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Stock Price Prediction and Analysis Using Neural Network Models

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Abstract: As the global economy becomes more interconnected and financial markets face increasing risks, stock price volatility has also risen. For the numerous stock traders and investors in our country, conducting scientific and effective stock price prediction and analysis is crucial. This process enables the formulation of sound investment strategies and the achievement of higher returns. Additionally, the rapid advancements in machine learning in recent years have made stock price factor analysis using neural networks increasingly feasible.This paper reviews key studies from the past few decades and provides a summary of the research methods and models used in stock price factor analysis. It also explores two primary research approaches: horizontal research and vertical research. Furthermore, the paper compares long-term and short-term investment strategies, highlighting the neural network models most suitable for each scenario.

Keywords: Neural network, Stock price factor analysis, Financial market

1. Introduction

In 2024, as the global economy gradually recovers and China's economic structure undergoes transformation, capital markets are presented with new opportunities and challenges. Amidst the increasing risks in global markets, stock price prediction and stock price factor analysis have emerged as critical topics in the financial sector. The rapid development and continuous innovation of machine learning technologies have made them indispensable worldwide, providing vital technical support for stock price prediction and analysis, and leading to significant advancements in financial forecasting.

With the rise in global financial trade risks, stock price volatility is also on the increase. For investors, stock price prediction has become of paramount practical importance. According to recent statistics, as of 2024, China has approximately 220 million stock investors. Through effective stock price factor analysis and prediction, this large group of investors can gain a better understanding of stock price movements and market trends, allowing them to make informed and rational investment decisions and, ultimately, achieve higher returns. Additionally, stock price prediction analysis serves as crucial data support for policymakers and market regulators.

This paper begins with a literature review, summarizing key studies on stock price factor analysis using neural networks over the past few decades. From this, it identifies the research methods and approaches utilized in stock price prediction. The subsequent section provides a theoretical discussion, exploring the research methodologies of these papers, categorized into horizontal and vertical research approaches. A comparison of long-term and short-term investment strategies will also be addressed.

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2. Literature review

The use of neural networks in stock price prediction has garnered significant attention globally, driven by the rising risks in financial markets and the inherent uncertainty of stock prices. This literature review examines key theoretical and empirical studies in this field.

In a case study examining the S&P 500, DAX, TOPIX, and FTSE from 1965 to 1999, Jasic et al. [1] proposed a univariate neural network framework that directly processes raw financial time series data (e.g., closing prices) to generate next-day index return forecasts. Through rigorous out-of-sample testing on four major indices (S&P 500, DAX, TOPIX, FTSE), the trading signals derived from LSTM-based predictions exhibited statistically significant deviations from unconditional daily mean returns ($p<0.01$, two-tailed test) [2]. Empirical simulations incorporating realistic transaction costs ($\leq 0.35\%$ per trade) revealed that the neural network-driven strategy could achieve 18-24% annualized excess returns over buy-and-hold benchmarks [3]. This aligns with recent findings that GRU and CNN architectures excel in capturing nonlinear market patterns through raw data inputs, particularly in directional accuracy metrics (68-72% in testing phases) [2].

In recent years, there has been significant research on various models related to time series analysis for stock price prediction. One notable study by De Oliveira et al. [4] applied Artificial Neural Networks (ANN) to predict stock prices and improve the directional prediction index, focusing on the case of PETR4 (Petrobras, Brazil). The study developed a hybrid forecasting framework that synergistically combines technical analysis (examining price patterns and indicators) with fundamental valuation metrics (assessing financial statements and macroeconomic factors), augmented by time series analysis (TSA) methodologies. Four distinct predictive approaches were systematically implemented: Fundamental Analysis, Evaluating price-to-earnings ratios and revenue growth trajectories; Technical Analysis, Applying moving average convergence divergence (MACD) and Bollinger Bands; Traditional TSA, Implementing ARIMA models for volatility pattern recognition; Machine Learning, Deploying LSTM networks to capture nonlinear temporal dependencies. Additionally, a list of companies was selected based on their growth potential and economic fundamentals, with price changes analyzed to determine the optimal negotiation strategy at the right time. In this research, De Oliveira et al. [4] aimed to understand the information within financial markets and identify the key variables that influence stock prices, considering factors such as sector-specific activities, macroeconomic indicators, and industry trends.

Time series analysis has also garnered significant attention from researchers. Berradi [5] and Lazaar [6] integrated Principal Component Analysis (PCA) with Recurrent Neural Networks (RNN) to forecast stock prices on the Casablanca Stock Exchange. They collected stock prices of Total Maroc over a 29-day period. As is well known, the Recurrent Neural Network (RNN) is a widely used model for prediction tasks. The researchers also employed PCA to reduce the number of features from eight to six. The results indicated that dimensionality reduction improved the accuracy of the RNN model, providing more reliable stock price predictions.

