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Algorithmic Innovation and Practical Application of Financial Asset Pricing Models under the Emerging Digital Financial System

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SUMMARY: *With the development of Internet finance, the original method of financial asset value assessment has been challenged, on this basis based on the application of blockchain technology and machine intelligence models, which provides new ideas for the innovation of the financial market. In this study, a set of data analysis models combining deep neural networks and blockchain are designed as a method for financial product valuation, in which a multilayer perceptron is used to realize the operation for high-dimensional input vectors, in addition to the combination of LSTM-Adaptive Attention model for the value assessment of digital financial products. The above model is empirically tested using large-sample, cross-market data, and a variety of digital currencies such as bitcoin, ethereum, and decentralized financial protocol tokens are selected for comparative study, which statistically significantly proves that the method has a high degree of accuracy and effectively manages risks. In summary, the model proposed in this paper can better capture the value characteristics embedded in digital currencies, improve the effectiveness and reliability of risk control while enhancing the accuracy of price prediction, and provide a powerful support for the healthy development of the financial market of the digital economy as well as the prevention and control of systemic risks.*

KEYWORDS: *digital finance; asset pricing; deep learning; blockchain; long and short-term memory network*

1 Introduction

With the rapid development of science and technology, digital finance has changed the face and operation of the global financial system. The traditional financial model is gradually being replaced by a digital, intelligent and innovative model, and financial institutions are at the crossroads of innovation [1, 2]. The digital revolution has given rise to a series of cutting-edge technologies, such as blockchain, artificial intelligence (AI), big data analytics, and other technologies, which have not only triggered revolutionary changes in the field of financial business, but also unleashed infinite possibilities in risk management, regulatory tools, and user experience [3-6]. The development of digital finance has also affected financial asset pricing. Asset pricing refers to the revaluation of the price or value of future assets under uncertainty [7]. Financial markets are very complex and constantly changing and developing systems, and traditional asset pricing models range from capital asset pricing model to arbitrage pricing

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model to discounted cash flow method, relative pricing method and option pricing method, etc., which construct linear correlations with market historical data [8-11]. However, under the digital financial system, the market presents non-linear relationship and dynamic change characteristics, pricing needs to pay attention to not only financial data, but also includes social media and other data in the digital environment, these factors lead to the traditional asset pricing model is difficult to cope with [12]. And digital finance with the help of a variety of digital technologies to integrate and analyze financial market data, and can optimize the traditional model defects, for asset pricing model innovation provides a method.

Machine Learning (ML) and Reinforcement Learning (RL) in AI technology improve the computational efficiency of traditional asset pricing models, which can effectively extract the nonlinear features in asset pricing and help to perform dynamic pricing optimization. Literature [13] found through comparative analysis that ML methods such as decision trees and neural networks can effectively capture the nonlinear predictive interactions in asset pricing, and their predictive ability based on signals such as momentum and liquidity can bring significant excess returns for investors. Literature [14] uses neural network algorithm to solve the fractional order derivative option pricing model, and optimizes the parameters with Chinese market data to verify the predictive ability and practical feasibility of the model (especially the space-time fractional model) in financial derivatives pricing. Literature [15] constructs an asset pricing framework with the help of ML method, proposes logarithmic transformation for the right-skewed distribution of data, and introduces the LASSO sparse module to eliminate the multicollinearity among features. Empirical evidence shows that the method effectively improves the explanatory ability and robustness of the model, and provides theoretical support for dealing with complex financial data structures. Literature [16] combines RL and Bayesian optimization to construct a dynamic pricing framework. Reinforcement learning learns the optimal strategy through interaction, while Bayesian optimization fine-tunes its hyperparameters, which significantly improves the revenue and customer satisfaction compared with the traditional method, showing good potential for practical application. Literature [17] explores how to incorporate economic structures such as the no-arbitrage constraint into ML algorithms (e.g., factor models, neural networks) to improve the estimation accuracy of asset pricing models, and empirically demonstrates that the constraint significantly enhances the model's performance in terms of the Sharpe ratio and pricing error. Literature [18] proposes an ML framework that integrates multi-source data and multi-language sentiment analysis for dynamic pricing optimization, and the XGBoost model with integrated sentiment features performs optimally, which can effectively achieve real-time, adaptive and customer-oriented pricing strategies with both profitability and fairness.

Big data is an important financial technology in digital finance, and big data-driven asset pricing integrates and analyzes multimodal and multidimensional data to mine and improve the effectiveness of pricing information. Literature [19], based on data from 2011-2023, reveals that corporate application of big data can effectively reduce asset pricing bias, and its mechanism lies in strengthening internal control and mitigating information asymmetry, thus enhancing financial transparency and promoting a fairer and more efficient operation of the capital market. Literature [20] establishes a carbon-sensitive green asset pricing model that incorporates both physical and transition risks, where a single climate risk positively affects asset returns, while climate big data overlaid with dual risks accelerates the impairment of high-carbon assets, to which emerging markets are more sensitive, providing a new paradigm for guiding the green allocation of capital. Literature [21] constructs a multidimensional dynamic pricing optimization model integrating big data and RL, using a hybrid architecture of random forests and long- and short-term memory networks, which significantly improves the prediction accuracy and revenues, and the cumulative revenues increase by 14.7%.

