lending risks. Unsecured, pure credit lending, small quotas, and scattered customers characterize consumer credit. It is positioned in the long-tail market. The difficulty and cost of post-loan supervision are relatively high. Therefore, pre-loan credit assessment is used by financial institutions to reduce information asymmetry and is an essential means of controlling credit risk [3]. The essence of credit evaluation is dividing loan customers into different groups according to their characteristics, compared with manual review analysis in literature [9]. Using credit scores, financial institutions can better predict the default rate of borrowing customers, and loan default rates can drop by 50% or more. From the perspective of credit scoring methods, the most used methods include discriminant analysis, logistic regression, support vector machines, classification trees, and neural networks. Academics and industry have been widely concerned with logistic regression due to its simple calculation method, good prediction effect, and strong model interpretability [14]. However, traditional credit scoring methods often divide customers into "non-defaulting customers" and "defaulting customers" and then build a credit scoring system based on binary statistical methods. However, in practical applications, sometimes the distinction between "non-defaulting customers" and "defaulting customers" does not necessarily have an obvious boundary, and some customers' lending risk is between "non-defaulting customers" and "defaulting customers." Customers are usually referred to as "gray customers"; that is, the default risk of three types of customers has an orderly relationship of "default customers" > "gray customers" > "non-default customers" [12]. Because the risk of "gray customers" is not easy to accurately identify by the Model and its characteristics are unstable, financial institutions often directly delete the "gray customers" samples during modeling and analysis and then use the binary classification method in statistics and machine learning to construct the Model. The main problem of this method is that it does not fully utilize all the sample data; that is to say, the sample data of "gray customers" is not used in the Model. This will bring about the problem of sample selection bias, which will affect the estimation results of the model [6]. Reference [20] builds a credit scoring model dealing with three or more ordered response variables.

With the development of information technology, there are more and more sources of information, and the dimension of data is getting higher and higher. For example, the variable dimension of personal information that can be collected in the risk control of consumer finance companies can often reach hundreds of thousands or even tens of thousands. High-dimensional data is usually sparse, with much noisy information; only a few independent variables are significant to the dependent variable, and most independent variables are insignificant [10]. If they are not screened during modeling, too many variables will be introduced, theoretically making the Model unstable and significantly reducing estimation and prediction accuracy. From the application point of view, data acquisition of independent variables often requires a specific cost. If some unnecessary or unimportant independent variables are included in the Model, this will inevitably bring unnecessary economic waste to practical applications. Therefore, it is necessary to screen independent variables in statistical modeling. For the variable selection of high-dimensional ordered multi-classification models, traditional methods include the optimal subset method, stepwise (forward, backward) regression method, etc. Still, these methods have high computational costs, lack stability, and are very sensitive to small changes in data. Sensitive.

Reference [16] proposes a continuous ratio model based on z-penalty, adding z-penalty terms to the loss function of the constant ratio model so that the Model can also screen variables while estimating the coefficients. Still, this method does have A strong constraint; that is, it is assumed that the coefficient values of the same variable in different sub-models are equal. This assumption is too strong and often inconsistent with consumer finance risk control. In addition, high-dimensional ordinal multi-classification models usually involve two or more sub-models. The coefficients between these submodels tend to have group effects. Because credit-scoring variables have group or structure effects, some scholars have applied group or variable selection methods considering my country's network structure relationship between variables to credit scoring [4]. Aiming at the ordered multi-classification and high-dimensional problems in credit scoring, literature [15] proposed a continuous ratio model with a sparse structure, which considered the group effect of coefficients between sub-models and allowed the coefficients of different sub-models to be different.

## 3 INTERNET FINANCIAL RISK RESEARCH

Investors who buy wealth management products are equivalent to buying a combination of bonds and call options, with the product issuer holding the short position. In E-commerce, these products can be managed and sold online, enhancing accessibility. Effective Human-Computer Interaction (HCI) is crucial in designing these e-commerce platforms to ensure user-friendly interfaces, clear information, and smooth transactions, thereby improving the investor experience and building trust. The issuer is the seller of part of the income of the option, so it must be hoped that the higher the option value, the better; that is, the higher the set implied volatility, the better. This implied volatility can be calculated from the participation rate b to calculate the option value $C\ S_0$ and then reversed by the Black-Scholes formula.