In a later study, Adebiyi et al. [7] compared ARIMA and Artificial Neural Network (ANN) models for stock price prediction. The study utilized publicly available stock data from the NYSE and developed ARIMA and ANN models. EViews software was used for the ARIMA model, while Matlab's Neural Network Toolbox (version 7) was employed for the ANN model.

The data used in Adebiyi et al. [7]'s research consisted of historical daily stock prices, including open, low, high, and close prices, as well as trading volume. The study focused on Dell Inc. stock data, covering the period from August 17, 1988, to February 25, 2011, with a total of 5,680 observations. The empirical results demonstrated the superiority of the neural network model over the ARIMA model in predicting stock prices.

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In another study, Agrawal [8] applied a Deep Learning (DL) model to predict stock prices based on technical indicators, using data from November 17, 2008, to November 15, 2018. The study examined datasets from HDFC, Yes Bank, and SBI. The proposed model utilized a Deep Learning approach to establish the concept of Correlation-Tensor. Agrawal [8] conducted extensive experiments to analyze the correlation between various technical indicators (STIs) and stock price trends. The results indicated that the proposed EDLA model, combined with STIs, frequently outperformed other state-of-the-art algorithms.

In a comprehensive investigation of equity return predictability, Wang et al. [9] conducted a multi-decadal analysis (from 1971 to 2021) comparing machine learning architectures under various factor specifications. The study leveraged 49 firm-level characteristics spanning valuation, momentum, and liquidity dimensions while incorporating 14 macroeconomic indicators categorized into three clusters: Financial market dynamics, Term spreads, credit default swap indices; Real economy proxies, Industrial production growth, PMI composites; Sentiment metrics, Consumer confidence index, VIX derivatives. The findings revealed that neural network models performed consistently across different stock return measures, with their performance in predicting abnormal returns being almost identical to their performance in predicting excess returns.

In a study combining neural networks and the attention mechanism to predict stock prices based on the fusion of CNN-GRU, Cai [10] proposed a CNN-GRU-attention model. This model utilized three data decomposition methods—EMD, EEMD, and CEEMDAN—for data preprocessing, selecting the optimal method for the model. The experimental dataset in Cai [10]'s study was downloaded from the Tushare official website, using the closing prices of 000001.SZ from April 4, 1999, to March 29, 2023, with a total of 7,594 data points and 600 validation sets. Cai [10] found that the CNN-GRU-attention model achieved the highest prediction accuracy.

To address the non-linear characteristics of stock opening prices, a stock price prediction model combining principal component analysis (PCA) and the BP neural network was established. Tang et al. [11] used Python to crawl historical market data of the Shanghai and Shenzhen 300 from the BaoStock system and conducted an empirical analysis based on the collected data. The results showed that the relative error of the training was controlled within 4%, and the prediction accuracy exceeded that of a model constructed solely using the BP neural network.

Li [12] and Shi [13] explored a hybrid preprocessing approach for accurate stock price prediction in their research. The researchers developed a multi-resolution hybrid preprocessing framework that integrates empirical wavelet transform (EWT) and dynamic time warping (DTW) variants for financial time series analysis7. This methodology operates through two sequential phases: 1. Multi-Scale Signal Decomposition, Empirical Wavelet Transform (EWT) was employed to decompose raw stock price sequences into low-frequency components (capturing macroeconomic trends and long-term market cycles) and high-frequency components (reflecting short-term volatility and noise). Unlike traditional Fourier-based methods, EWT adaptively optimizes wavelet boundaries to achieve superior frequency resolution, reducing noise interference by 42% compared to empirical mode decomposition (EMD) variants. Temporal Pattern Recognition, Dynamic Time Warping (DTW) addressed temporal misalignments in financial data by identifying nonlinear correlations between decomposed components, accommodating asynchronous market reactions. Differential Dynamic Time Warping (DDTW) enhanced local pattern sensitivity through first-order derivative integration , improving cyclical pattern detection accuracy by 27% in high-volatility scenarios compared to standard DTW. This derivative-based approach effectively captured inflection points during market regime transitions. The dataset, sourced from Kaggle, contains daily stock data for Canada's top 30 stocks from January 2010 to October 2023, totaling 3460 data points, with 75% used for training and 25% for testing. The results demonstrate a 30% improvement in prediction accuracy when these techniques are integrated into neural network models, highlighting the potential of hybrid

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preprocessing methods to enhance stock price prediction accuracy and providing valuable insights for financial market analysis.

Another study on Stock Price Prediction Method Based on the GAN-LSTM-Attention Model exists. Li et al. [14] introduces an advancements in financial forecasting have introduced a hybrid GAN-LSTM-Attention architecture that synergistically integrates three core components: Generative Adversarial Networks (GANs) for synthetic data augmentation and noise reduction; Long Short-Term Memory (LSTM) networks to capture temporal dependencies in financial time series; Attention mechanisms for dynamic feature weighting during market regime shifts. The experimental validation framework incorporated four U.S. equities representing distinct market dynamics: Standard & Poor's 500 Index stock; Apple Incorporated stock; Advanced Micro Devices Incorporated stock and Google Incorporated stock. This cross-sector validation corroborates emerging research on hybrid architectures, where the integration of generative adversarial networks and attention mechanisms enables robust pattern recognition in stochastic financial environments. The results demonstrate quantifiable improvements over traditional linear models and standalone neural architectures observed in both U.S. and international markets.

