

The Application of Artificial Intelligence to Stock Forecasting: A Literature Review

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Abstract. Due to the non-linearity, high volatility and noise characteristics of stock prices, the prediction of stocks has become a challenging issue. The results of stock prediction algorithms rely on the selected indicators, including financial indicators and market sentiment indicators, and the algorithm model. A large number of scholars have conducted studies and innovations from different perspectives respectively to optimize the prediction results. This paper reviews the development of artificial intelligence in stock application from two perspectives of index and algorithm model. Among them, the characteristics, advantages and disadvantages of 8 transformer models are shown, as well as the emergence of financial language models such as BloombergGPT and FinGPT. In addition, due to the particularity of China's stock market, when making predictions about stocks in Chinese stock market, we are expected to focus on taking into account market sentiment, policy factors and adjusted financial indicators., so as to enhance the accuracy of prediction.

1 Introduction

The non-linearity, uncertainty and dynamic nature of financial market make stock price forecasting a very challenging subject. Stock data has the characteristics of high dimensional, noisy and non-stable, and integrates structured financial indicators such as financial data and technical analysis factors with unstructured text data such as news opinions and investor comments, making it difficult for traditional statistical models to capture its complex correlation. The development of artificial intelligence technology provides a new way to solve this problem. It can help investors determine when to join and quit and build successful hedging strategies. It can also help investors determine when to join and quit and build successful hedging strategies.

From the perspective of the relationship between machine learning, deep learning and artificial intelligence, machine learning uses feature engineering to mine nonlinear relationships (such as random forest screening key factors), while deep learning uses neural networks to realize end-to-end feature learning (such as LSTM to capture timing dependence). And the breakthrough of large language model (LLM) further improves the semantic parsing ability of unstructured text (real-time analysis of the impact of news sentiment on stock prices). The three forms a technological progression: machine learning lays a data-driven

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foundation, deep learning strengthens complex pattern modeling, and large language model expands text semantic understanding to jointly build a multi-modal prediction framework.

The core steps of stock prediction include: i) data preprocessing, integration and cleaning of structured and unstructured data; ii) Feature engineering, selecting traditional financial indicators, macro variables and market sentiment indicators as variables; iii) Model construction, select adaptation algorithms (such as LSTM and Transformer) and optimize parameters; iv) Dynamic evaluation, improve model performance through cross-validation and real-time data update. Compared with traditional methods, artificial intelligence has significant advantages in data processing scale, nonlinear modeling accuracy and real-time response ability, and enables more people to make stock predictions at low cost. However, the lack of explainability and overfitting risk caused by its "black box" characteristics still need to be optimized by means of attention mechanism visualization and regularization technology.

This paper studies more than 40 articles about artificial intelligence in stock forecasting or financial asset forecasting in the past six years. These articles are all from SpringerLink, scopus, CNI, Google Academic. The authors are screened according to the relevant degree of the topic, article quality, data source and other indicators. Finally, 25 of them were selected to make a detailed review of the development of artificial intelligence application in stock forecasting. Since input predictor variables and selection algorithm are the two most important steps in stock prediction, in order to show the development process more clearly, this paper reviews the optimization of input predictor variables and the change of algorithm selection, and discusses the challenges of large models in the context of Chinese market.

2 The evolution of artificial intelligence

2.1 Development of artificial intelligence

In 2006, Jeffrey Hinton introduced the concept of deep learning, which drove the Renaissance of neural networks. In 2012, Hinton's team achieved breakthrough results using deep Convolutional neural networks (CNN) in the ImageNet competition, triggering a revolution in artificial intelligence. Since then, deep learning has made breakthroughs in speech recognition, image recognition, natural language processing and many other fields. At the end of 2022, ChatGPT debuted, based on GPT-3.5 architecture, designed for conversational interaction, capable of back-and-forth dialogue with users and maintaining context. Since then, the era of artificial intelligence closer to people's lives has been ushered in. China's AI has also flourished, such as deepseek through its distillation technology and optimization algorithm. To achieve results close to large models with less computing power, focusing on lightweight and localization. Meanwhile, artificial intelligence trained specifically on financial data, such as FinGPT and BloombergGPT, has also been developed, showing higher accuracy in predicting small samples of data.