At the beginning of the duration period, when the issuer sells one bond and $\frac{b}{S_0}$ European call options $C_0$, The principal can be received:

$$N = \mathrm{Bond} + \frac{b}{S_0} \times C_0 \tag{1}$$

For the convenience of empirical analysis, N is set to 1, which will not affect the final result. Bond's initial price of zero-coupon bonds, $Bond = N \times e^{-rT} = e^{-rT}, r$ represents the market interest rate (annualized), T is the product term, and S0 is the closing price of the underlying asset on the day before the product start date[18].

$$C_0 = \frac{S_0\ 1 - \mathrm{Bond}}{b} = \frac{S_0\ 1 - e^{-rT}}{b} \tag{2}$$

When the option price is determined, the relevant parameters are then substituted into the Black-Scholes option pricing formula shown below, and a reliable program can calculate the implied volatility of the options part of the product.

$$c_0 = S_0 N\ d_1\ - K e^{-rT} N\ d_2 \tag{3}$$

$$d_1 = \frac{\ln\ S_0 / K\ +\ r + \sigma^2 / 2\ T}{\sigma\sqrt{T}} \tag{4}$$

$$d_2 = d_1 - \sigma\sqrt{T} = \frac{\ln\ S_0 / K\ +\ r - \sigma^2 / 2\ T}{\sigma\sqrt{T}} \tag{5}$$

Using the Brown Bridge process to simulate the stock price sequence can fix the prices at both ends of the path, and the volatility of the simulated stock price sequence can be changed by changing the volatility parameters in the process. The following formula can be used in the specific simulation:

$$S\ t\ = S\ 0\ e^{\frac{t}{T}\log\left(\frac{S\ T}{S\ 0}\right)+\sigma\left(W^*\ t - \frac{t}{T}W^*\ T\right)} \tag{6}$$

The GARCH family of models is one of the most popular methods for forecasting volatility in time series. The volatility of the underlying assets during the duration of this paper will be estimated by the GARCH(1,1) model. Apart from the sameness as other regression models, GARCH(1,1) further models the variance of the error, and its expression is[11]:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{7}$$

In GARCH (1,1), $\sigma_n^2$ is calculated from the long-term mean-variance $V_L$ and $u_{n-1}$ and $\sigma_{n-1}$, and (1,1) means that $\sigma_n^2$ is calculated from the most recent observation of $u_n^2$ and the latest variance. Since the sum of the weights is 1, there is $\gamma + \alpha + \beta = 1$.

When $\omega = \gamma V_L$, we can write the GARCH (1,1) model as:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{8}$$

The expression of this Model is for parameter estimation. When $\omega$, $\alpha$, and $\beta$ are estimated, we can calculate $\gamma$ and long-term variance $V_L = \omega / \gamma$ from $\gamma = 1 - \alpha - \beta$.

The GARCH (1,1) model decreases the weight of $u^2$ Exponentially. In the past, it has given some weight to the long-term average floating rate.

Over time, the variance in the GARCH (1,1) model is pulled back to its long-term average $V_L$. The GARCH(1,1) model is equivalent to the following stochastic process concerning V and has mean-reverting properties:

$$dV = a\ V_L - V\ dt + \xi V dz \tag{9}$$

Among them, time is in days, $a = 1 - \alpha - \beta$, and $\xi = \alpha\sqrt{2}$. The variance is dragged back to $V_L$ with velocity a when $V > V_L$ and the drift rate of variance is unfavorable. However, when $V < V_L$, The drift rate of the variance is positive, and the Model adds volatility $\xi$ to the drift rate[5].

The Delta($\Delta$) variable is the ratio of the option's price change to the underlying asset's price change, namely $\Delta = \frac{\partial c}{\partial S}$, where c is the call option price, and s is the underlying stock price.

The stock price movement process conforms to geometric Brownian motion, so the stock price movement process is as follows[13]:

$$dS = \mu S dt + \sigma S dW \tag{10}$$

$$\frac{dS}{S} = \mu dt + \sigma dW \tag{11}$$

$X\ t$ represents the portfolio of assets held by the issuer at the time t using the Delta dynamic hedging strategy. It consists of a short A-call option $C_t$, a long of $\Delta\ t$ of the underlying stock $S_t$, And the current full account M, namely:

$$X_t = \Delta_t S_t - C_t + M_t \tag{12}$$

We get:

$$M_t = X_t + C_t - \Delta_t S_t \tag{13}$$

Among them, $\Delta\ t$ has an analytical solution,

$$\Delta_t = \frac{\partial c}{\partial S} = N\ d_1 \ = C_s^{'}\ \sigma_h \tag{14}$$

