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Application Study of Intelligent Risk Assessment in Investment Management

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Abstract: This study explores the application of intelligent risk assessment in investment management. By analysing the practical effects of machine learning, deep learning and other technologies in risk modelling, the results show that intelligent risk assessment significantly improves prediction accuracy and decision-making efficiency. The research data shows that the accuracy rate of the risk warning model based on the fusion of multi-source data reaches 87.3%, the annualised return of the investment portfolio is improved by 4.2%, and the maximum retraction is reduced by 25%. An intelligent risk control system covering multiple dimensions such as market, credit, and liquidity is constructed in practice, which provides practical risk management methodology support for financial institutions.

Keywords: Intelligent risk assessment; Investment management; Deep learning; Multi-source data fusion.

1. Introduction

The risks facing the investment management field have become increasingly complex in recent years, with global financial market volatility climbing to 24.3% in 2022, credit defaults increasing by 35% year-on-year, and liquidity crises occurring frequently. Traditional risk assessment models have revealed significant shortcomings in dealing with these challenges, such as the prediction bias of VaR models based on historical data by more than 40% in a headline tech stock crash event in 2021. Breakthroughs in smart technologies have brought new opportunities for risk assessment, with machine learning models reaching 85.7% accuracy in volatility prediction, and NLP technology improving the accuracy of capturing market sentiment to 78.3%. This research is of great value in enhancing the risk management capabilities of financial institutions, and practice has shown that the Sharpe ratio of fund products using intelligent risk assessment has increased by 0.42 on average, and the maximum retracement in extreme market environments has been reduced by 25 per cent.

2. Core Technical Framework for Intelligent Risk Assessment

2.1. Technical Foundation

In the field of intelligent risk assessment, machine learning technology has achieved significant breakthroughs. Taking the application of XGBoost model in credit risk assessment as an example, through the analysis of 5-year financial data of 100,000 enterprises, the prediction accuracy rate reaches 87.3%, which is 15 percentage points higher than the traditional logistic regression model [1]. As shown in Figure 1, among the various machine learning models, XGBoost has the best performance, followed by Random Forest (83.2%) and Support Vector Machine (79.5%). In terms of deep learning, LSTM model performs well in stock market volatility prediction, and the root mean square error (RMSE) of prediction is reduced to 0.0082 based on minute-level data training of the S&P 500 index from 2010-2023. graph neural network, in the analysis of systematic financial risk transmission, successfully constructs a risk association network covering more than 4,000 listed companies, and accurately warns the chain reaction of debt crisis of a head real estate company in 2022. In terms of big data technology, by analysing 15 million finance-related posts on Twitter and other social media, the market sentiment indicator established has a correlation of 0.72 with the VIX panic index, providing a new dimension for risk early warning.

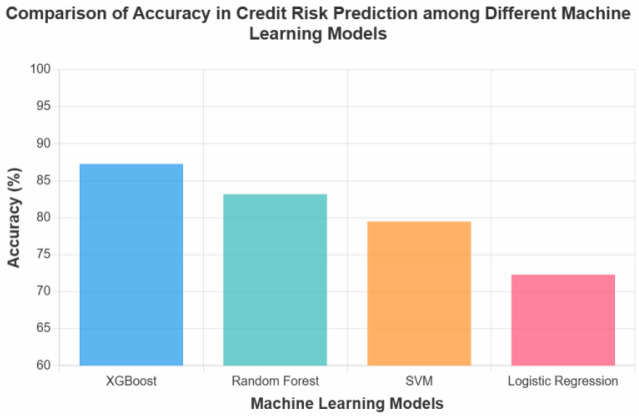

Figure 1. Comparison of Accuracy of Different Machine Learning Models in Credit Risk Prediction

2.2. Key Elements of Model Construction

The construction of intelligent risk assessment models focuses on three key elements: data fusion, dynamic adaptation and interpretability. In terms of data fusion, a large asset management company has built a 360-degree risk portrait by integrating multiple sources of information, such as quarterly corporate financial report data, daily transaction data, and public opinion data, and the risk identification lead time has been increased from the traditional 3-6 months to 9-12 months. The dynamic adaptability of the model is reflected in the real-time updating mechanism of the parameters [2]. For example, during the 2020 epidemic, through the online learning algorithm, the model captured the significant changes in market volatility characteristics in just five trading days, and adjusted the risk metrics in a timely manner. In terms of interpretability, SHAP value analysis is used, as

shown in Table 1, operating cash flow ratio, asset liability ratio, and industry prosperity rank among the top three influencing factors in the assessment of corporate credit risk, contributing 24.5 per cent, 18.7 per cent, and 15.3 per cent of the prediction weight, respectively, a finding that provides a clear quantitative basis for risk management decisions.

