Integration of CAPM and ANN in the Application of Stock Forecasting

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Abstract. The goal of this review is to integrate the two models of capital asset pricing model (CAPM) and artificial neural network (ANN) to predict stocks. First, the article introduces the basic theories of CAPM and ANN, their traditional roles in stock market analysis, and their respective advantages. This article emphasizes that although both CAPM and ANN have their advantages in stock prediction, their integration can bring comprehensive insights. The paper used CAPM's in-depth analysis capabilities in risk assessment and ANN's ability to process large-scale complex data and found that the accuracy and efficiency of stock market predictions can be significantly improved. However, this integrated approach also comes with new challenges and difficulties. It includes not only how to find the complexity of the model, but also how to meet the requirements for data quality, and how to find a way to integrate the two models to predict stocks effectively. This article further discusses future research directions, which can optimize the structure of the integrated model and improve its adaptability to market dynamics, including how to use this integrated model to promote more effective investment decisions in the rapidly developing financial technology field.

1 INTRODUCTION

Stock market prediction is very important. Because the stock market, as the core of capital flows, not only provides a key area for financial activity but also an important indicator of economic health. For retail investors, financial institutions, and policymakers, it is important to accurately predict stock price trends, impact, and contribute to investment decisions.

However, the complexity of the stock market is influenced by a variety of factors. Macroeconomic conditions, company performance, political events, and market sentiment all cause price fluctuations, making stock prices often difficult to predict. Stock market prediction will become a major challenge in the field of financial research.

Traditional stock market prediction methods such as moving averages and linear regression, although they have certain effectiveness in historical data and statistical analysis, have limited effectiveness in dealing with complex and non-linear market behavior. They always not fully consider the market sentiment, emergency, or even the macroeconomic fluctuations and so on. These key factors play a crucial role in predicting the stocks. In addition, these methods depend too much on historical data and the past trends in many stocks around the world, so they cannot capture the future changes in the markets, especially during situations of market conditions and economic environments change rapidly.

As technology is growing by leaps and bounds, especially in the fields of big data and machine learning, the tools and methods to predict stocks also develop fast. First of all, the Capital Asset Pricing Model (CAPM) is a classic financial theoretical model, which plays an important role in quantifying investment risks and evaluating expected returns (Sharpe 1964, Lintner 1965, Mossin 1966). Despite some limitations in these fields, their simplicity and universality are indispensable for market risks and asset pricing (Muhammad Ahmed Saleem 2016). However, when considering the complexity of the markets and their dynamic changes, it is unlikely to only use CAPM to predict the price of stocks (Yang et al. 2021). In this situation, artificial neural networks and other cutting-edge technologies are

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more used to predict and show their strong power in processing complex data and pattern recognition. Thus using artificial neural networks in the field of financial analysis and forecasting shows big potential (Wang 2017).

However, although ANN shows advantages in these fields, some obvious limitation also exists. For example, they need a high dependence on large amounts of high-quality data, the opacity of the decision-making process, the risk of overfitting, or even the sensitivity of parameter adjustment (Yang et al. 2021, Nabipour et al. 2020, Luyang et al. 2019, Ndikum 2020, Agrawal et al. 2016). At the same time, CAPM still has a key role in the stock price analysis and also provides the framework for assessing market risks and expecting returns. Thus integrating the CAPM and ANN, not only shows the theoretical depth of CAPM and data analysis capabilities in ANN but also offers new possibilities for stock market analysis and forecasting to achieve a qualitative leap in accuracy and efficiency (Yang et al. 2021, Ayub et al. 2020, Chen et al. 2022, Jan et al. 2022, Wang & Chen 2023).

By integrating CAPM and ANN, researchers not only overcome the limitations of traditional methods but also benefit from ANN in handling complex and nonlinear data when preserving the theoretical depth and risk assessment of the CAPM market (Loo 2020, Gunasekaran et al. 2013). This interdisciplinary approach offers a new perspective on stock market forecasting and promises significant improvements in precision and efficiency.