$$d_1 = \frac{\ln\ S_0 / K\ +\ r + \sigma^2 / 2\ T}{\sigma\sqrt{T}} \tag{15}$$

Portfolio X conforms to the following process:

$$dX = rXdt + \ \sigma_t^2 - \sigma_h^2\ \frac{S_t^2}{2}\mathrm{Gamma}\ \sigma_h\ dt \tag{16}$$

$$\mathrm{Gamma} = \frac{\partial \Delta}{\partial S} = \frac{\partial^2 c}{\partial S} = \frac{N'\ d_1}{S_0 \sigma \sqrt{T}} \tag{17}$$

Among them, $\sigma_h$ is the volatility used to calculate $\Delta_t$ when hedging, and $\sigma_t$ is the actual volatility of the underlying asset in the market during the duration. In this paper, $\sigma_h$ is a constant and has a fixed value, that is, the implied volatility $\sigma_{iw}$ of the option part sold by the product issuer. When $\sigma_h = \sigma_{iw}$, the theoretical value of the hedging portfolio after dynamic hedging is:

$$\mathrm{rofit} = \int_0^T e^{r\ T-t}\ \ \sigma_{im}^2 - \sigma_t^2\ \frac{S_t^2}{2} Gamma\ \sigma_h\ dt \tag{18}$$

The nonlinear risk of the income part is mainly determined by the relative magnitude of the implied volatility of the product option part, the actual volatility of the stock, and the Gamma value of the option. Furthermore, the gamma value of an option is also related to the implied volatility of the options portion of the product.

In discrete time, $X_k$ represents the value of the hedged portfolio at time k, and $\Delta_k$ represents the stock position in the hedged portfolio between time k and time k+1. After the rebalancing at time k, the stock position changes from $\Delta_{k-1}$ to $\Delta_k$, the cash account (money market account) is $X_k - S_k\Delta_k$, and the value of the hedge portfolio at time k+1 is $X_{k+1} = \Delta_k S_{k+1} + (1+r)(X_k - \Delta_k S_k)$. After sorting it out, we get:

$$X_{k+1} - X_k = \Delta_k (S_{k+1} - S_k) + r(X_k - \Delta_k S_k) \tag{19}$$

The above formula shows that the portfolio's income from time k to time k+1 is the addition of the capital interest income $\Delta_k (S_{k+1} - S_k)$ of the stock position and the interest income $r(X_k - \Delta_k S_k)$ of the money market account.

$$\text{Continuous time}: dX(t) = \Delta(t)\,dS(t) + r\big(X(t) - \Delta(t)S(t)\big)dt \tag{20}$$

At any time, k, the value of a money market account share is defined as $\mathrm{M_k} = (1+\mathrm{r})^{\mathrm{k}}$, Where r is the interest rate. $\Gamma_k$ represents the number of money market accounts after rebalancing at time k, and the portfolio value at time k becomes $X_k = \Delta_k S_k + \Gamma_k M_k$. Before rebalancing at time k+1, there are:

$$X_{k+1} = \Delta_k S_{k+1} + (1+r)\Gamma_k M_k = \Delta_k S_{k+1} + \Gamma_k M_{k+1} \tag{21}$$

The above two equations are subtracted to get:

$$X_{k+1} - X_k = \Delta_k (S_{k+1} - S_k) + \Gamma_k (M_{k+1} - M_k) \tag{22}$$

The gain between time k and time k+1 is the sum of the stock gain and the change in the money market account. After rebalancing adjustment at time k+1, we can get:

$$X_{k+1} = \Delta_{k+1} S_{k+1} + \Gamma_{k+1} M_{k+1} \tag{23}$$

Combining (23) with (21), the self-financing condition in discrete cases can be obtained, namely:

$$S_{k+1}(\Delta_{k+1} - \Delta_k) + M_{k+1}(\Gamma_{k+1} - \Gamma_k) = 0 \tag{24}$$

The above formula can be transformed and rewritten as[20]:

$$\left.\begin{aligned} & S_k \ \Delta_{k+1} - \Delta_k \\ & + \ S_{k+1} - S_k \ \ \Delta_{k+1} - \Delta_k \\ & + M_k \ \Gamma_{k+1} - \Gamma_k \\ & + \ M_{k+1} - M_k \ \ \Gamma_{k+1} - \Gamma_k \\ & = 0 \end{aligned}\right\} \tag{25}$$

Similarly, in continuous time, the self-financing condition is:

$$S \ t \ d\Delta \ t \ + dS \ t \ d\Delta \ t \ + M \ t \ d\Gamma \ t \ + dM \ t \ d\Gamma \ t \ = 0 \tag{26}$$

We assume the hedging transactions studied in this paper occur under ideal conditions. Daily hedging can be achieved during the product's life without considering the cost of hedging transactions. The duration T is divided into 63 parts, each one day long. The time interval is $\Delta t = 1$ day=1/252 years (the number of tradable days per year is about 252 days).