Blockchain technology can ensure that the data is not tampered with and is traceable, providing data authenticity and asset transaction security for asset pricing. Literature [22] proposes an asset transaction system based on blockchain consensus mechanism, which ensures that the records cannot be tampered with through multi-node verification, significantly reduces the manual recording workload and transaction time, and improves transaction security and efficiency. Literature [23] develops a digital currency value analysis and transaction monitoring system that combines deep learning and improved blockchain consensus mechanism, and establishes a traceable multi-chain integration model, which realizes stable quantitative analysis of digital asset value and effective transaction supervision. Literature [24] designs a blockchain-based "MetaRepo" system for securely storing and cross-platform use of digital assets in a meta-universe, integrating a user engine and an authentication mechanism, which ensures the safe transfer and interaction of assets between virtual environments without the need for repeated authentication, and effectively copes with the risk of theft and loss. Literature [25], based on A-share data from 2006-2023, shows that blockchain investment can improve asset pricing efficiency, and the dual equity structure plays a moderating role, the effect differs between SOEs and non-SOEs, and between southern and non-southern enterprises, and it is suggested that market pricing can be further optimized through policy guidance and technological infrastructures.

This paper establishes a research framework combining theory and empirical evidence, and on the basis of combing the research lineage and shortcomings of digital financial asset pricing, it proposes a hybrid pricing algorithm based on deep learning methods and blockchain data mining technology, using convolutional neural networks, recurrent neural networks and graph neural networks to capture the characteristics of on-chain transactions, temporal correlations, and network relationships from different perspectives, and using Bayesian optimization and Monte Carlo methods for parameter tuning and robustness testing. Using the data from Bitcoin and Ether and other markets from 2018 to 2023 processed by wavelet noise reduction, principal component analysis and other methods, and then using cross-validation combined with the sliding time window method and applying the integrated learning idea to complete the training process, the comparison found that the algorithm proposed in this paper is significantly better than the CAPM model, Fama-Monte Carlo model, and Fama-Monte Carlo model, in terms of both the RMSE index and the Sharpe index or the VaR value-at-risk. CAPM model, Fama-French three-factor model. It proves that it has better prediction effect and risk management.

2 Grounded theory

2.1 Theory of Digital Financial System

The budding stage of the theoretical research on digital financial system can be traced back to the e-commerce wave in the late 1990s, when scholars' research mainly focused on the analysis of the disruptive impact of electronic payment systems on the traditional business model of banks; the research on central bank digital currency has been one of the key issues of concern to the policy-making departments and research institutes in the recent years.The BIS has released a series of thematic reports to systematically discuss the impact of CBDC on the effectiveness of monetary policy and financial stability and the international financial landscape. systematic discussion on the impact on monetary policy effects, financial stability and international financial landscape. The underlying technical framework of blockchain financial application has obvious decentralization characteristics, and in the specific operation process, it is based on the technology of distributed database, and with the help of hash value and electronic signature, etc., it can safely and effectively authenticate each transaction and prevent the information from being tampered with. The application of blockchain smart contracts automates the process of financial contract fulfillment, which solves the credit problems in the financial field due to third parties to a certain extent, but also brings problems such as the threat of the security of the smart contract itself and the risk of distributed management.

Research on the economic effects of the digital economy and finance is increasingly tending to the interdisciplinary academic development path, and in monetary economics, it mainly discusses the impact of digital currencies on the effect of central bank monetary policy, and theoretically argues rigorously, pointing out that large-scale circulation of private currencies will have a negative impact on the effect of the central bank's monetary policy. At the same time, the strategic entry of the central bank's digital currency will also make the implementation of monetary policy tools more precise and targeted characteristics. The study of financial market microstructure theory reveals that the price discovery process in the digital financial market is different from that in the traditional financial market, and the extensive application of algorithmic trading strategies and automated market maker models leads to a stronger temporal heterogeneity in the volatility of market price liquidity. The order thickness and price shock curves of decentralized exchanges, on the other hand, obey the statistical law of deterministic power law distribution. Analytical validation from the perspective of behavioral finance theory fully illustrates the irrational behavioral characteristics of participants in the digital financial market in their investment decisions, and the role of network sentiment index, network influence factor, and follow-the-leader trading factor on the risk level of the digital currency market is significantly stronger than that of the general stock, and can be portrayed using the following improved capital asset pricing model:

$$P_t = E_t\left[P_{t+1}\right] + \alpha \cdot S_t + \beta \cdot N_t + \gamma \cdot H_t \tag{1}$$

In the above model, P_t represents the market price level of the digital asset at the moment t, S_t represents the social media sentiment composite index, N_t reflects the degree of intensity of the network propagation effect, H_t measures the degree of concentration of the herd behavior of the investor group, and the coefficients α, β, and γ indicate the specific weight of influence of these behavioral factors on the process of asset price formation, respectively.

