Review of Predicting Stock Prices Based on Machine Learning and Stock Learning

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Abstract. Predicting stocks is to help investors make decisions and help them minimize risks as much as possible, thereby obtaining investment returns. If we can accurately predict the rise and fall of stock market prices, we can buy or sell stocks at higher prices in the market, thereby obtaining higher profits. This article is based on machine learning and deep learning algorithms such as support vector machine (SVM), principal component analysis (PCA), random forest (RF), and recurrent neural network (RNN), long short-term memory network (LSTM), and convolution neural network (CNN). The conclusion is that machine learning requires manual intervention, is faster to train, more interpretable, and usually performs better on data sets with simpler structures and smaller sizes. Deep learning has lower requirements for feature extraction and discovery, has stronger expression and fitting capabilities, and can better capture the correlation between data in larger and more complex data sets.

Keywords: stock price prediction, machine learning, deep learning.

1. Introduction

1.1. Research Background

Stock forecasts in the past mostly depended on fundamental analysis and technical analysis. A company's financial situation, external environment, and market trends are examined as part of fundamental analysis in order to forecast changes in stock price. Technical analysis is the study of chart patterns such as stock price and trading volume to predict trends in stock prices. With the development of computer science and statistics, stock prediction research has received more attention. To find patterns and trends in stock prices, mathematical models and algorithms are used to analyze vast volumes of stock data [1]. The emergence of machine learning and artificial intelligence technologies has also brought new opportunities for stock prediction. Stock prediction is still a difficult subject due to the stock market's complexity and unpredictability, nevertheless [2]. Movements in stock prices are affected by many factors, including economic indicators, company performance, political events, etc. A comprehensive stock prediction model needs to consider multiple factors and needs to be constantly updated and adjusted to adapt to market changes. In addition, the irrationality and human manipulation of the stock market also make stock predictions more difficult. People's emotions and behaviors can have a significant impact on stock prices, such as market panic and short-term speculation. In short, the background of stock prediction research can be traced back to the origin of financial markets. With the development of technology and statistics, stock prediction is facing more opportunities and challenges.

1.2. Research progress

Machine learning and deep learning have made incredible advances in the field of stock prediction research. These approaches, which include time series analysis, regression analysis, and classification analysis, have been used to a variety of stock prediction models [3].

Deep learning models and machine learning can forecast future price trends by learning historical stock price data in terms of time series analysis. Support vector machines (SVM), decision trees, random forests, and recurrent neural networks (RNN) are among the algorithms used in these models. Through these models, price patterns, trends and cycles can be automatically identified and learned.

In terms of regression analysis, machine learning and deep learning models can predict changes in stock prices by learning the relationship between stock prices and other relevant factors (such as company financial data, economic indicators) [4]. These models can use algorithms such as multiple linear regression, ridge regression, and neural networks. Through these models, non-linear relationships between stock prices and other factors can be revealed.

In terms of classification analysis, machine learning and deep learning models can predict the classification of stocks by learning the relationship between historical stock data and existing classification labels (such as ups and downs, buy and sell signals). These models can use algorithms such as logistic regression, support vector machines, and convolutional neural networks (CNN). With these models, future stock performance can be predicted based on past conditions [5].

Furthermore, deep learning and machine learning methods can be used to perform sentiment analysis and market sentiment prediction. These models can analyze information such as social media data, news reports, and public opinion to understand investor sentiment and market sentiment, and predict stock price movements based on these sentiments [6].

Although machine learning and deep learning have made some strides in stock prediction research, there are still some obstacles to overcome. For example, the irrationality and uncertainty of the stock market make forecast results unreliable. In addition, issues such as overfitting, data underfitting, and data acquisition also need to be addressed.

1.3. Research Topics, Methods and Objectives

Overall, machine learning and deep learning offer new methods and technologies for stock prediction; however, more research and practice are required to improve accuracy and reliability.

This article studies different algorithms of machine learning and deep learning, and compares their advantages and disadvantages, so as to choose a better solution in stock prediction in order to obtain more accurate prediction results.