At the beginning of the period, the product issuer sells one bond and $b / S_0$ European call options have the same principle as face value. This part of the funds is divided between the stock account and the cash account, namely:

$$\left.\begin{aligned} Initial \ principal \ &= \ initial \ value \ of \ stock \ account \\ & + \ initial \ value \ of \ cash \ account \\ &= \ face \ value \ of \ product \end{aligned}\right\} \tag{27}$$

According to the above, the issuer started the dynamic hedging process of the short position of the call option and the extended position of the underlying asset before the product start date; that is, the stock position for the hedging transaction has been bought at time 0. The initial value of the stock account is:

$$Stock(0) = b / S_0 \times \Delta \ 0 \ \times S_0 \tag{28}$$

The cash account should be the remaining part after purchasing the corresponding number of shares, namely:

$$\begin{aligned} M \ 0 \ &= N - b / S_0 \times \Delta \ 0 \ \times S_0 \\ &= b / S_0 \times C_0 + Bond - b / S_0 \times \Delta \ 0 \ \times S_0 \end{aligned} \tag{29}$$

From the perspective of the asset portfolio, the asset portfolio held by the issuer at the beginning of the period consists of a short position in a bond (a zero coupon bond with a face value of N and a maturity of T), $b / S_0$ short positions in European call options, and $b / S_0 \times \Delta \ 0$ Long positions in the underlying stock.

The program needs to recalculate the value of the hedge ratio ΔtSt every day because the closing price of the underlying stock changes daily. To ensure that the entire hedging portfolio remains as delta-neutral as possible, each asset position needs to be adjusted at each time point, that is, rebalanced. The rebalancing described in this paper occurs at the end of each day or the beginning of the next day.

The product issuer adjusts and manages the underlying stock and cash accounts mainly according to the change in the value of the put option. During the hedging operation, it should also be noted that the asset positions and account values have changed due to the rebalancing at the end of each day. At the same time, it is necessary to distinguish whether each account situation corresponds to before or after rebalancing at each point in time. Before any rebalancing operation, each account change and related asset value change follow the following quantitative relationship[21].

$$Stock(t+1) = b / S_0 \times \Delta \ \ t \ \ \times S_{t+1} \tag{30}$$

Among them, the variable t in formula (30) represents the end of any trading day between 0 and T.

The remaining funds, other than the funds used to invest in the underlying assets, are stored in the cash account, and this part of the funds can obtain corresponding interest at the market interest rate r; that is, the cash account follows the following changes:

$$M \ \ t+1 \ \ = M \ \ t \ \ \times e^{r_{\Delta t}} \tag{31}$$

After any rebalancing operation, the changes in each account and the value of related assets follow the following quantitative relationship:

$$Stock((t) = b / S_0 \times \Delta \ \ t \ \ \times S_t, t \tag{32}$$

Stock account: is any end of the day between 0 and T.

The cash account becomes:

$$M \ \ t+1 \ \ = M \ \ t \ \ \times e^{r\Delta t} - b / S_0 \ \ \Delta_{t+1} - \Delta_t \ \ \times S_t \tag{33}$$

In the empirical analysis, the focus is on stock and cash account changes and option value changes.

There is no longer a separate pre- and post-rebalance operation on the product expiry date because the hedging operation is automatically terminated on the expiry date. In the final earnings settlement, the still-held stock positions will be sold and realized as funds used to pay investors, so Delta's hedging ratio will instantly become 0.