How to realize the benign interaction between regulatory technology and the development of digital finance is an important theoretical proposition of concern to the academic community. Under the traditional financial regulatory system, the development of digital finance, which is basically characterized by the distributed mode of operation, the nature of transnational transactions and covert operations, faces certain institutional obstacles. The Crypto Asset Market Regulation issued by the European Union, the Operational Guidelines for the Regulation of Digital Assets issued by the U.S. Securities and Exchange Commission, and the Digital Renminbi Pilot Test conducted by the China Banking Regulatory Commission are the specific choices of regulatory paths under different regulatory concepts, respectively. Scholars have conducted comparative studies on the effects of these different regulatory actions in order to form an overall understanding of the regulatory process of digital finance. There is a natural conflict between the requirements of anti-money laundering and counter-terrorist financing laws and regulations and the goal of maintaining the privacy of the digital financial system, and cryptography based on the zero-knowledge proof mechanism, ring-signing scheme and other encryption technologies can dissolve this basic conflict. However, its actual regulatory effect needs to be tested by more practice before it can be determined.

2.2 Financial asset pricing theory

Beginning with Markowitz's modern portfolio theory, which utilized the mean-variance approach to provide a quantitative measure of the risk of an investment and gave mathematical possibilities for subsequent developments; scholars have since built on it by proposing the famous CAPM model, which occupies an important position throughout the field of modern finance, explaining the expected rate of return in terms of a single risk factor, with the simple and straightforward advantages. It is argued that in equilibrium in the market, the expected return on any risky asset can be expressed as the risk-free rate plus a risk premium, and that the risk premium is determined only by the risk of the asset relative to the market portfolio.

Later, the theory of arbitrage pricing was proposed, and a general form of asset pricing model, the multifactor arbitrage pricing model, was developed from the perspective of an arbitrage-free equilibrium, under the relaxation of the prerequisites in the CAPM with respect to the utility function of the investor and the probability distribution of the investment rate of return. And it is proposed that the expected return of an asset depends on a series of macro-factors, which can be described by constituting a multivariate regression equation between these macro-factors. At this point, the pricing of financial derivatives has truly entered the era of science.The BSM model uses the SDE to describe the pattern of change in the price of an asset, and uses a risk-neutral measure to obtain the value of a European option under the premise of no arbitrage. Assuming that the price of the underlying asset obeys the geometric Brownian motion, constructing a risk-free portfolio consisting of the option and the underlying asset, eliminating the risk factor of the underlying asset, and finally obtaining the expression of the value of the option.The Cox-Ross-Rubinstein binomial tree model gives a more graphic analysis of discrete time, which handles a continuous process at discrete points in time, making the complicated option prices easy to calculate, suitable for the price analysis of American options.

With the deepening of the test of CAPM, people realize that there are many unreasonable assumptions of CAPM in reality, and the market capitalization factor and B/M are found to have strong explanatory power for stock returns in a large number of cross-sections, which shakes the foundation of CAPM.Fama and French proposed a three-factor model, which pushes forward the research of empirical asset pricing to the era of multi-factor model. The addition of size factor and value factor greatly improved the explanatory power of cross-sectional differences in stock returns. In addition, some scholars introduced the momentum factor on the basis of the three-factor pricing model to explain the short-term continuation of the phenomenon of stock prices; and then appeared at the same time, including the profitability factor and the investment factor, including the five-factor model, to a certain extent, enriched the content of multi-factor pricing theory.

The rise of behavioral finance for asset pricing theory to bring new life, on the basis of the original psychological bias and cognitive limitations of investors to explain the phenomenon that can not be explained by the efficient market theory, and found that behavioral biases such as overconfidence, loss aversion, anchoring effect and other behavioral biases will have a greater impact on the price of the asset, scholars began to establish a hybrid asset pricing model that includes rational expectations and behavioral biases.

With the development of the digital economy, the traditional financial asset price discovery has certain deficiencies, in the digital financial environment, many traditional asset pricing theories can not well describe the price generation process of digital financial assets, based on the premise of the efficient market assumption of the asset pricing model is no longer applicable to the digital financial environment. Changes in the composition of investors, changes in trading methods, and fundamental changes in the law of value have brought great challenges to asset pricing theory. As the factors affecting the price of digital financial assets are more intricate and complex, such as the degree of network effect, protocol rule setting, technological maturity and other factors, they cannot be reflected in the price determination model of traditional financial assets. In addition, the price of tokens in decentralized financial applications may also depend on many new variables such as the total margin size, the transaction fee share ratio, the liquidity incentive rate, etc. The above evaluation metrics are not applicable to the traditional linear-based pricing method, as the digital market's continuous mode of operation, extremely high market volatility, and algorithmic-driven as the main price discovery process are all different from those in the traditional sense. financial markets in the traditional sense.

Valuing financial assets based on machine learning methods is a new way of thinking to deal with the dilemma of financial asset valuation in the digital financial environment. Deep neural networks have the characteristics of strong nonlinear fitting ability and can handle high-dimensional information, which help to explore the complex valuation characteristics of digitized financial assets.

Based on the advantages of RNN and LSTM models for modeling time series, they are applied to the price prediction of digital financial assets to extract the long-term correlations and complex dynamics existing in the price series; RL methods are used to find the optimal decision rule to obtain the maximum return, and new insights about the price of digital financial assets are obtained by combining with the information of current market prices.