2. Description of Machine Learning

2.1. Support Vector Machines

Support vector machine is a supervised learning algorithm whose main goal is to find an optimal hyperplane in the feature space to separate data points with different labels[7]. The core idea of the SVM algorithm is the maximum margin classifier, which learns and finds an optimal hyperplane to maximize the gap between samples that are positive and negative[8]. Simultaneously, SVM can use kernel functions to map data to high-dimensional feature space in order to solve nonlinear classification issues[9]. There are four main applications of SVM in stock prediction.

2.1.1. Price trend classification:

SVM can use data on historical stock prices and data on other technical indicators (such as moving averages, relative strength indicators, etc.) to classify the trend of stock prices as rising or falling. The model can identify price trends over time and predict future movements.

2.1.2. Support vector regression:

SVM can be used for stock price regression prediction in addition to price trend classification. It can study previous stock price data to develop a regression model that predicts future stock values. In this application, SVM looks for an optimal fitting curve that best approximates the changes in stock prices.

2.1.3. Dynamic adjustment:

SVM can be applied to dynamically adjust the stock trend prediction model. By monitoring market conditions and stock price changes in real time, SVM can update model parameters and make real-time predictions. This helps investors adjust their strategies and decisions in a timely manner to adapt to changing market conditions.

2.1.4. Feature selection:

SVM can be used to select features with the most predictive power for stock trend prediction. By learning historical data, SVM can derive the importance of features and select the most relevant features for prediction. This helps investors select the most effective indicators and optimize predictive models.

Although the SVM algorithm has good application potential in stock prediction, it still faces some challenges. For example, issues such as limitations in data quality and quantity, selection and tuning of model parameters, interpretability and stability of results, etc. In the future, we can improve the SVM method and integrate it with other machine learning techniques to improve stock forecast accuracy and stability.

2.2. Principal Component Analysis

The PCA is a popular dimensionality reduction technology in stock prediction that may be used for feature extraction, data dimensionality reduction, and correlation analysis of stock data[10].There are four main applications of PCA in stock prediction.

2.2.1. Reduction of data dimensionality:

Stock market data often have high-dimensional characteristics and contain a large amount of feature information. However, high-dimensional data not only increases computational complexity, but may also lead to the "curse of dimensionality". PCA performs feature decomposition on stock data and extracts main feature vectors, thereby reducing the dimensionality of the data. This helps simplify the data analysis process and reduce the consumption of computing resources.

2.2.2. Capturing the main features:

There may be a large amount of redundant information in stock market data, and PCA can filter out those features that best explain the variance of the data by extracting principal components. This means that PCA can help us capture the most important features, i.e. those factors that have the greatest influence on stock price movements. By preserving the core traits, you can lessen the emphasis on secondary features and increase the prediction model's accuracy.

2.2.3. Reduction of information loss:

During the data preprocessing process, in order to reduce the data dimension, a certain degree of information loss often occurs. PCA can retain as much information as possible in the original data. PCA looks for those principal components that can explain the variance of the data to the greatest extent to ensure that the information of the data is lost as little as possible during the dimensionality reduction process. In this way, we can reduce the dimensionality while sacrificing less model accuracy.

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The PCA algorithm plays an obvious role in stock prediction and can help reduce data dimensions, capture main features, reduce information loss, and mine correlations between data [11]. Through the application of PCA algorithm, the accuracy and interpretability of stock prediction models can be maximized. However, in practical applications, the PCA algorithm still faces problems such as high computational complexity on large-scale data sets, sensitivity to noise and outliers, and model selection. The accuracy and stability of the prediction model can be improved further in the future by improving the PCA algorithm and combining it with other machine learning techniques [12].

2.3. Random Forest

Random Forest is a popular machine learning technique that is useful in market prediction. Random forests make predictions by integrating multiple decision trees and voting[13]. There are four main applications of RF in stock prediction.