The stock account balance before the stock is realized, that is, the amount that can be learned is:

$$Stock(T) = b / S_0 \times \Delta \ \ T-1 \ \ \times S_T \tag{34}$$

The ending cash account balance is:

$$M(T) = M(T-1) \times e^{r\Delta t} \tag{35}$$

Distributable income = balance of stock account at the end of the period after realization + balance of cash account at the end of the period, namely:

$$Distributable\ income = Stock(T) + M(T) \tag{36}$$

$$\left.\begin{aligned} Investor\, income &= Bond \times e^{rT} + b / S_0 \times N \times \max(S_T - S_0, 0) \\ &= N + b / S_0 \times N \times \max(S_T - S_0, 0) \\ &= 1 + b / S_0 \times \max(S_T - S_0, 0) \end{aligned}\right\} \tag{37}$$

$$Issuer\ Income = Distributable\ income - Investor\ income \tag{38}$$

From the perspective of the asset portfolio, the issuer's return is calculated, and the asset portfolio is represented by V, as follows:

$$\left.\begin{aligned} V(T) = &-Bond \times e^{rT} \\ &-b / S_0 \times C(S_T, K, r, T) \\ &+b / S_0 \times \Delta_{T-1} \times S_T \\ &+M(T-1) \times e^{rat} \end{aligned}\right\} \tag{39}$$

Among them, K is the European call option $K = S_0$ strike price and $V(0) = 0$. Since the value of the option at the time of expiration T is set to $C(T) = \max(0, S_T - S_0)$, And the bond Bond can receive N at the time of expiration T, and the value is 1, so $V(T)$ It can be simplified as follows:

$$\begin{aligned} V(T) = &-1 - b / S_0 \times \max(0, S_T - S_0) \\ &+b / S_0 \times \Delta_{T-1} \times S_T + M(T) \end{aligned} \tag{40}$$

The revenue of the product issuer can also be calculated by $V(T) - V(0)$. Because $V(0) = 0$ can be obtained only by observing the value of $V(T)$.

## 4 RESEARCH ON INTERNET FINANCIAL RISK CONTROL BASED ON DEEP LEARNING ALGORITHM

Through the overall planning of risk control, this paper establishes an anti-fraud collaborative working mechanism with joint participation and extensive cooperation of all departments, improves the anti-fraud measures of each business product, and establishes a cross-business product fraud risk joint prevention and control mechanism. The overall functional architecture of the risk control platform is shown in Figure 1.

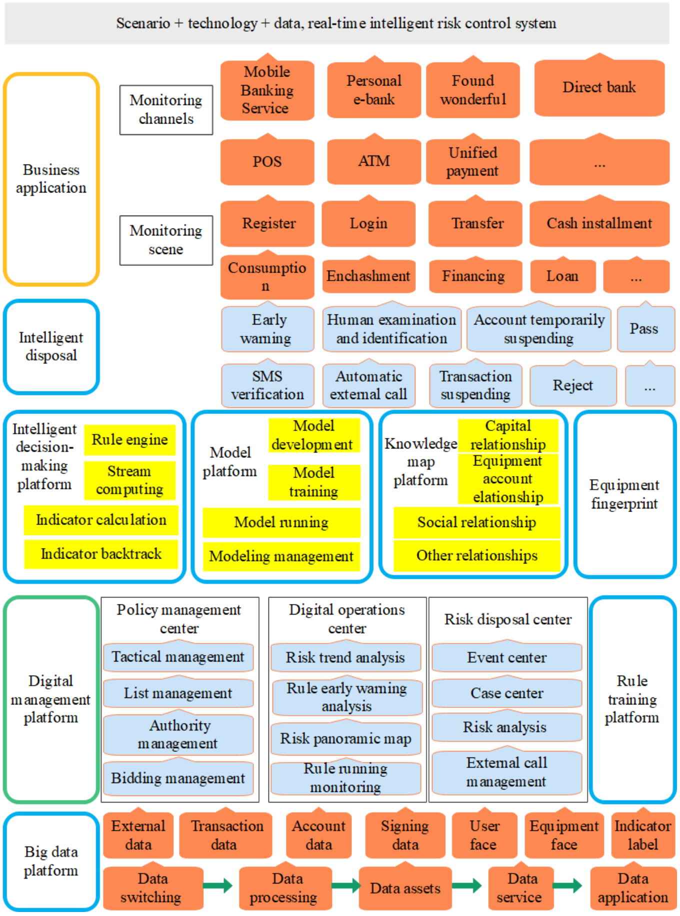


**Figure 1:** Overall functional architecture of the risk control platform.

This paper analyzes and mines transaction data through risk control operations and extracts risk characteristics of cases so that each business link scenario realizes the continuous accumulation and completion of data and the continuous optimization and upgrading of model strategies in the interaction of information and decision-making. As shown in Figure 2, this forms a self-improving anti-fraud ecosystem.