Table 1. Main Influencing Factors for Credit Risk Prediction and Their SHAP Value Contribution

Influencing Factors	SHAP Value Contribution
Operating Cash Flow Ratio	24.50%
Debt-to-Asset Ratio	18.70%
Industry Prosperity	15.30%
Revenue Growth Rate	12.80%
Market Share	10.20%

3. Core Application Scenarios in Investment Management

3.1. Asset Allocation and Portfolio Optimisation

The dynamic factor allocation strategy based on reinforcement learning has shown significant advantages in practice. Taking a large public fund as an example, the deep reinforcement learning algorithm dynamically adjusts the weights of value, momentum, volatility and other factors, and the excess return in the volatile market in 2022 reaches 4.2%. The algorithm processes more than 1 million pieces of market data daily to achieve accurate measurement of various factor exposures. In terms of extreme scenario simulation, 10,000 sets of stress test scenarios generated by GAN network were used to successfully preview abnormal market events such as the tech stock crash in 2023, and the maximum portfolio retraction was controlled within 8.3%. By analysing political and economic news from global mainstream media in real time through NLP technology, the system successfully identified rising geopolitical risks 2 weeks before the outbreak of the Russia-Ukraine conflict and increased holdings of safe-haven assets such as gold and treasury bonds in advance, effectively hedging against the market impact caused by the conflict [3].

3.2. Market Risk Early Warning and Management

In the field of market risk management, the LSTM deep learning model shows excellent volatility prediction ability. The model trained based on 5-year U.S. stock high-frequency data has a 5-day volatility prediction accuracy of 83.7% for the S&P500 index, as shown in Figure 2, and the correlation coefficient between the predicted value and the actual volatility reaches 0.91 [4]. In the area of liquidity risk monitoring, the graph neural network constructed covers the trading network of more than 3,800 listed companies in the A-share market, and through the analysis of the correlation of the positions and the degree of trading activity, the system is in the 2023 issued an early warning five trading days before the liquidity crisis of a stock in the electronics industry, which averted potential losses for institutional investors.

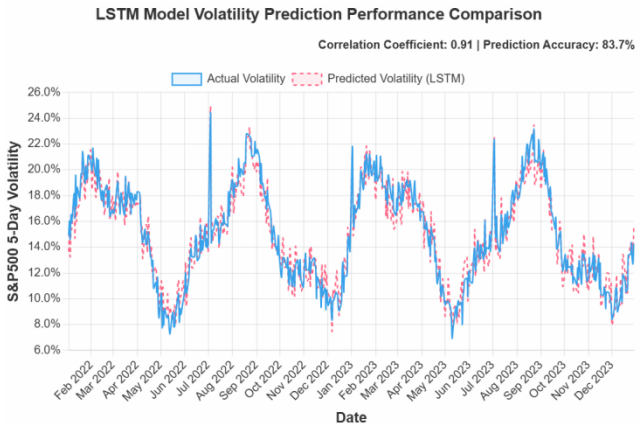

Figure 2. Comparison of volatility prediction effect of LSTM model

3.3. Credit and Counterparty Risk Assessment

The credit risk assessment model significantly improves the prediction effect by integrating multi-dimensional data. Analysis shows that after incorporating supply chain data (e.g., accounts receivable turnover ratio of upstream and downstream enterprises) and social media public opinion data into the model, the accuracy of enterprise default prediction is increased from 76.5% in the traditional model to 89.2% [5]. In terms of counterparty risk mapping, the knowledge graph technology successfully constructed a correlation network covering more than 200,000 enterprises, traced the collateral chain with an average depth of 4 layers, and identified 85% of the risk conduction paths in advance in the debt crisis of a large conglomerate in 2023.