2 RELATED WORK

2.1 Classic Models

2.1.1 CAPM Model

Emerged in the 1960s, the CAPM (Capital Asset Pricing Model) was independently proposed by William Sharpe, John Lintner, and Jan Mossin (Sharpe 1964, Lintner 1965, Mossin 1966). As an imperative extension of modern portfolio theory, especially the portfolio selection theory according to Harry Markowitz, the core idea of CAPM is that the expected return of an asset can be evaluated by calculating its correlation with the overall market (Markowitz 1952).

$$E(Rt) = Rf,t + (E(Rm,t) - Rf,t) \times \beta i \qquad (1)$$

This is the traditional CAPM model formula. E (Rt) here is the expected return on assets at time t, Rf, t is the risk-free interest rate time t, E (Rm, t) is the market expected return time t, beta is the beta value of assets, we used to measure the relative to the sensitivity of market movement.

Using the risk-free interest rate, the CAPM model calculates the expected return of an asset, which is generally represented by the output on short-term government bonds. The correlation coefficient between the asset and the market portfolio, like the beta coefficient and the expected return of the market portfolio. This beta reflects the risk of individual assets relative to the market. In CAPM, the risk coefficient (beta, β) of the asset can be obtained by calculating the covariance between the asset return rate and the market return rate, and then dividing by the variance of the market return rate: $\beta_i = \frac{cov(R_i,R_m)}{\sigma_m^2}$.

The cov(Ri, Rm) is the covariance of the return rate (Ri) of the asset (i) and the return rate (Rm) of the market, which represents the difference between these two variables Common Volatility. The σ_m^2 is the variance of market returns, it indicates the volatility of market returns.

The CAPM assumes that investors are not willing to take the risks, but the investors also understand that higher risks can lead to higher returns. Therefore, the model plays a crucial role in evaluating investment options for investors, especially in deciding whether stocks are worth investing in.

Time flies, the CAPM has been expanded several times to adapt to the complexity of financial markets. Robert C. Merton made an important extension of the CAPM by introducing continuous-time models (Merton 1973). Its continuous-time CAPM model focuses on the stochastic development of asset prices and is suitable for analyzing financial assets whose prices fluctuate frequently.

The Fama-French three-factor model is another important extension of the traditional CAPM. This model was proposed in the 1990s by Eugene Fama and Kenneth French to enhance its capability to explain differences in asset returns by introducing two additional risk factors (Fama & French 1993). These two factors are the size of the company (size) and the book-to-market ratio (book-to-market ratio).

CAPM as a theoretical framework, not only plays an important role in academic research but also holds a key position in the actual functioning of financial markets to help investors better understand market dynamics and value assets.

2.1.2 ANN Model

The origin of ANN dates back to the 1940s, initially inspired by research on the human brain and nervous system (McCulloch & Pitts 1990). As a computational model that imitates the information processing function of the human brain, ANN has showcased extraordinary capabilities in pattern recognition and nonlinear data processing. ANN incorporates an input layer, several hidden layers, and an output layer, and each layer encompasses multiple neurons, which interact with each other through weighted connections.

The simple structure of the ANN model is as Figure 1.

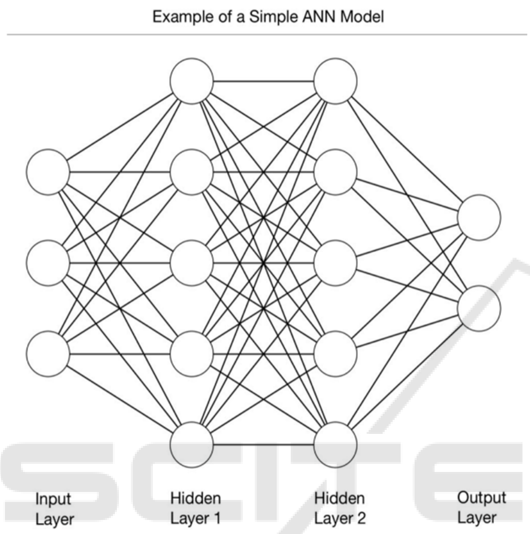

Figure 1: The simple structure of the ANN model (Picture credit: Original).

2.2 Input Layer

The input layer consists of three neurons, labeled I1, I2, and I3. This layer is responsible for receiving external input signals. In a variety of application scenarios, these signals can be in the form of image pixels, sensor data, or other digital inputs. Each neuron represents an independent input feature, for this model, can be regarded as a 3 d vector data processing.