2.2 Development of artificial intelligence algorithms in stock prediction

In the field of stock price prediction, traditional methods are based on statistical models and can exhibit good prediction effects when dealing with stationary time series data. However, their limitations are also quite significant. In the face of the widespread non-linearity, non-stationarity, and sudden fluctuations brought by the financial market, traditional methods struggle to capture complex market patterns and their prediction accuracy drops significantly.

With the development of artificial intelligence technology, machine learning algorithms have brought new breakthroughs to stock price prediction. The Support Vector Machine

(SVM) algorithm, with its outstanding nonlinear classification and regression capabilities, finds the optimal hyperplane to fit the complex relationships of stock price data, effectively solving the predicament of traditional methods in nonlinear problems. However, SVM has problems such as low computational efficiency and complex parameter adjustment when dealing with large-scale data, limiting its further application.

The rise of deep learning has pushed stock price prediction into a new stage. Convolutional Neural Networks (CNN) can efficiently extract spatial features from stock price data through local perception and weight sharing mechanisms, capturing local patterns of price fluctuations. Recurrent Neural Networks (RNN) and its derivatives such as Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRU) focus on processing time series data. LSTM was proposed in 1997 and successfully solved the problem of long-term dependencies in RNN by introducing memory units and gating mechanisms, enabling it to effectively read data relationships over long time spans and mine long-term trends in stock price changes. GRU simplifies LSTM and reduces model parameters while maintaining good prediction performance. However, these algorithms still have problems of insufficient capture of key information when dealing with the complex and variable information in the financial market.

To better cope with market complexity, researchers have included multi-dimensional information such as market sentiment in the consideration scope and introduced the attention mechanism (Attention). This mechanism enables the model to automatically focus on key information that has a significant impact on stock price prediction when processing data, ignoring redundant information interference, significantly promoting the development of stock price prediction algorithms towards more intelligent and accurate directions. There are also innovative algorithms such as using XGBoost algorithm to build multi-factor duration timing model [1] and dynamic CAPM model [2].

2.3 Future development trend

But machine learning, especially deep learning and other algorithms do not have good interpretability, to a certain extent belongs to the "black box" algorithm, the application of such algorithms to the real stock prediction will lead to a series of problems, such as algorithm discrimination, algorithm resonance problems, people will focus on the interpretability of artificial intelligence. If artificial intelligence has comprehensive explainability, the "black box" algorithm of artificial intelligence is expected to be governed to a certain extent, and the performance of the model is not in place or deviates from the target.

Emerging technologies such as quantum computing and edge computing will provide more powerful computational support for AI. Meanwhile, the deep integration of AI with big data, Internet of Things, blockchain and other technologies will create more application scenarios.

3 The application of artificial intelligence to stock price prediction

3.1 Analysis about optimization of the input predictor variables

3.1.1 Traditional financial indicators

Technical indicators are crucial for stock price prediction models. Stock price prediction is mainly predicted by the characteristics of historical data sets, including the corresponding opening price, high price, low price, close price and trading volume for each date, which can be easily obtained by data analysts from various data platforms. For example, Chen et al.

built a CNN model in addition to the other four indicators of trading volume [3]; Zhou et al. built a bidirectional gated cycle unit model of convolutional neural network based on the above five indicators [4]. Vishwakarma et al. state that the Adjusted Closing Price is worthy of consideration, as it reflects the last-minute sentiment of the stock by professional investors and traders [5]. The Adjusted Closing Price refers to the final closing price of a stock, which is the stock value after all outstanding orders have been executed and any corporate actions have been taken into account. Some studies also input important information from financial statements into the formula as indicators, such as price-to-earnings ratios.