3 Algorithmic innovations in financial asset pricing models

3.1 Traditional financial asset pricing models

CAPM is one of the most representative achievements in modern portfolio theory, which involves numerous assumptions in its establishment, rational man assumption, efficient market assumption, zero transaction cost assumption and divisibility assumption. And the CAPM model to a certain extent on the average rate of return on risky assets and risk between the establishment of a simple intuitive relationship, so as to make a more accurate judgment on the value of financial products.CAPM's basic assertion is that in the premise of the efficient market, all the expected return on risky assets can be decomposed into the risk-free rate of interest plus the reward for the excess risk of the two parts. Of these, the excess risk reward depends only on the degree of risk that a particular asset bears to the overall market, i.e., the magnitude of the non-exclusive risk ratio β between the asset and the market in which it resides. This takes the form of:

$$E(P_i) = R_f + \beta_i (E(R_m) - R_f) \tag{2}$$

where $E(P_i)$ represents the expected return on asset i, R_f represents the level of the risk-free interest rate, β_i is the beta coefficient of asset i, and $E(R_m)$ represents the expected return on the market portfolio.

Where β is the ratio of the covariance between the asset return and the market return divided by the variance of the market return, an indicator used to measure the sensitivity of an individual asset's price to the volatility of the market as a whole. If the value of β is greater than 1, it means that the degree of change in the price of the asset is higher than the average level of change in the market, and it is a high-risk, high-yield, aggressive investment; if the value of β is less than 1, it means that the degree of change in the price of the asset is lower than the average level of change in the market, and it means that the price of the asset has less volatility, and it is a defensive type of investment.

The arbitrage pricing theory is an important milestone in the development of asset pricing theory from single-factor to multi-factor. The arbitrage pricing theory relaxes the requirements of the capital asset pricing model on the form of the investor's utility function and the distribution of asset returns, and establishes a more general model for determining the price of an asset under the condition of no-arbitrage equilibrium.The APT model considers the expected return on an asset, which can be expressed as the form of the sum of a linear function of a number of major systematic risk factors, and each of the risk factors describes the macroeconomic variables that have an effect on the return on an asset, such as changes in inflation, interest rates, and changes in industrial output and market risk premiums. macroeconomic variables that have an impact on asset returns, such as changes in inflation rates, changes in interest rates, changes in industrial output and changes in market risk premiums, etc. The above model assumes that asset returns are subject to a multifactor generating process and that the factor loadings reflect the differences in the sensitivity of different assets to each risk factor. The risk decomposition from multiple perspectives can better describe the various complex economic factors that lead to changes in asset prices. The innovation and development of option pricing theory has led to a reasonable price determination method for financial derivative products, and the BSM model utilizes a risk-neutral measure to derive an explicit expression for the price of European options. The model assumes that the price of the underlying asset follows a geometric Brownian motion process volatility and the risk-free rate remain constant, and the price volatility risk is eliminated by constructing a dynamic hedging portfolio containing the option and the underlying asset to obtain a pricing formula in which the value of the option depends only on observable parameters such as the current price of the underlying asset, the exercise price, the expiration time, the risk-free rate and the volatility.

The context of digital finance poses new challenges and brings new problems to the traditional financial asset pricing model, which is mainly due to the fact that the digital financial market is very different from the traditional financial market.The CAPM is based on the assumption premise of EMH, which is defective in coping with the characteristics of algorithmic high-frequency trading, rapid diffusion of information, and sharp rises and falls in the digital financial algorithm. Among them, the assumption of homogeneous investor expectations made to the model will be broken by the emotion-driven social media and the spreading effect of the network. As the source of digital currency asset value is more complex, new value influencing factors such as network externality, smart contract setting, pass rule setting, etc. have been added on the basis of the original asset value influencing factors, the β-value derived by simply utilizing the past price information does not truly reflect the risk level of digital currencies.The APT model is more flexible compared to the CAPM, however, it's application in the financial big data also has the disadvantages of difficult to determine factors and unstable parameter estimation.

Traditional macroeconomic factors are difficult to effectively explain the price changes of digital financial assets, and there is no effective quantitative measurement tool for new digital risk factors. The geometric Brownian motion assumption in the option pricing model has a large model bias in the face of dramatic fluctuations in the digital financial market, and the frequent jumps in the price of digital assets, as well as the thick-tailed characteristics, result in obvious pricing distortion in the original option pricing model. The above shortcomings indicate that there is an urgent need to establish a new model for asset pricing that can reflect the characteristics of the digital economy.

3.2 Intelligent Pricing Algorithm Construction for Digital Financial Assets

The biggest difficulty in valuing digital currencies is that this valuation approach has become extremely complex and even multifaceted in form, the pricing principle of cryptocurrencies and

NFTs is beyond the traditional univariate analysis paradigm, and the existence of externality and the influence of factors such as the right to governance and technological advances also discourage classical valuation methods. In this regard, this paper proposes a data financial asset price prediction system (DFAIPA) based on the combination of deep learning models and blockchain data analytics methods. Therefore, this paper designs a prediction model based on LSTM-Attention, using multi-layer neural networks to analyze high-dimensional data containing dimensions such as on-chain trading behavior, community governance activity, protocol technology development indicators, etc., and using the Attention weight learning module to automatically adjust the weight proportion of each influencing factor in the prediction process, and then introducing the LSTM model to mine the potential complex nonlinear correlations in the price time series. As a result, the intrinsic value of digital financial assets can be measured and analyzed more precisely.