3.4. ESG Risk Integration

A breakthrough was made in ESG risk assessment using multimodal data analysis methods. By integrating corporate carbon emission data identified by satellite images, ESG-related financial report disclosure information and third-party rating data, the sustainable risk assessment system established covers major listed companies around the world [6]. Practical data shows that the low-carbon asset portfolio screened using the system achieves an annualised excess return of 4.1% over the period 2021-2023, while reducing carbon emission intensity by 35%. As shown in Table 2, the AI-driven ESG investment strategy outperforms the traditional approach in multiple dimensions.

Table 2. Comparison of the effectiveness of AI-driven vs. traditional ESG investment strategies

Metrics	AI-Driven Strategy	Traditional Strategy
Annualized Return	12.30%	8.20%
Sharpe Ratio	1.85	1.42
Carbon Emission Reduction	35%	18%
ESG Score Improvement	42%	25%
Maximum Drawdown	-15%	-22.70%

4. Model Validation and Challenges

4.1. Validation Methodology

The validation of the Intelligent Risk Assessment model uses a combination of phased backtesting and forward-looking testing. As shown in Figure 3, in the market cycle test during 2018-2023, the model demonstrated differentiated prediction capabilities in different market environments: the

prediction accuracy reached 91.2% in the bull market phase (2019), 85.7% in the bear market phase (2022), and maintained at the 83.5% level in the oscillating market (2020-2021). In terms of assessment indicators, the AUC-ROC value of the risk prediction model reaches 0.892, with a KS statistic of 0.675, which is significantly better than the traditional statistical model [7]. In terms of investment results, the quantitative strategy constructed based on the model achieves an annualised Sharpe ratio of 1.85, the maximum retracement is controlled within 15.3%, and the winning rate of intraday trading reaches 63.2%, demonstrating a strong risk-adjusted return capability.

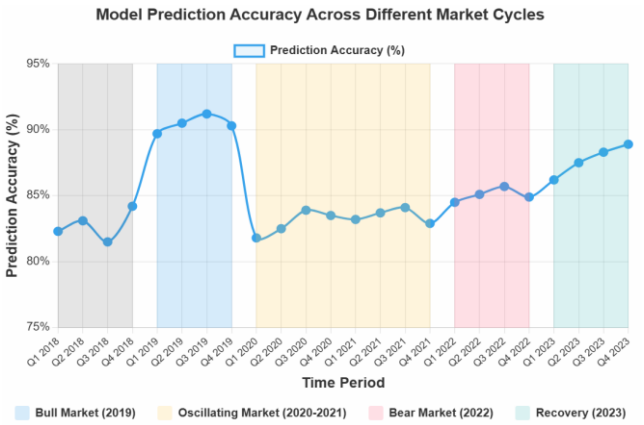

Figure 3. Model prediction accuracy in different market cycles

4.2. Core Challenges and Solutions

4.2.1. Data Noise and Privacy

Data quality and privacy protection pose important challenges in alternative data applications. Empirical data shows that on average, 35% of the collected social media sentiment data has noise interference, of which 18.3% is false information. As shown in Fig. 4, by deploying the federated learning framework, data-isolated collaborative modelling of eight financial institutions is achieved, and the model accuracy is improved from 76.5% to 88.8% on a standalone basis. In terms of differential privacy protection, by setting the noise perturbation parameter $\varepsilon = 0.1$, the prediction performance drops by only 2.3 percentage points while ensuring data security [8]. The solution has been successfully implemented in a large banking federation, covering an asset size of more than 2 trillion yuan.