The data intelligent risk control platform is a comprehensive application platform for extensive data collection, storage, analysis, calculation, and display. It has vital functions such as a distributed file system, memory analysis engine, and real-time online data processing engine. The specific logic function design is shown in Figure 3.

Through the analysis of the requirements of the financial big data intelligent risk control platform, a financial big data intelligent risk control platform architecture with a distributed file system, a distributed memory analysis engine, and a real-time online data processing engine is designed and constructed. The centralized collection, storage, processing, analysis, and application of massive data can be realized through the integrated deployment and application of advanced significant data components.

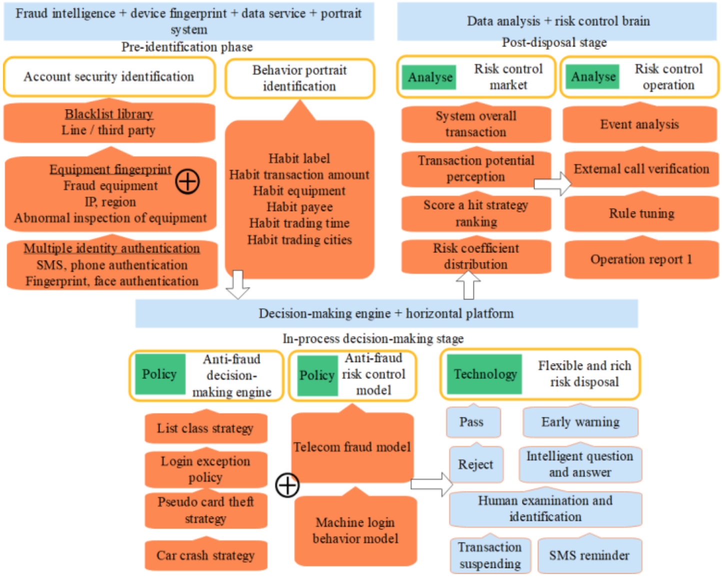


**Figure 2:** Intelligent risk control of echelon defense.

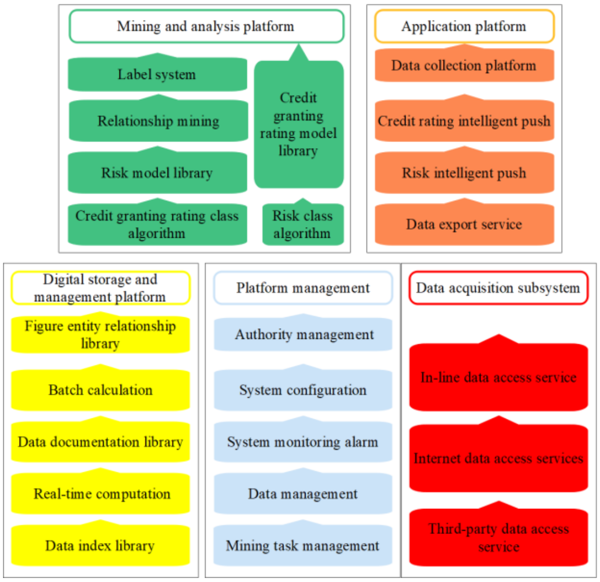


**Figure 3:** Logic function diagram of intelligent risk control platform.

The platform logic architecture design scheme is shown in Figure 4. The technical architecture diagram of the financial big data intelligent risk control platform is shown in Figure 5. The big data collection module mainly completes integrating, processing, and applying various data sources inside and outside the bank. Figure 6 shows a flow chart of data collection and management.