Hidden Layer 1 consists of five neurons, labeled H1 to H5. It serves as the primary processing layer between the input layer and the output layer, and the neurons in this layer perform weighted and nonlinear transformations of the input data. Hidden layers in the multi-layer network play a key role and can be extracted and processed in the complicated features of the input data.

Hidden Layer 2 also consists of five neurons, labeled H1 to H5. This layer further processes information from the first hidden layer, increasing the depth of the network in terms of data processing and helping to capture more complex features and patterns.

Output Layer consists of two neurons, labeled O1 and O2. As the final layer of the network, the output layer converts the information processed by the hidden layer into the final output, which can be classified as results, predicted values, or other forms according to the different application scenarios.

In this simple ANN model, the data processing process demonstrates the basic mechanism of ANN. First, the data starts in the input layer, which consists of three neurons, each neuron corresponding to a characteristic dimension of the input data. For example, when people process financial market data, these neurons can represent various market indicators such as stock prices, trading volumes, or technical indicators.

Then the data flows to hidden layers that are responsible for discovering sophisticated patterns and relationships in the input data. In the model, there are two hidden layers and 5 neurons each. These neurons weigh the input from the previous layer, where the weight represents the importance of the input features relative to the output. The output of each neuron is a weighted sum of its inputs, which is then transformed by an activation function. The alteration of activation functions is critical to the network's capabilities because they introduce nonlinearity and allow the network to learn complex data relationships. Common activation functions include the Rectified Linear Unit (ReLU) or the sigmoid function.

After that, the data is transferred to the output layer. In the model, the output layer consists of two neurons, which represent the final output of the network. In different application scenarios, these results may represent different things. For example, in a classification task, they can represent different class probabilities; In a regression task, they can represent the prediction of a continuous value.

This data flow from the input layer to the hidden layer to the output layer allows the network to adapt and recognize complex patterns in the data by learning the optimal weights between different layers. For this reason, ANN has demonstrated strong capabilities in various machine learning tasks such as image and speech recognition, natural language processing, financial market analysis, etc. In addition, its flexibility makes this architecture suitable for many different data types and tasks, from simple binary classification to complex time series prediction.

Over time, many classic articles have gradually advanced the development of the field of modern artificial neural networks and introduced key concepts and technological advances. Rosenblatt's work on the perceptron laid the foundation for further theoretical and practical development (Rosenblatt, 1958). The error backpropagation algorithm by David E. Rumelhar is a multi-layer feed-forward neural network—effective impact training (Rumelhart et al. 1986). Sepp Hochreiter and Jürgen Schmidhuber's LSTM paper proposed a special type of recurrent neural network that had a profound impact on natural language processing and sequence analysis (Hochreiter 1997). Research by Yann LeCun et al. applied convolutional neural networks (CNNs) to document recognition and image processing, making CNNs widely used in the fields of computer vision and image recognition (Lecun et al. 1998). And Alex Net's success in the ImageNet competition. Excellent performance marks a breakthrough in deep learning in the field of computer vision (Krizhevsky et al. 2012).

These groundbreaking articles illustrate the evolution of the original simple perceptron to complex deep learning architectures. Each article has played a crucial role in the understanding and development of modern neural network models.

3 INTEGRATION METHOD OF CAPM AND ANN

3.1 CAPM Review Methodology

3.1.1 Estimation Method and Empirical Research

In the field of modern financial analysis, when combining estimation methods and empirical research play an important role in stock forecasting. As shown in the research of Man Fang, the expected return rate and systemic risk of stocks are estimated by combining multiple models such as E-V, E-S, and GLS, especially in specific markets such as the Shanghai A-share market and the Tehran Stock Exchange. Its value has been shown in empirical research (Wang 2017). The main advantage of this approach is its ability to provide an in-depth understanding of the effectiveness of CAPM in a specific market or scenario and to take into account market-specific factors and conditions. However, this method also has certain limitations, mainly manifested in its over-reliance on historical data and market-specific scenarios, which may result in limited generalization capabilities in different markets or different periods. Furthermore, combining multiple models may increase model complexity and computational difficulty.