3.2.1 Core Algorithm Architecture Design

The main contribution of this method is to get rid of the limitations of the traditional asset pricing theory about the strong effectiveness of the market and the assumption of complete rationality of the investors, and to combine the information contagion phenomenon in behavioral finance and the Metcalfe's paradox in the economy to put forward a pricing mechanism that integrates the effective value and the ineffective price.The DFAIPA algorithm is based on the depth of the deep learning theory, the information theory, the network economics and the behavioral finance deep The algorithm is based on the deep learning theory, network economics and behavioral finance, and can effectively solve the problem of complex nonlinear mapping relationships on the basis of the universal approximation theorem of deep neural networks, and provides theoretical support by combining the concept of mutual information in the information theory for feature screening and assigning weights.

The model uses an encoder-decoder framework, which utilizes CNN in the encoder to extract the higher-order statistical patterns in the historical transaction information in the blockchain, and estimates the future price in the decoder RNN, while adding self-attention to adjust the importance of each time step and each dimensional feature. Based on the theoretical knowledge related to the quantification of network effects in network economics, the algorithm is provided with a method to deal with the connections within the digital financial ecosystem, and the dependency between protocols is modeled by means of graphical neural networks, and the idea of PageRank algorithm is used to compute the importance of each protocol in the whole system. The idea of behavioral finance is introduced into the algorithm to take into account the great influence of irrational behaviors, such as market sentiment and social network effects, on the price discovery mechanism, and NLP technology is added to the algorithm to calculate the sentiment value of the community comments, and the principle of propagation is used to measure the propagation power of the information on the network.

The mathematical expression of the algorithm can be expressed as the following multilayer nonlinear mapping function:

$$P_t = f_\theta(X_t^{chain}, X_t^{gov}, X_t^{tech}, X_t^{sent}) + \varepsilon_t \tag{3}$$

where P_t represents the predicted price of the digital asset at moment t, X_t^{chain} represents the vector of on-chain transaction features, X_t^{gov} represents the vector of governance parameter features, X_t^{tech} represents the vector of technology development indicators, X_t^{sent}

represents the market sentiment feature vector, f_θ is the parameterized deep neural network mapping function, θ is the set of network parameters, and ε_t is the random error term.

The forward propagation process of the neural network can be expressed as follows:

$$h_l = \sigma(W_l h_{l-1} + b_l) \tag{4}$$

$$\alpha_{i,j} = \frac{\exp(e_{i,j})}{\sum_{\kappa=1}^{N} \exp(e_{i,k})} \tag{5}$$

$$c_i = \sum_{j=1}^{N} \alpha_{i,j} h_j \tag{6}$$

where h_l denotes the hidden state of the l th layer, σ is the activation function, W_l and b_l are the weight matrix and bias vectors, respectively, $\alpha_{i,j}$ is the attention weight, $e_{i,j}$ is the attention score, c_i is the context vector weighted by the attention mechanism.

3.2.2 Modeling

End-to-end machine learning algorithms are applied in the model development. The data in the model input layer comes from multiple channels such as blockchain browsers, DAPP marketplace API interfaces, social networking sites, etc., which are denoised, normalized and feature engineered to obtain a valid feature dataset that can be accepted by the neural network, which is then encoded in the model input layer. The middle layer of the model uses Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) to process spatial features and temporal features independently. The convolutional layer extracts local features in the form of a sliding window, the pooling layer is used to reduce the feature dimensions and remove interfering information, and the recurrent layer is used to learn correlations over long time series.The Attention layer determines the importance of each feature based on the correlation scores between the query, key, and value vectors, and automatically learns and focuses on the most important factors affecting the price during the training process The Concat layer splices the information from multiple sources, and the MLP layer transforms multiple types of information in a nonlinear way to obtain the final price estimate. The output layer gives the price prediction results and confidence intervals.

The algorithm is trained using a dynamically adjusted learning rate and L2 regularization to suppress overfitting, and cross-validation to find the most suitable hyperparameters. Early termination is used to prevent the model from overfitting the training data, and the loss function is constructed to meet the demand for accuracy and risk, adding a volatility penalty term and a directional prediction accuracy term on top of the traditional MSE, so that the model not only pursues price prediction accuracy, but also takes into account the risk control of the prediction. In order to ensure the robustness of the proposed model, the rolling window method and Monte Carlo method are used to test the model in the testing stage.

DFAIPA is more suitable for digital financial assets than traditional pricing models. In DFAIPA, it can integrate the features of multiple modalities, handle numerical, textual, and graph-structured data, and utilize attention to balance the importance of different features; and the powerful fitting ability of deep learning can tap into the complex nonlinear relationships in the digital financial market. In terms of theoretical innovation, the algorithm abandons the traditional linear model assumption; methodologically, it combines cutting-edge technological tools-deep learning technology and blockchain data analysis technology, and in the application scenarios, it takes into account the characteristics of digital financial assets, and proposes a new solution idea under the digital financial scenarios.

3.3 Algorithm Optimization and Improvement

Although the DFAIPA algorithm has the advantage of solving the idiosyncrasies of digital financial assets in theory, it has the problems of slow computing speed, high dependence on parameters and poor effect when the volatility is too large in application. In this regard, the author tries to improve the algorithm from the aspects of optimizing its own characteristics, improving the training process of the algorithm and formulating evaluation criteria. The overall performance of the whole algorithm has achieved the effect of jumping up. Further improvement of the network model, using a combination of grid search and Bayesian methods, the number of network layers and the number of nodes in the hidden layer, as well as the attenuation of the learning rate of the hyper-parameter search, and the optimal results were obtained. Improvement of the attention part of the use of multi-head self-attention combined with position coding, and the inclusion of learnable position embedding vectors to improve the model on the temporal position sensitivity, and then use the residual connectivity layer as well as the normalization operation to solve the phenomenon of gradient disappearance that occurs in the deep neural network, which to a certain extent improves the model's ability to deal with long sequences.