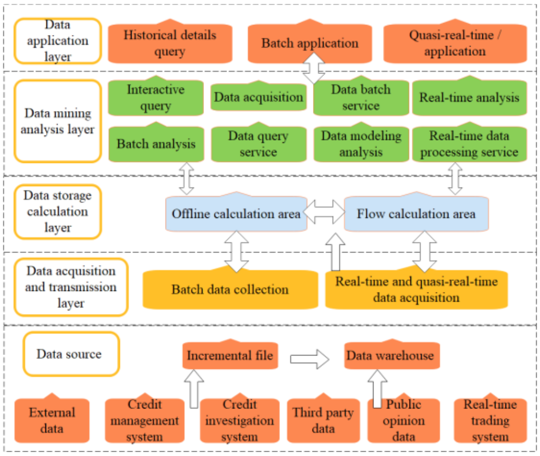


**Figure 4:** Logical architecture of risk control platform.

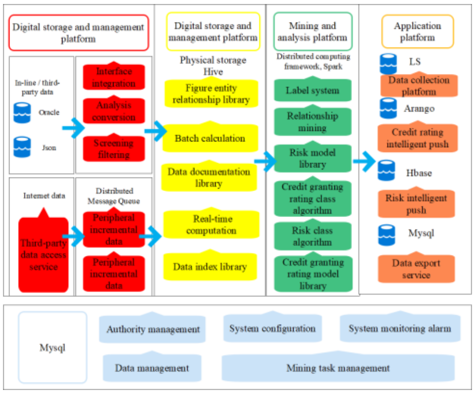


**Figure 5:** Technical architecture diagram of risk control platform.

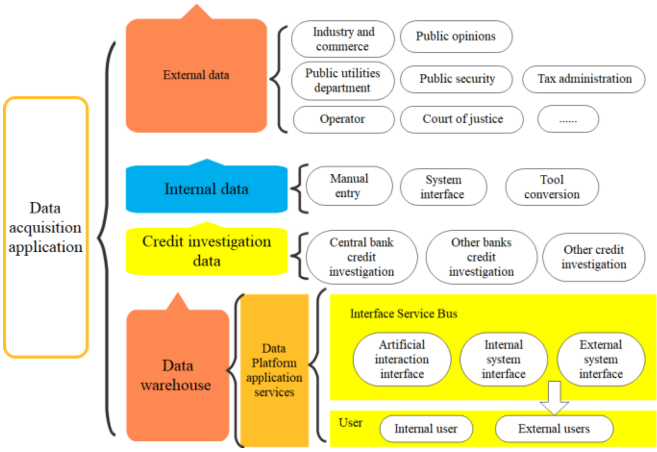


**Figure 6:** Flowchart of data collection and management.

Format conversion is required for text format files imported into HDFS via Data Acquisition. Spark supports "text" and "JSON" reading, which can be encoded into Parquet storage. Moreover, various data imported into HDFS through "Data Acquisition" needs to be cleaned, as shown in Figure 7.

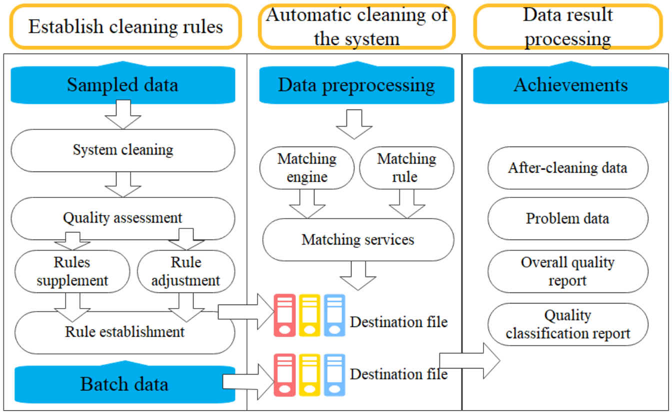


**Figure 7:** Data cleaning process.

The system identifies customer behavior and relationship information through extensive data mining and analysis and draws a customer management relationship map. Moreover, the system assigns weights to potential risks and establishes customer intelligence credit scores based on different weighted proportions. In addition, the system combines the association relationship with the enterprise's data to form associated variables, uses in-depth algorithms for risk prediction and warning, and builds an associated risk model, as shown in Figure 8.

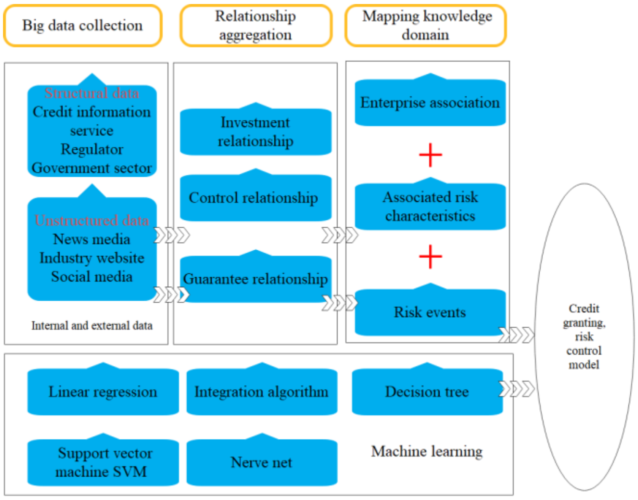


**Figure 8:** Logic diagram of the Internet financial intelligent risk control model based on deep learning.

Based on the above research, the Internet financial intelligent risk control model based on deep learning proposed in this paper is compared with the traditional risk control model. The clustering method is used to evaluate and compare risk identification and risk control perspectives, and the results shown in Figure 9 below are obtained.