3.1.2 Standard Formula and Market Complexity Analysis

Researchers such as Yajuan Yang, and R Jagannathan, when they used the standard formula of CAPM to calculate expected returns, emphasized the importance of considering market complexity in practical applications (Yang et al. 2021, Jagannathan, & Wang 1996). The advantage of this approach is that it provides a concise and generally accepted way to estimate a stock's expected return. However, it may not fully take into account the complexity and dynamics of the market, especially during periods of high volatility or atypical market events. For example, the conditional CAPM model proposed by R Jagannathan, although it considers the time changes in β coefficient and market risk premium and additional factors (such as human capital return rate), there may be challenges in accurately capturing rapid changes in market conditions.

3.1.3 Market Portfolio and Beta Analysis

Market portfolio and beta analysis are other important method for stock prediction. Researchers such as P Ndikun, Smita Agrawal, L Chen, and others use market portfolios (such as the US S&P 500 Index) and risk-free rates of return to estimate the beta value of assets and calculate the CAPM of stocks Beta and volatility to predict stock prices (Luyang et al. 2019, Ndikum 2020, Agrawal et al. 2016). The advantage of this approach is its ease of implementation, especially in standardized large markets such as the S&P 500. The beta analysis provides an intuitive understanding of the correlation between individual stocks and the market as a whole. However, this approach may not adequately represent the dynamics of the market in small or unconventional markets. In addition, the calculation of Beta value relies on historical data and may not accurately reflect future market conditions when market conditions change rapidly.

3.2 ANN Review Methodology

3.2.1 Stock Price Prediction Based on Traditional and Efficient ANN Architecture

Recent studies, especially those conducted by Ndikun, have shown that the use of backpropagation neural network (BPNN) based on opening price, high price, low price, volume, and closing price and efficient ANN architecture to process Publicly traded U.S. stock data can effectively predict stock prices (Ndikum 2020). These methods achieve predictions by analyzing patterns and trends in historical data. Advantages include being able to effectively learn patterns in historical price data, adapting to different types of stock and market data, and being relatively easy to implement and apply to actual trading systems. However, these methods also have some limitations, such as the risk of overfitting, dependence on high-quality historical data, and possible insufficient response to market emergencies and new information.

3.2.2 Application of Deep Learning Technology in Stock Price Prediction

The application of deep learning techniques, especially in research conducted by L Chen and Prakash K. Aithal, demonstrated feedforward networks, recurrent neural networks (RNN), long short-term memory networks (LSTM), and generative adversarial Networks (GAN) and other technologies have the potential to handle non-linear relationships and time series dynamics of stock price data (Luyang et al. 2019, Gunasekaran & Ramaswami 2014). These deep learning models are capable of processing more complex patterns and larger data sets, are particularly suitable for processing time series data of stock prices, and effectively capture the non-linear relationships of stock price data. However, these models also face several challenges, including requiring significant computing resources and time to train, model building and optimization requiring deep expertise, and the model's decision-making process potentially lacking transparency and explainability.

3.2.3 Application of Artificial Neural Networks in Processing Raw Data and Simulating Nonlinear Relationships

In terms of the application of ANN, especially research conducted by Smita Agrawal and Yajuan Yang has shown that ANN can directly process raw data, thereby reducing the need for complex feature extraction (Yang et al. 2021, Agrawal et al. 2016). At the same time, a multi-layer feedforward neural network is used to adapt to the nonlinearity and complexity of the stock market. The merits of this way include the ability to directly process raw stock market data, identify and simulate complex nonlinear relationships, and have a flexible network structure that can adapt to different data characteristics. However, this method also has some disadvantages, such as the large amount of data required to train the model, the complexity of network structure and parameter selection, and the challenge of updating the model in real-time in a rapidly changing market environment.

3.3 CAPM and ANN Integration Review Methodology

3.3.1 Beta Classification Prediction Method Combining CAPM Theory and ANN

Usman Ayub and colleagues relying on the CAPM theory, divided stocks into different Beta portfolios based on systematic risk (Ayub et al. 2020). This classification is based on the core assumption of CAPM, which is that the expected return of a stock is directly proportional to its market risk (Beta value). Through this classification, researchers can focus on analyzing stock portfolios with similar risk characteristics, thereby providing more accurate risk assessments and predictions.