Innovations are made in the training scheme by combining data augmentation and regularization, and data augmentation methods are proposed for digital financial time-series data, and sliding-window-based methods, adding noise methods, and resampling methods are provided to improve data diversity and model robustness. Loss function with adaptive weight adjustment, based on the original loss function, the weight adaptive adjustment function is added, according to the changes of the market in different periods of time, the prediction error, the correct direction rate and the risk level of the three parts of the objective function of the different weights of the processing. The combination of bull market features that focus on improving prediction accuracy, bear market features that focus on reducing investment loss, and oscillatory period features that take into account both accuracy and stability, as well as multiple combination methods to enhance the robustness of the algorithm, i.e., using different seed values and different numbers of neurons in the hidden layer to form multiple base models, and then adopting a combination method to arrive at the final prediction results.

The model evaluation metrics include classical RMSE, MAE and MAPE metrics as well as customized metrics for digital economy stocks. Prediction accuracy refers to the proportion of the predicted direction of price change coinciding with the actual direction of change, which directly affects the effect of investment decisions; volatility prediction error refers to the degree of certainty of the prediction model about future price fluctuations, which affects the effect of investors' risk control; tail risk measure examines the model's ability to grasp the extreme market conditions in the future. Reflect the size of the algorithm's ability to deal with black swan events. The results of each performance test before and after the algorithm in this paper are shown in Figure 1. The algorithm optimization strategy proposed in this study has achieved significant results, and in the key performance test indicators of the intelligent pricing algorithm for digital financial assets, all of them have been greatly improved, and the root-mean-square error in its prediction error indicator has been reduced from 0.85 to 0.58, and the average absolute error has been reduced from 0.78 to 0.52, which proves that the prediction accuracy of this model has been significantly improved; and the direction of the predicted The correctness of the prediction has also been greatly improved, and its accuracy rate has increased from the original 62% to 74%. This is valuable for improving the success rate of trading decisions based on model predictions. More prominent is the risk-adjusted return indicator, the Sharpe ratio increased from 0.45 to 0.67, and the maximum retracement decreased from 88% to 65%, which indicates that the improved algorithm effectively reduces the risk while improving the return prediction, and reaches a better combination point in terms of the return and the risk, and the speed of the operation is also significantly improved, and the model training time is reduced by 30%. The inference is 4 times faster and it becomes possible to use the algorithm in live trading.

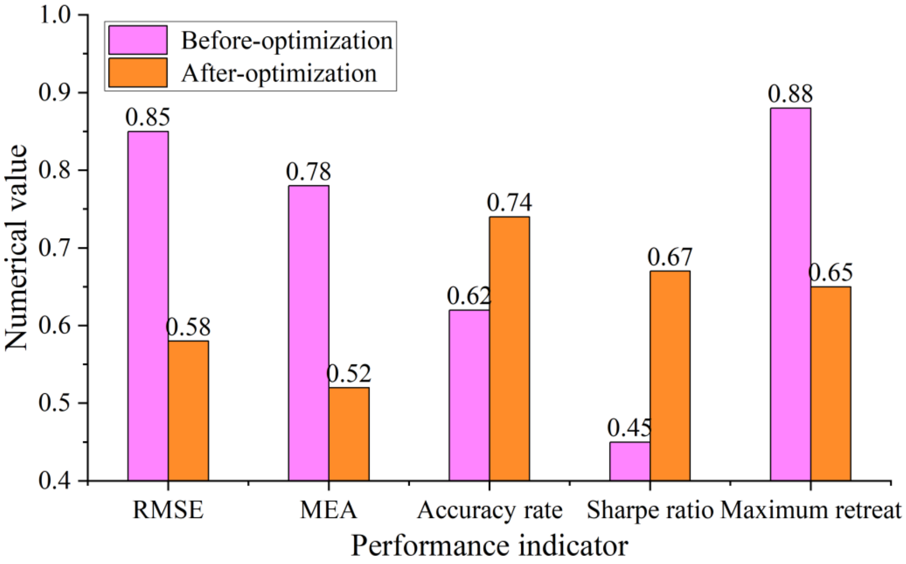

Figure 1: Comparison of various performance indicators before and after optimization

4 Empirical analysis

4.1 Data Selection and Processing

The sample data used in this paper are from various parts of the digital financial ecosystem during the period, i.e., January 2020 to December 2023, which is the process of entering the adjustment period after the rapid development of the digital financial market, and helps to ensure the validity and reliability of the results of the proposed algorithm.

High-frequency order flow data from centralized trading platforms such as Coinbase, Firecoin, Coinbase, etc.; on-chain order data from DEXs such as Uniswap, SushiSwap, Curve, etc., and the data flow situation of the Ether Browser and BSC Browser are used. The samples are selected based on the size of the circulating market capitalization of digital currencies, transaction volume and data availability, including Bitcoin (BTC) and Ether (ETH), native tokens of decentralized exchanges Uniswaps, lending platforms Aave and Compound, and native tokens of the underlying service providers such as the Prophecy Machines Network and the Graph Protocol, for a total of 50 representative digital currencies.