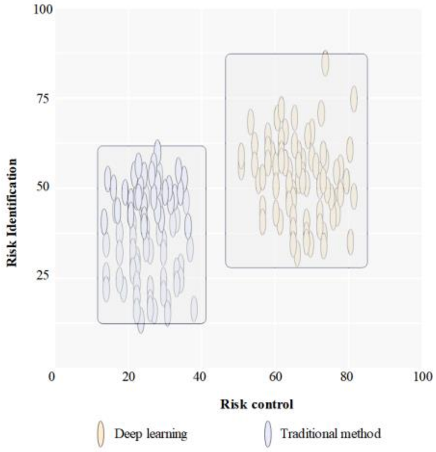


**Figure 9:** Simulation diagram of the Internet financial intelligent risk control model based on deep learning.

Based on the above research, the effect evaluation of the Internet financial intelligent risk control model based on deep learning is carried out, and the results shown in Table 1 below are obtained.

| *Number* | *Evaluation* | *Number* | *Evaluation* | *Number* | *Evaluation* |
|---|---|---|---|---|---|
| *1* | *85.414* | *19* | *81.762* | *37* | *79.283* |
| *2* | *84.779* | *20* | *76.891* | *38* | *86.607* |
| *3* | *77.387* | *21* | *86.793* | *39* | *87.682* |
| *4* | *86.268* | *22* | *78.786* | *40* | *76.362* |
| *5* | *85.446* | *23* | *78.049* | *41* | *81.183* |
| *6* | *83.991* | *24* | *81.244* | *42* | *83.225* |
| *7* | *77.941* | *25* | *84.021* | *43* | *87.635* |
| *8* | *87.430* | *26* | *82.261* | *44* | *86.703* |
| *9* | *77.719* | *27* | *83.720* | *45* | *76.587* |
| *10* | *77.087* | *28* | *83.450* | *46* | *77.795* |
| *11* | *83.397* | *29* | *85.350* | *47* | *80.614* |
| *12* | *77.612* | *30* | *82.017* | *48* | *83.598* |
| *13* | *83.189* | *31* | *87.345* | *49* | *79.030* |
| *14* | *77.306* | *32* | *86.476* | *50* | *82.842* |
| *15* | *87.301* | *33* | *81.911* | *51* | *83.312* |
| *16* | *80.050* | *34* | *85.388* | *52* | *84.679* |
| *17* | *87.076* | *35* | *80.264* | *53* | *79.443* |
| *18* | *83.070* | *36* | *81.792* | *54* | *79.356* |

**Table 1:** Evaluation of the effect of Internet financial intelligence risk control model based on deep learning.

The above research shows that the Internet financial risk control system based on the deep learning algorithm proposed in this paper has sound effects and can be applied to Internet financial risk control.

## 5 CONCLUSIONS

The risk control platform supports the flexible configuration of rules and policies and the real-time deployment of models and realizes real-time modification and real-time effect of regulations and guidelines. In design, the rule decision engine and the indicator calculation module are independent, and the rule engine can run many complex rules in parallel. Through the collected real-time transaction data, relevant primary data, and other internal and external data, the rule decision engine analyzes bank customers' transaction data and behavior data from multiple dimensions, such as abnormal transactions, risk labels, list libraries, and critical information identification. Moreover, by setting relevant lists, rules, strategies, and models, it can screen, identify, warn, and block risky transactions in the transaction process and realize real-time risk decision-making at the millisecond level to protect the security of customer funds and information in an all-around way. This paper combines deep learning algorithms with E-commerce and Human-Computer Interaction (HCI) principles to construct an Internet financial risk control system. The system identifies financial risks and formulates control strategies, ensuring user-friendly and accessible interactions. Simulation results demonstrate that this deep learning-based system effectively controls Internet financial risks and is well-suited for application in E-commerce environments, providing a robust tool for managing online financial transactions.

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