Next, use ANN to process the stock data for these different beta combinations. ANN plays a key role here, especially in identifying and processing non-linear features in stock market data. By training ANN models, especially using the backpropagation algorithm, researchers can fine-tune model parameters to more accurately capture the complex relationship between market risk and stock returns.

J Wang applied a similar approach, emphasizing the ability of ANN in capturing the nonlinear dynamics of stock market data (Wang & Chen 2023). This method allows researchers to learn from historical stock market data and predict future market trends, especially for stocks that are affected by market fluctuations and external economic factors.

The advantage of this method is that it combines the systematic risk assessment of CAPM theory with the efficient ability of ANN in data processing. It can provide deep insights into the non-linear dynamics of stock markets, thereby improving the accuracy and reliability of forecasts. Especially in analyzing market risks and predicting stock prices, this method is more efficient and accurate than traditional financial models.

3.3.2 Integrated Analysis Method of Advanced Neural Network and CAPM

YC Chen applied the combination of BPNN and CAPM to improve the accuracy of stock price prediction (Chen et al. 2022). This method first uses BPNN to analyze and predict the price and growth trends of stocks. In this process, BPNN exerts its advantages in identifying complex patterns in market data and processing large amounts of data. These prediction results are then used as input to the CAPM model to integrate the prediction capabilities of BPNN and the theoretical basis of CAPM in stock pricing and market risk assessment. This integrated approach is particularly suitable for those situations that require in-depth market data analysis and highly accurate stock price predictions.

WK Loo adopted a similar approach, combining ANN technology and CAPM to predict the yield of Hong Kong Real Estate Investment Trusts (HK-REITs) ((Loo 2020). The ANN technology here is not limited to BPNN but covers a wider range of neural network applications to identify and process complex patterns in market data. This approach leverages the capabilities of ANN in data processing and pattern recognition while incorporating the theoretical framework of CAPM in assessing market risk and stock pricing. Through this integration, the study can provide a deeper understanding of HK-REIT market dynamics and improve forecast accuracy.

The main advantage of this method is that it combines the data processing capabilities of neural networks and the theoretical framework of CAPM to provide a more comprehensive and accurate stock price prediction method. It is particularly suitable for complex and dynamic market environments, capable of processing and analyzing large amounts of data, and providing predictions based on in-depth analysis.

3.3.3 Dynamic Market Forecasting Method of Three-Layer ANN and CAPM

Jan's methods use the structure of a three-layer neural network, including the input layer, hidden layer, and output layer, to analyze and predict dynamic changes in the stock market (Jan et al. 2022, Gunasekaran & Ramaswami 2014). This structure takes advantage of the advanced data processing capabilities of ANN and is particularly suitable for capturing complex patterns and non-linear relationships in market data.

The input layer is responsible for receiving market data, such as stock prices, trading volumes, macroeconomic indicators, etc. Hidden Layers analyzes this data in-depth and learns the relationship between market dynamics and potential influencing factors. The output layer ultimately generates predictions that provide insights into the future direction of the stock.

Combined with the CAPM model, this method can not only analyze historical data but also predict the future performance of stocks, especially in assessing market risks and expected returns. In addition, through the rolling window method, the model can adapt to new market information to ensure the timeliness and accuracy of predictions. To evaluate the performance of the model, statistical tools such as mean square error and the Diebold-Mariano test were used. These tools help quantify forecast errors and ensure that models reliably reflect the true dynamics of the market.

The advantage of this method is that it can comprehensively process large amounts of market data and predict stock prices by learning hidden patterns in the data. It can adapt to rapid changes in the market, provide timely and accurate stock price predictions, and is especially suitable for dynamic and changing market environments.

3.3.4 CAPM Integrated Strategy Method of Fuzzy Logic and ANN Optimization

M Gunasekaran and R Barua integrated the technologies of Adaptive Neuro-Fuzzy Inference System (ANFIS) and Elman Recurrent Neural Network (ERNN) respectively and combined them with the CAPM (Gunasekaran et al. 2013, Markowitz 1952). This integrated strategy optimizes the application of the CAPM model so that it can more accurately reflect stock values in complex and dynamic market environments. The ANFIS method combines the learning ability of neural networks and the processing ability of fuzzy logic to optimize the parameters in the fuzzy logic system. This process covers the various steps starting from fuzzifying the input data, establishing fuzzy rules, and then using the rules for reasoning. Next, these rule parameters are trained and adjusted through the neural network and finally defuzed to obtain the final prediction output. The application of ERNN emphasizes the efficient processing of time series data, especially when dealing with dynamic changes in the stock market. ERNN can capture the time correlation in stock price movements, providing the model with deeper market insights.