Based on historical price, volume, or open interest information, there are various technical indicators considered as inputs that help forecast future price movements. Key technical indicators include the Relative Strength Index (RSI), Moving Averages (MA), Bollinger Bands, Stochastic Oscillator, Moving Average Convergence Divergence (MACD), and Chaikin Money Flow (CMF). The RSI measures the speed and magnitude of price changes to identify overbought or oversold conditions. MA, including Simple Moving Average (SMA) and Exponential Moving Average (EMA), helps smooth price data to determine trend direction. Bollinger Bands, consisting of a middle SMA and two outer bands representing standard deviations, indicate market volatility and potential overbought or oversold conditions. The Stochastic Oscillator compares a security's closing price to its price range over a specified period to generate buy and sell signals [6-8]. MACD analyzes the relationship between two moving averages to identify changes in trend strength, direction, momentum, and duration. CMF calculates the volume-weighted accumulation and distribution over a given period to assess buying and selling pressure. These technical indicators are either singled out or integrated as variables in the equations for stock prediction, assisting investors in making more informed market decisions [6].

3.1.2 Market sentiment

Financial data, like indicators on quarterly or annual reports are generally insufficient and not timely enough for stock prediction. As data technology develops, data sources are no longer solely relying on traditional data, but also some alternative data, like individual behaviors (media posts, product reviews, search trends, etc.). This reflects timely market trends.

Extracting investor sentiment from social media can be regarded as a combination of Data Acquisition, Text Sentiment Mining, and Sentiment Aggregation [9]. In terms of data sources, 35.5% of researchers in traditional social media use Twitter data, which is rich in data and easy to use API. Investor e-communities are also important sources, such as StockTwits, Yahoo! Finance and Eastmoney BBS, which account for 42.1% of the usage, are highly professional and less noisy [10]. Text emotion mining mainly uses text analysis methods to extract effective emotional information. This is mainly through the "text package" technology (which simplifies a large amount of text information into a two-dimensional matrix under the assumption that the text order does not affect the understanding of the text), including the vocabulary classification dictionary method, text vocabulary weighting method and a variety of classification methods based on machine learning (such as naive Bayes method), and other text features (such as text readability, text narrative methods, etc.). To infer the views or sentiments held by the text creators and examine the corresponding market reactions [11]. Emotional aggregation includes two types: aggregation based on emotional polarity, such as the semantic output of text analysis is mostly classified as "positive, negative and neutral", and aggregation based on emotional intensity, aiming to measure the degree of emotion in social media texts [9]. Finally, the market sentiment is digitized and incorporated into the stock prediction model as an indicator.

3.2 Analysis about change in algorithm choice

3.2.1 Algorithm Development

Support vector machine (SVM), long short-term memory network (LSTM) and random forest (RF) are more widely used in stock prediction algorithms [5]. Billah et al. used a diverse real-world data set to confirm that LSTM's average prediction accuracy in financial market forecasting reached 89.7%, significantly better than the benchmark model [12]. From machine learning to deep learning, many scholars have made improvements on the basis of deep algorithms in recent years to improve precision of prediction. A deep reinforcement learning (DRL) method for stock market training automation was created by Kabbani and Duman [13]. It minimizes the computational cost of allocation and prediction processes. Das et al. improve the accuracy of stock market trend prediction through ensemble learning and dimensionality reduction techniques [14].

The model is further optimized as the market sentiment index is taken into account in the model. Although various online platforms have a large amount of information, the quality, reliability and comprehensiveness of information related to financial markets vary greatly, and a large part of it is even composed of low-quality news, evaluations and rumors [15]. Many scholars optimized the existing models. For example, the Hybrid Attention Network, as developed by Hu et al., categorizes various news items based on their significance [16]. The Transductive Long Short-Term Memory (TLSTM) was proposed by Peivandizadeh et al.[17]. The problem that it is difficult to accurately identify a minority of common emotions caused by the overwhelming presence of more common emotions (majority class) was optimized. Liu et al. integrated expert suggestions based on LSTM model to provide more accurate investment direction [18], and tested the model with a large number of real phenomena [19].