3. Discussion

Based on the previous literature review, this paper discusses the research on stock price factors from two perspectives.

Perspective 1: Research Approaches. This paper categorizes research approaches into horizontal and vertical research. Horizontal research examines how, within a short time frame or even on the same day, stock prices and market conditions can influence the prediction of stock prices and investment directions for the following day. Vertical research, in contrast, employs time series analysis to summarize and identify historical factors that influence stock price fluctuations, using these findings as a basis for predicting future stock market movements. The paper analyzes the performance of different models across these approaches. In their study of out-of-sample short-term forecasts of daily returns for the S&P 500, DAX, TOPIX, and FTSE stock market indices, Jasic et al. [1] employed a horizontal research approach. The research team implemented a multi-model benchmarking framework to validate trading strategy efficacy, employing three core analytical dimensions, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and sign and direction change statistics. Their findings indicated that such models could yield substantial net profits when implemented with reasonable decision rules and trading cost assumptions. Regarding vertical research approaches, De Oliveira et al. [4] introduced several methodological models. Fundamental analysis examines market economic factors, utilizing statistical data, forecasts, supply and demand dynamics of goods and services, and the economic fundamentals of enterprises. Time series analysis predicts future market behavior by establishing linear or nonlinear regression models. These methods rely on vertical research principles—summarizing historical data, inductively identifying influential factors, and subsequently predicting future stock prices. In a study by Adebiyi et al. [7], the researchers compared two forecasting models through experimental research spanning nearly 30 years and incorporating thousands of observations of various stock price data. Their results demonstrated that within the vertical research framework, neural network models exhibited superior predictive accuracy compared to the ARIMA model.

Perspective 2: Data time span, i.e., long-term or short-term investment. Long-term investment typically refers to holding assets for an extended period, usually years or longer. This strategy primarily focuses on the gradual appreciation of assets, with investors rarely engaging in frequent buying and selling, preferring instead to maintain their positions over time. In contrast, short-term investment aims to generate profits within brief periods, with investors actively trading based on market fluctuations. For short-term investment strategies, technical analysis predominates. This

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approach utilizes historical market data, including charts, technical indicators, and trading volume, to analyze price trends and market sentiment. De Oliveira et al. [4] explore this methodology in their research. Regarding long-term investment, Wang's [9] comprehensive study examines the U.S. stock market over a 50-year period from 1971 to 2021. This research incorporates 49 stock characteristic variables to capture fundamental aspects of stocks alongside various macroeconomic indicators. In Wang's work, factor models evolved from the Capital Asset Pricing Model (CAPM) to the more sophisticated Fama-French Five-Factor Model. To conduct a thorough comparative analysis of abnormal returns, Wang extensively investigated returns generated by various factor models, including the CAPM model, the Fama-French Three-Factor Model (FF3), and the Fama-French Five-Factor Model (FF5). The findings revealed that incorporating macroeconomic variables significantly enhanced the prediction accuracy of excess stock returns. In another notable long-term investment study, Cai [10] introduced the CNN-GRU-attention model. This research examined the 000001.SZ index from April 4, 1999, to March 29, 2023, and demonstrated that this model offers effective predictive capabilities for long-term investment strategies.

4. Conclusion

With the globalization of financial markets and the diversification of risks, stock price volatility and increased market instability have become important issues of concern in today's capital markets. Therefore, based on this context, this paper conducts research on stock price forecasting and stock price factor analysis, applying neural networks for in-depth analysis of relevant issues.

In this paper, the background of the problem is introduced first. That is, under the rapid development and continuous innovation of machine learning, stock price prediction and analysis have received significant technological support, making financial forecasting more feasible. The practical value and significance of stock price factor analysis are then emphasized, which can help investors and capitalists gain more profit. Afterward, a literature review summarizes and reviews recent papers on stock price factor analysis and neural network models over the past few years and even decades. These papers were categorized according to research ideas, methods, scenarios, conditions, etc. Subsequently, a discussion focuses on horizontal and vertical research ideas as well as long-term and short-term investments, resulting in the application effects of different neural network models in various scenarios.

In light of this, it is vital to concentrate on future related research. Multimodal data analysis, which analyzes non-unique data structures, quickly extracts features from different modal data and effectively integrates them, is an efficient research method for dealing with the complex and diverse conditions of the stock market. It belongs to the domain of data science. It is also a good idea to conduct research on multi-source heterogeneous data, integrating data from different sources, formats, or structures to perform more comprehensive and accurate analysis and decision-making. Given the increasingly complex global financial market, it is necessary to broaden the scope of research, innovate research methods, and better prepare for future challenges.

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