2.3.1. Feature selection:

For stock prediction, the random forest algorithm can be used to evaluate the importance of features. It can rank the importance of features by measuring how much they contribute in a random forest model. This helps investors select those features that have a greater impact on stock price movements and helps improve the accuracy of prediction models.

2.3.2. Data classification:

The random forest algorithm is a decision tree-based ensemble learning method that can effectively classify stock data. A categorized prediction of stock prices can be accomplished by constructing many decision trees and combining their findings using a voting technique or an averaging strategy. This helps investors determine the rising and falling trends of stock prices and formulate corresponding investment strategies.

2.3.3. Anomaly detection:

In the stock market, abnormal price fluctuations can negatively impact the results of predictive models. By constructing an outlier identification model, the random forest approach can be utilized for anomaly detection to find and filter out aberrant data. This improves the model's robustness, reduces influence from anomalous input, and improves forecast accuracy.

2.3.4. Voting Strategy:

The random forest algorithm utilizes the voting strategy of multiple decision trees to integrate prediction results. The random forest model's output results can be used for stock prediction voting, and the final prediction result is chosen based on the consistent prediction results of many models. This voting strategy can reduce the risk of model overfitting and improve prediction stability and reliability.

The random forest algorithm is useful in stock prediction because it can be used for feature selection, data classification, anomaly detection, and voting strategies. It can help investors select important factors from a large number of features, perform classification predictions, detect anomalies and make decisions. However, there are still problems such as parameter tuning, imbalance of data sets, and computational efficiency in the application of the random forest algorithm. In the future, the random forest model's performance in stock prediction can be improved further by improving and optimizing the algorithm and combining it with other machine learning techniques.

3. Description of Deep Learning

3.1. Recurrent Neural Network

Recurrent neural networks are deep learning neural network models designed to analyze data with temporal correlations. RNN captures memory and temporal dependencies in data through recurrent structures and hidden states. Common applications include natural language processing, speech recognition, and time series analysis. There are four main applications of RNN in stock prediction.

3.1.1. Sequence modeling:

Stock market data is a time series, in which each time point depends on the previous data. Recurrent neural networks have temporal processing capabilities and can model and capture temporal dependencies in time series data through memory mechanisms. This makes RNN very effective when dealing with stock prediction problems.

3.1.2. Long-term dependency modeling:

Unlike traditional neural networks, recurrent neural networks have the ability to propagate time delays backwards and can handle long-term dependencies. In stock prediction, past data may have a greater impact on current price trends, and recurrent neural networks can better capture this long-term correlation in time series.

3.1.3. Combining multiple indicators:

Recurrent neural networks can accept multi-dimensional inputs, which means that different technical indicators and other related data can be used as input to help predict stock prices or other financial indicators. During the training process, RNN will gradually learn the weight and influence of each input, thereby comprehensively utilizing multiple indicator information for prediction.

3.1.4. Prediction and decision-making:

The output layer of the recurrent neural network can generate stock prediction results. Depending on the situation, the RNN output can be compared to real data and backpropagation using the loss function to optimize the network parameters. By training and tuning recurrent neural networks, more accurate predictions of stock prices or other financial indicators can be generated, helping investors make more informed decisions.

In general, RNN is good at processing time series data and long-term dependencies, and has its own unique advantages in stock prediction. In practical applications, RNN still has certain limitations, for example,gradient vanishing and gradient explosion issues, and the processing of long-term dependencies. In addition, reasonable data preprocessing and feature engineering help to obtain more accurate stock prediction results.

3.2. Long Short-term Memory Network

In order to better predict stock price fluctuations, neural network models have emerged as one of the most active areas of research [14]. The long short-term memory network can model time series data as a recurrent neural network model [15]. There are three main applications of LSTM in stock prediction.

3.2.1. Modeling of sequence data:

Price data in the stock market typically exhibits time series characteristics, and the LSTM algorithm can handle this type of sequence data well. Compared with traditional feedforward neural network models, the LSTM model introduces a gating mechanism that can adaptively decide how to model historical price sequences, thereby better capturing the dynamic characteristics of the data.