3.2.2 Large language model

Based on the Transformer model, today's innovative big language model architecture improves sentiment analysis capability. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs), two classic deep learning models, still face big challenges. RNNs struggle to capture long-term dependencies effectively [20], while CNNs excel at capturing local patterns but struggle to process global context information in textual data [21]. Therefore, an increasing number of scholars are using the transformer model to improve sentiment analysis capabilities through innovative self-attention mechanisms and two-way processing capabilities [22]. Bashiri et al. have summarized the advantages and disadvantages of eight transformer models [23], as shown in Table 1, and come to the conclusion that the generality of Text-to-text transfer transformer (T5) enables it to perform well in a variety of tasks, while other models have advantages in certain scenarios.

Table 1. introduction of 8 transformer model

Model	Advantages	Limitations	Unique characteristics
BERT	Strong context understanding for a wide variety of NLP tasks	Computationally intensive, large model size	Bidirectional context, NSP task

RoBERTa	Outperforms BERT in several benchmarks and handles long text better	Training requires a lot of computing resources	Larger training data, dynamic masks, no NSP tasks
XLNet	Combining the advantages of autoregressive and bidirectional models, good at handling long distance dependencies	The training process is complex and the calculation cost is high	Permutation based language modeling, dealing with long range dependencies
ELECTRA	The pre-training process is efficient and resource efficient	The training objectives are not very intuitive	Efficient training based on replacement mark detection
DistilBERT	The model's small size and fast reasoning speed retain most of BERT's performance	There is a slight performance loss compared to the complete BERT	Knowledge distillation, small and fast model
ALBERT	Fewer parameters, less memory usage, faster training	Parameter sharing and embedding techniques require careful adjustment	Parameter sharing across layers, factorization and embedding
T5	Strong versatility, excellent performance in multiple tasks	Large model size, challenging to deploy and fine tune	Uniform text-to-text framework
GPT	Strong text generation ability, with zero sample, same copy and small sample learning ability	Unidirectional context, less effective on tasks that require deep understanding of context	Strong generative ability, large-scale models demonstrate zero sample learning ability

The development of large language models (LLMs) has opened up new avenues for the application of AI in the financial sector. However, the lack of text datasets in financial industry limits the creation of financial language models (FinLLMs). An open source framework called FinGPT was created to solve this issue. It automatically gathers and filters real-time financial data from various internet sources. This framework aims to improve the accessibility, transparency and adaptability of finLLMs to researchers and practitioners, and promote low-code development, robo-advisory services and transactional sentiment analysis in the financial sector [24]. In terms of other financial language models, Wu et al. trained BloombergGPT with 50 billion parameters [25], which performs well on financial tasks and general language understanding, helping to improve natural language processing capabilities in financial field. Due to the lack of pre-training models in the financial industry, Yang et al. developed FinBERT for the financial field [26], which is superior to the general BERT model in the task of financial emotion classification, and provides valuable resources for financial natural language processing. BloombergGPT, FinGPT, FinBERT and other models show high accuracy in financial prediction and analysis, but there are also limitations in data quality and domain specificity [24].

3.2.3 Further development

With the maturation of cloud platform technology, leading providers like AWS and Google Cloud offer stable serverless computing infrastructure, renowned for their elastic scalability, high availability, and low operational costs. Capitalizing on these advantages, Wang et al. developed StockAICloud using the FastAPI framework to deliver scalable stock prediction services [27]. FastAPI's asynchronous programming and type hinting features optimize resource utilization and boost response speed. Performance tests showed that under 400 concurrent requests, StockAICloud achieved a maximum throughput of 21.2 requests per minute, validating its stability in high - traffic scenarios. This platform innovatively integrates deep learning models with serverless cloud computing, enabling dynamic resource allocation. It adapts to fluctuating workloads, ensuring cost - effective operation during off - peak periods and rapid response during trading surges. StockAICloud expands the application scope of stock prediction services, catering to both individual investors and financial institutions. Its excellent scalability in high - concurrency environments sets a precedent for future fintech applications, highlighting the vast potential of serverless cloud - deep learning integration in finance.