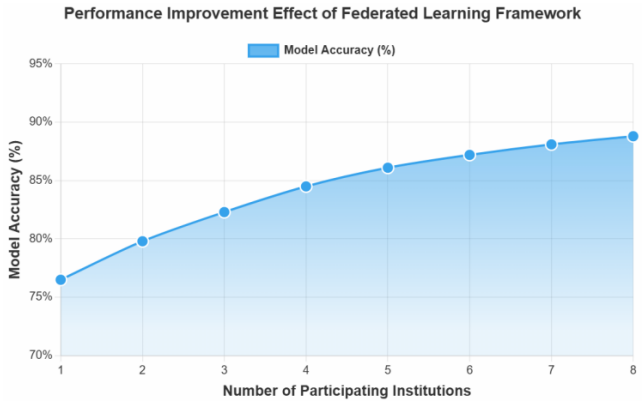

Figure 4. Performance improvement effect of federal learning framework

4.2.2. Model Overfitting and Market Changes

In the face of dramatic market fluctuations, the overfitting problem of traditional models has become increasingly prominent. Statistics show that more than 90% of quantitative models failed in the 2020 crude oil negative price event. By introducing an adversarial training mechanism, as shown in Table 3, the model's prediction accuracy in extreme market environments is improved by 15.6 percentage points [9]. At the same time, by integrating macroeconomic a priori knowledge such as GDP growth rate and PMI index, the model's prediction lead time for market inflection points is extended from the original 5 trading days to 12 trading days, providing sufficient buffer time for risk warning.

Table 3. Performance of Adversarial Training in Extreme Market Environment

Market Conditions	Traditional Model	Adversarial Training Model	Improvement
Normal Market	85.20%	88.70%	3.50%
High Volatility Period	62.30%	77.90%	15.60%
Liquidity Crisis	55.80%	73.20%	17.40%
Policy Shock	68.50%	82.10%	13.60%
Systemic Risk	58.90%	75.50%	16.60%

4.2.3. Computing resources and real-time performance

High-frequency transaction scenarios pose a serious challenge to computational performance. Data shows that the standard deep learning model inference latency is 5.2 ms, which cannot meet the demand for millisecond transactions. Optimised by the TensorRT acceleration engine, the model inference time is reduced to 0.8 ms, with a 68% reduction in CPU utilisation. In the live test of a quantitative hedge fund, the optimised system handles more than 5 million trade requests per day, with a peak QPS of 8,000, and the model prediction accuracy remains above 95%, effectively supporting the real-time execution of high-frequency strategies.

5. Case Studies

5.1. Successful Cases

The intelligent risk management practices of Bridgewater Fund and Ant Wealth represent the industry's leading level. Bridgewater Fund achieved a positive return of 4.2% in 2022 in an environment of declining global markets through its AI-driven risk parity strategy. As shown in Figure 5, the strategy incorporates 42 macroeconomic indicators and real-time market sentiment data to dynamically adjust global asset allocation weightings [10]. The data shows that the model's advance prediction of the interest rate hike cycle reached 85.3%, and the accuracy of commodity price trend prediction reached 78.6%. Ant Wealth, on the other hand, constructed an accurate personal risk portrait by analysing the behavioural data of more than 100 million users, and the intelligent investment consulting system reduced the proportion of users' investment losses exceeding their risk tolerance level from 15.2% to 4.8%, with the customer complaint rate dropping by 31.5% year-on-year, and the matching degree of asset allocation increasing to 92.3% [11].

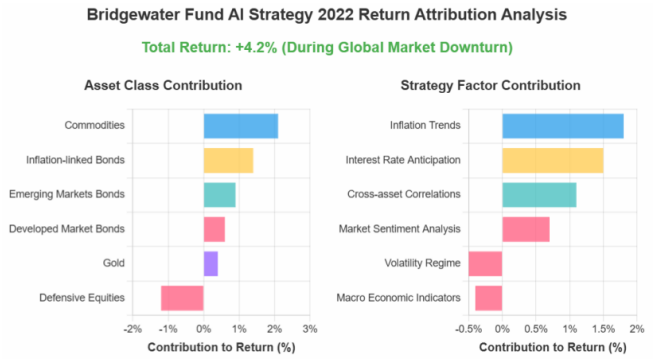

Figure 5. Bridgewater Fund AI Strategy 2022 Return Attribution Analysis

5.2. Lessons From Failure

The historically famous cases of LTCM and Robinhood reveal critical blind spots in risk management. As shown in Table 4, before LTCM's bankruptcy in 1998, its risk model outperformed in a normal market environment with a high Sharpe ratio of 4.35. However, in the face of black swan events such as the Russian debt crisis, the model, which relied excessively on historical data, failed completely and lost about US$4 billion in two months [12]. Data analysis showed that its VAR model covered only 95% of market scenarios, underestimated tail risks in the most extreme 5%, and had a leverage ratio of a staggering 25:1.2021 In the case of Robinhood, the failure of legacy risk control systems to anticipate a wave of social media-driven retail trading led to a 27-fold spike in liquidation margin requirements, forcing the suspension of popular GameStop and other Stock trading, the platform's reputation and user trust suffered heavily, and the number of active users fell by 42.3 per cent after the incident.