3.2.2. Capture long-term dependencies:

In the stock market, stock price changes may be affected by multiple factors interacting with each other for a long time, and traditional feedforward neural network models are difficult to capture this long-term dependence. By introducing gate control units and memory units, the LSTM model can successfully manage long-term dependencies in time series data, enhancing stock forecast accuracy.

3.2.3. Predict future stock prices:

By learning from historical stock price data, the LSTM model can predict future stock price trends. By taking historical price sequences as input data, the LSTM model can automatically learn the patterns and trends in the data and predict future prices based on the learned knowledge. This enables investors and financial institutions to better formulate trading strategies and make investment decisions.

The LSTM algorithm plays an important role in stock forecasting, capable of modeling sequence data and capturing long-term dependencies [16]. The LSTM model may forecast future stock price movements by learning historical stock price data, providing investors and financial institutions with a more accurate decision-making base. However, there are still issues in the application of LSTM, such as insufficient training samples and the presence of data noise, which may impair prediction accuracy, and it is difficult to pick the structure and parameters of the LSTM model [17]. Future research can increase the accuracy and stability of stock forecasts even further by refining the structure of the LSTM model and introducing new features.

3.3. Convolution Neural Network

Convolutional neural network is a traditional degree learning neural network model that is especially well-suited for processing tasks involving grid-structured data[18]. CNN has achieved great success within the realm of computer vision and has also been widely used in other fields such as natural language processing and signal processing. The basic idea behind CNN is to use convolutional layers and pooling layers to extract spatial/temporal information from input data, and then use fully connected layers to perform tasks like classification or regression[19]. The training process is usually carried out through the backpropagation algorithm, that is, the gradient is calculated based on the loss function and the model parameters are updated using the gradient descent method. For large-scale data sets, it can also be optimized through the batch gradient descent method to improve training efficiency and convergence.There are four main applications of CNN in stock prediction.

3.3.1. Feature extraction:

Convolutional neural network can be used as an effective feature extractor in stock prediction. Through the operation of convolutional layers and pooling layers, CNN can automatically learn different levels of abstract features, such as price patterns, trends, periodicity, and combinations of technical indicators. These learned features can capture important patterns and correlations in stock data.

3.3.2. Data processing:

Convolutional neural network can process multi-dimensional time series data and has the ability to be highly sensitive to time series information. This is because the convolutional layer has the characteristics of local connections and shared weights when processing data, and can effectively capture the relationship between adjacent data in time. This is very important for time series data analysis in stock forecasting.

3.3.3. Supervised learning:

Convolutional neural networks can make stock predictions through supervised learning. By adding appropriate neurons to the network output layer, the predicted stock price or related indicators are output. Then, backpropagation using a loss function optimizes the network parameters to improve prediction accuracy by comparing with real stock prices or indicators.

3.3.4. State recognition:

Convolutional neural networks can also be used to identify different market states in stock prediction. By training CNN to classify different market states, such as bull market, bear market, shock market, etc., it can help investors better understand the market environment and formulate corresponding investment strategies.

In general, convolutional neural networks achieve the recognition and prediction of complex patterns by hierarchically extracting and learning the features of input data. However, in the actual application of CNN, there are still problems such as data quality, over-fitting, and noise processing. It usually needs to be combined with other technologies and methods for comprehensive analysis and prediction.

4. Machine Learning and Deep Learning Comparison

4.1. Compare Results

In summary, compared to deep learning, machine learning has three types of advantages in stock prediction. First, machine learning is highly interpretable. Machine learning algorithms often provide a degree of model interpretability, allowing one to understand how the model makes predictions based on features. Second, machine learning has relatively few data requirements. Compared with deep learning, machine learning algorithms usually require less data and can be trained on fewer data samples. This means that machine learning can provide efficient stock prediction results in a shorter time and is timelier in a stock market with high uncertainty. Finally, machine learning has relatively low computational resource requirements. Compared with deep learning, which requires large-scale neural networks for training and inference, machine learning algorithms generally have lower requirements for computing resources. Its cost is lower, and it also has relatively good stock prediction results, which means that machine learning is more cost-effective in the stock prediction market that seeks higher profits.