4. Discussions on occasions in China

In the context of Chinese market, China's stock market has unique characteristics. Policy intervention, retail-led investor structure and information asymmetry put forward higher requirements for the adaptability of forecasting models. This requires quantifying the irrational influence of investor sentiment and strengthening the semantic analysis module of policy texts.

The investor structure of China's stock market is dominated by retail investors. Yi et al. found that factors such as momentum, reversal and trend following have a greater impact on the return rate of Chinese stocks [28], and small-market stocks are more predictive, which indicates that the investment behavior of retail investors has strong herding effect and emotion-driven characteristics. With the rapid dissemination of information on platforms such as social media and stock bar, investors are susceptible to the influence of group sentiment, which leads to the aggravation of market volatility. When using market sentiment indicators to make predictions, it is necessary to analyze and filter such information more accurately to avoid being interfered with by false or misleading information. At the same time, due to the relative lack of retail investment knowledge and experience, there are a lot of irrational trading behaviors in the market, which also increases the uncertainty of stock price trends, requiring the model to have stronger adaptability and robustness.

Compared with the stock markets of other countries, policy factors have a greater impact on China's stock market. The frequent adjustments of macroeconomic policies, industrial policies and stock market supervision policies directly affect the business environment and market expectations of enterprises. At present, most of the financial language models are based on the English system, but Jiang et al. combined with the unique characteristics of the financial market with Chinese characteristics [29], trained a Chinese financial large language model that is more suitable for China's financial field, which is more sensitive and accurate than other language models in sentiment measurement. The government's support policies for emerging industries will promote the stock prices of related enterprises to rise, while the regulation policies for some industries may lead to the stock prices to fall. Therefore, forecasting models must track policy dynamics in a timely manner, take policy variables into account, and accurately interpret the impact of policies on different industries and enterprises.

The information disclosure system and supervision mechanism of China's stock market are still being improved, and there is a problem of information asymmetry. Some enterprises

may conceal important information and manipulate financial data, making it difficult for investors to obtain true and comprehensive corporate information. In the process of data collection and processing, it is necessary to screen and verify data sources more carefully, and cross-check information through multiple channels to improve the reliability of data. In addition, irregularities such as insider trading occur from time to time, which will also distort stock price movements and affect the accuracy of forecasts, which requires regulators to strengthen supervision and safeguard market fairness and justice.

5. Conclusion

This paper focuses on the application of artificial intelligence in stock prediction, explores how to improve the accuracy of prediction, and analyzes key points of its application in China's stock market. This paper reviews the technological evolution of machine learning, deep learning and large language models from two key perspectives of input predictor variable optimization and algorithm selection reform. By analyzing more than 40 related literatures, 25 were selected for in-depth research to analyze the mechanism of various models and indicators in stock prediction. The study finds that the multi-modal prediction framework built by artificial intelligence has significant advantages and far outperforms traditional methods in data processing, nonlinear modeling and text semantic parsing. Using traditional financial indicators and market sentiment indicators to optimize input variables, combined with diversified algorithms, can effectively improve the accuracy and efficiency of prediction. This provides investors with a more accurate basis for decision-making, helps to build a more reasonable investment strategy, and also provides strong support for financial institutions to improve their services and products. However, there are certain limitations in this study. Artificial intelligence faces problems such as data quality, model interpretability and overfitting in stock prediction, and the uniqueness of China's stock market also increases the difficulty of prediction. In the future, these problems can be solved by optimizing data processing technology, exploring interpretable models and improving algorithms. For example, data cleaning technology can be used to improve data quality, visualization technology can be used to enhance model interpretability, regularization method can be used to prevent overfitting, market rules can be deeply studied, and more influencing factors can be incorporated into the model to further improve the reliability of prediction.

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