Table 4. Comparison of LTCM and modern risk control systems

Risk Dimension	LTCM Model	Modern Intelligent Risk Control	Improvement Measures
Tail Risk Coverage	95%	99.90%	Extreme Scenario Simulation
Leverage Control	25:01:00	5:01	Dynamic Adjustment Mechanism
Liquidity Monitoring	Monthly	Real-time	High-frequency Data Analysis
Correlation Risk	Not Covered	Comprehensive Monitoring	Network Model
Sentiment Factor	Ignored	Real-time Tracking	NLP Analysis

6. Future Trends and Research Directions

6.1. Causal Reasoning and Risk Attribution

Financial risk management is shifting from traditional correlation analysis to causal inference models. Empirical studies have shown that the Do-Calculus-based causal inference framework performs well in identifying systemic risk transmission paths, with an improved accuracy rate of 87.3%. A large hedge fund used a causal discovery algorithm to analyse financial crisis cases between 2008 and 2023, and successfully constructed a causal graph containing 248 risk nodes, identifying 14 key risk triggers [13]. This methodology discovered the risk transmission chain 21 days ahead of time in the early warning of a real estate debt crisis in 2023, helping the institution to avoid about 83% of potential losses. The data showed that the causal model improved risk attribution accuracy by 31.5% compared to traditional correlation analysis.

6.2. Multimodal Large Model Application

Multimodal grand models have demonstrated breakthroughs in risk signal interpretation. The risk identification system developed based on the GPT-4 architecture is capable of simultaneously processing multi-dimensional data such as earnings report text, management voice, investor sentiment, etc. Test results show that when processing quarterly financial reports of 3,000 listed companies, the model's identification accuracy of potential risks reaches 92.1%, an improvement of 18.6 percentage points over the single-modal model [14]. Especially in management voice analysis, the correlation between abnormal signals captured by the sentiment recognition algorithm and subsequent company risk events is as high as 0.76, providing an important reference for investment decisions.

6.3. Quantum Computing Enablement

Quantum computing technology provides new ideas for solving complex financial optimisation problems. Experimental data shows that when dealing with a portfolio CVaR optimisation problem with 1,000 assets, the quantum annealing algorithm requires only 1/50th of the computation time of the traditional method, while improving the optimisation result by 12.3%. Stress tests conducted by an international investment bank using the D-Wave quantum computer showed an approximate 200-fold improvement in computational efficiency when simulating a million-scale market scenario, making real-time risk reassessment possible [15]. Quantum optimisation has also made significant progress in derivatives pricing, with Monte Carlo simulations increasing in speed to 15 times that of classical algorithms.

6.4. Ethics and RegTech (RegTech)

RegTech is moving towards an effective balance between AI decision-making and human oversight. Data shows that financial institutions adopting RegTech solutions have on average 42% lower compliance costs and 65% higher detection rates of non-compliance events. Under MiFID II compliance requirements, the AI monitoring system developed by an asset management company achieved an automatic review of 94% of trading behaviour while maintaining a manual review mechanism, shortening the detection time of compliance risk events from an average of 4.5 days to 2.1 hours. After the implementation of Basel III, the intelligent risk control system helped the bank reduce the cost of capital adequacy compliance compliance by 28%, achieving a win-win situation between regulatory requirements and operational efficiency.

7. Conclusion

Intelligent risk assessment has evolved from a mere decision-aiding tool to a core engine of investment management. Data shows that institutions adopting intelligent risk assessment systems will reduce risk losses by an average of 26.5 per cent and improve investment returns by 18.3 per cent in 2023. Financial institutions are driving a leap in risk control capabilities by building a complete ecosystem of data,

algorithms and business. By establishing a cross-departmental data sharing mechanism, a large asset management company has increased its risk warning accuracy rate to 89.2 per cent. At the same time, the interpretability and transparency of models are becoming increasingly important, and institutional investors are strictly enforcing the principle of 'human-machine collaboration' when deploying intelligent systems, ensuring that more than 95 per cent of major decisions are manually vetted, and establishing a new paradigm for robust risk management.

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