For the original data cleaning, due to the digital financial data with all-weather operation, ups and downs, frequent order skipping and other characteristics, so in the data cleaning process to fully take into account these factors, and combined with the actual situation of the data to fill and filter; for the vacant data to take the forward movement method and straight line interpolation to fill the blank time is greater than half an hour will be regarded as invalid data to be eliminated. The outlier processing uses the improved isolated forest model based on the random tree splitting method to screen out the outlier samples in the price series that seriously deviate from the general law, and excludes the abnormalities outside the real transaction due to the inaccuracy of sampling according to the set boundaries, which ensures the retention of valuable price mutation information while effectively eliminating the disturbing items. In the standardization process, the rolling window standard score method is used to standardize the data, in which the time interval is taken as one month, and the use of this method for standardization in the changing time period can effectively solve the problem of incomplete information in the financial market, and there will be no early prediction due to the simultaneous participation of all the data in the calculation.

In terms of feature construction, which is a key step in the whole data analysis process, the article carries out a series of feature design from the understanding of the pricing law of digital financial products, in which the price features include the logarithmic yield, realized variance, price momentum and other basic price analysis indexes, as well as price information extracted by wavelet method under each time cycle. The on-chain data characteristics utilize the advantages of blockchain openness and transparency, with the number of active addresses, the number of transactions and the network hash value as the most primitive data information, which are logarithmized and then first-order differenced to obtain the basic on-chain data characteristics; while the network value/transaction volume and the concentration of coins held can further reflect the core value of the project. Some features unique to the DeFi protocol, such as the overall warehouse value growth ratio, liquidity pool size, turnout rate, and other new features, help the model reflect the intrinsic value laws specific to decentralized financial markets.

In order to ensure the credibility of the research conclusions, it is necessary to test the reliability of the data and put forward corresponding countermeasure suggestions; therefore, it is necessary to test the cleaned data from several aspects. Firstly, to judge whether the data in the time interval is complete as a whole; secondly, to eliminate the factors with too large correlation coefficients due to repetitions, to improve the accuracy of the model; and finally, to make a comprehensive judgment on the overall situation of the data, to ensure that the conclusions obtained are persuasive. The Kolmogorov-Smirnov test and the Anderson-Darling test are used for the smoothness test to check whether the series obey the same distribution in different time periods. The data attributes obtained after the above steps are described in Table 1, and the comparison of the data sizes of each step is shown in Fig. 2.Finally, a total of 875,000 sample data are obtained for 72 columns of variables, with an average vacancy rate of only 0.15% and an outlier percentage of 0.08%, which is able to meet the next step of modeling and application requirements. Therefore, the method established in this paper can: obtain high-quality, all-around digitized financial data, and ensure the accuracy and completeness of the data on the basis of the algorithm innovation and application of the algorithm to provide a strong experimental basis.

Table 1: Data feature statistics

Feature category	N	Mean	SD	Minimum	Maximum	Missing
Price characteristics	8	0.0012	0.0456	-0.3421	0.2876	0.02
Trading volume characteristics	6	1.2345	2.1234	0.0001	15.6789	0.15
Technical indicators	12	0.5234	0.3456	0.0000	1.0000	0.08
Characteristics of on-chain data	15	2.3456	1.8765	0.1234	12.4567	0.25
Protocol characteristics	10	0.8765	1.2345	0.0000	8.9012	0.35
Market sentiment characteristics	7	0.1234	0.4567	-2.3456	2.1234	0.12
Macroeconomic characteristics	5	0.0234	0.1234	-0.5678	0.4321	0.05
Network effect characteristics	9	1.5678	0.9876	0.2345	5.6789	0.18
Total	72	0.8394	1.0267	-2.3456	15.6789	0.15