Combining these two methods, this strategic approach not only enhances the predictive power of the CAPM model under static market conditions but also enables it to adapt and reflect more complex and changing market environments. This approach provides greater accuracy and reliability in predicting stock market risk and returns and is particularly good at predicting stocks that are affected by multiple market factors.

The main advantage is that it combines the advantages of fuzzy logic and neural networks to improve the adaptability and accuracy of the prediction model under complex market conditions. By combining time series analysis capabilities, dynamic changes in the stock market can be better understood and predicted.

4 CHALLENGES AND LIMITATIONS

This approach holds significant advantages when integrating the CAPM and the ANN for stock market forecasting. First of all, by combining CAPM's market risk analysis with ANN's advanced data processing capabilities, this integrated approach is capable of providing detailed insights into market dynamics, including the capture and analysis of market characteristics—non-linear market data. Also, the flexibility and learning ability of ANN makes this method excellent for dealing with complex market situations and large amounts of data, especially when market conditions change quickly.

Nevertheless, this integrated method does face certain challenges. Highly dependent on the quality of the input data, any inaccuracies or even incompleteness of the data can affect the accuracy of the forecast outcome. The ANN may be at risk of overfitting historical data, which may result in a reduced ability of the model to generalize to new data. On top of that, the process of integrating CAPM and ANN can be excessively complex and time-consuming, especially when data is large.

Due to the "black box" nature of the ANN, this integrated model lacks transparency and interpretability, which causes uncertainty in the investment decision-making process. ANN performance depends heavily on the selection and adjustment of network parameters, thus they require a lot of experimentation and expertise. Furthermore, the effective implementation and application of this integrated approach requires extensive technical knowledge and expertise. Although the integrated approach improves forecasting capabilities, uncertainties remain in forecasting under extreme market conditions or emergencies.

Although the integrated approach of CAPM and ANN to stock market forecasting presents some challenges, it is an overall valuable tool due to its significant advantages in terms of providing detailed market analysis and processing complex data. When using these methods in practice, these issues must be fully considered and handled carefully to ensure the accuracy and reliability of the forecasts.

5 CONCLUSION

Challenges exist such as data quality dependencies, model overfitting, and computational resource requirements. However, its significant advantages in providing in-depth market analysis and processing complex data make it a valuable tool for predicting stocks. In the future, people more willing to see further integration and innovation of CAPM and ANN, especially in improving model adaptability, incorporating more data types and sources, applying deep learning and other advanced machine learning techniques, enhancing model interpretability and transparency, and more Adapt well to developments in irrational market behavior.

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Deeper integration of ANN with other traditional financial models such as the Fama-French model and arbitrage pricing theory (APT) is also expected. For example, utilize LSTM-RNN to analyze and predict stock returns based on the Fama-French 5-factor model, or combine APT and ANN to improve the efficiency and accuracy of portfolio management. These integrated approaches not only improve understanding of market behavior but also show potential in predicting market trends and stock returns.

Future research will focus on how to better integrate traditional financial theory with advanced data analysis techniques to respond to the changing and emerging challenges of global financial markets. With the development of financial technology, this approach will play a more important role in the field of financial market analysis and prediction, especially in providing people with more powerful and flexible tools.

By way of conclusion, the integration of CAPM and ANN represents an important development direction in the field of financial market analysis and prediction. Future research and applications will likely focus on how to better integrate traditional financial theory with advanced data analysis techniques, not only CAPM and ANN to respond to the changing and emerging challenges of the global financial market. This process will require close collaboration between financial professionals, data scientists, and technology experts to jointly drive innovation and progress in the field of financial analytics.

AUTHORS CONTRIBUTION

All the authors contributed equally and their names were listed in alphabetical order.

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