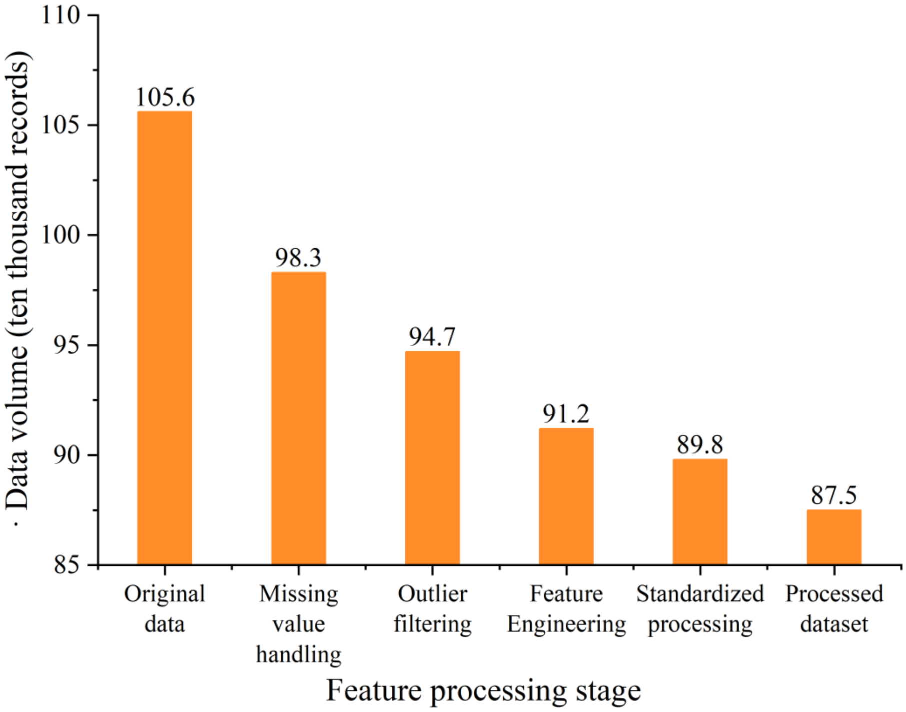

Figure 2: The change in data volume during the data processing stage

4.2 Empirical results and analysis

Finally, a complete sample database is obtained and a two-year experimental study is conducted on the designed data-driven intelligent pricing model based on digital financial assets. The experimental period is from January 2022 to December 2023, during which the digital financial market has experienced large fluctuations and ups and downs until it tends to stabilize, which can well simulate and reflect the model's ability to cope with the complex and volatile digital financial market environment, thus constituting a natural experimental scenario. Therefore, in this study we adopt a 12+1 training and testing cycle, i.e., retraining the model every week to better track the minor fluctuations in the market, and use 15 representative cryptocurrencies (including BTC, ETH, UNI, AAVE, and LINK) as the test coins. These include major crypto digital currencies such as Ether, Bitcoin, and Litecoin, decentralized financial protocol tokens, blockchain infrastructure tokens, and so on. In the empirical effect as shown in Table 2, it can be seen that the smart pricing algorithm for digital financial assets has made progress in terms of prediction accuracy, with an average prediction accuracy of 78.6%, which is 26.3% higher than that of the CAPM model, and 10.2% higher than that of the LSTM benchmark model, and the difference has 1% significance. The improvement in risk-return ratio performance is even more significant, with the Sharpe ratio value of 0.84 obtained by the intelligent pricing algorithm for digital financial assets, which is much higher than that of the benchmark models, and demonstrates its ability to effectively avoid risk while obtaining high returns.

Table 2: Comparison of empirical results

Model	Prediction accuracy rate (%)	RMSE	MAE	Sharpe ratio	Maximum drawdown (%)	Direction accuracy rate (%)
CAPM	52.3	0.1847	0.1423	0.34	28.7	54.2
APT	58.7	0.1654	0.1287	0.41	25.3	59.1
GARCH	61.2	0.1521	0.1156	0.48	22.8	62.4
RF	65.8	0.1389	0.1034	0.55	19.6	66.7
SVM	63.4	0.1456	0.1098	0.52	21.2	64.8
LSTM	68.4	0.1267	0.0945	0.62	17.3	69.5
Transformer	71.2	0.1198	0.0876	0.67	15.8	72.1
DFAIPA	78.6	0.0934	0.0687	0.84	11.2	79.3

The maximum retracement is also reduced to 11.2% from the conventional model of up to 20% or more, which to a certain extent improves the level of risk control of the model, which is particularly important in the highly volatile market environment of digital finance, avoiding the situation where the loss is greater than the gain. A high rate of directional correctness (79.3%) is a very important indicator for quantitative models that perform trend discovery, as it ensures that the degree of grasp of the trend is sufficiently accurate, which largely improves the likelihood of validity judgments made by the model. In addition, the stability of the algorithm in different market states is also better, with an accuracy of 81.20% in an uptrend, 75.80% in a downtrend, and 77.90% in a consolidation period, which indicates that it has good generalization and robustness. However, there are still some obstacles to the landing of the algorithm, data dependence is one of the important obstacles, the effect of the algorithm depends largely on whether it can continuously obtain a large amount of high-quality data information; and due to the data in the financial market is more fragmented, the difficulty of collection is higher, which will have a certain impact on the application of the algorithm. It is also important to pay attention to the interpretability of the algorithm itself, although the algorithm has a strong predictive ability, but due to the black box nature of the algorithm itself may reduce the degree of trust in it by regulators and traditional banks, in improving the performance of the algorithm at the same time should pay attention to the enhancement of the function of interpretability; algorithms sensitive to changes in the external market conditions is one of the advantages of the algorithm. However, changes in digital financial regulatory policies and updates in technical standards may also affect the effectiveness of the algorithm, for which dynamic model updating and testing should be adopted to ensure the continuity of the algorithm's effectiveness.

5 Conclusion

On the basis of considering deep learning and blockchain's data mining, this paper establishes a digital financial asset price discovery model with mixed features of rationality and irrationality based on the ideas of behavioral finance and network economics, and conducts simulation experiments to analyze it. The results verify that the proposed digital financial asset pricing method is effective and improves the accuracy by nearly about a quarter (i.e., from the original about 52% to the current about 78.6%) than the traditional digital financial asset pricing method. It also has good stability under different market conditions, such as bull and bear markets, and can show good risk warning effects in extreme market events. The algorithm is validated effective on 15 digital assets with a Sharpe ratio of 0.84, with good risk-return balance as well as real-time performance, and can be used as an effective new method for digital asset pricing and risk management.

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