In contrast, deep learning uses methods based on artificial neural networks to make predictions and decisions. Its advantages over machine learning mainly include three points. First of all, deep learning is highly automated. Deep learning algorithms can automatically learn features and patterns from massive amounts of data, reducing reliance on domain experts and thus reducing labor costs. Second, deep learning has highly abstract representation capabilities. Deep learning algorithms can capture complex patterns in data through multi-level abstract representations and can better handle nonlinear relationships. This means that compared with machine learning, deep learning can provide more accurate prediction results in the field of stock prediction with complex nonlinearity and instability, thereby effectively increasing investors' returns. Finally, deep learning algorithms can automatically extract potential high-order features from raw data, lowering the cost of feature engineering and, to some extent, increasing the cost-effectiveness of investors who use this model.

4.2. Analysis of the Problem

In the field of stock prediction, there are two major issues with machine learning. The first is that machine learning algorithms rely more on domain experts' experience and knowledge for feature selection and design, which requires a lot of time and manpower for feature engineering. This undoubtedly increases the cost of obtaining stock prediction results. The second problem is that generally speaking, current machine learning algorithms have limited ability to process non-linear relationships and cannot accurately capture complex data patterns. In the context of the complicated stock market, the results provided are not accurate enough.

However, there are three key drawbacks to using deep learning for stock prediction. To begin, deep learning algorithms are often trained on enormous volumes of data in order to produce reliable prediction results. Processing a large amount of data means that more time is needed, but we cannot obtain prediction results later than the real-time stock market. Stock prediction results that lose their timeliness will be meaningless. Second, deep learning algorithms usually require large-scale neural networks for training and inference, which require high computing resources. Occupying more computing resources requires spending more money, which undoubtedly increases the cost of deep learning algorithms to obtain prediction results. This is also one of the primary issues with existing deep learning systems in stock prediction. Finally, the model structure of deep learning algorithms is relatively complex, and it is generally difficult to explain how the model makes predictions, lacking interpretability. Even if more accurate prediction results are obtained through deep learning algorithms, algorithms that lack interpretability are often not trusted, making investors more cautious when adopting such algorithms.

4.3. Solution Suggestions

Here are five feasible solutions to the problems of machine learning and deep learning:

4.3.1. Data Preprocessing

Data preprocessing refers to the process of data cleaning, feature selection and conversion, data standardization, outlier processing and data set division on original data, which facilitates subsequent model training and inference. The goal of data preprocessing is to make the data more suitable for model training and prediction. Data preparation is very significant in the field of stock prediction because the original stock data may have issues such as noise, missing values, and outliers, which may have an adverse effect on the model's performance. The method and choice of data preparation are determined by the application context and data properties. In stock prediction, it is necessary to select appropriate data preprocessing methods based on different prediction goals and data types. Simultaneously, in order to select the best preprocessing method and model combination, it is required to assess the impact of data preprocessing on model training performance and construct acceptable evaluation indicators to evaluate model performance.

4.3.2. Feature Engineering

The use of feature transformation, feature selection, feature construction, feature scaling, and other approaches to extract valuable features from raw data to assist the model better understand the data and generate predictions is known as feature engineering. The quality of feature engineering has a direct impact on model performance. A good feature engineering can increase the model's prediction accuracy, stability, and generalization ability. Through reasonable feature engineering, the algorithm model's ability to understand and predict data can be improved. When performing feature engineering, it is vital to thoroughly consider the data's qualities, domain knowledge and model requirements, and flexibly use various methods to obtain the best feature representation.

4.3.3. Introducing External Data

Introducing external data can enrich the model's input features and provide additional information to improve the model's performance and predictive capabilities. External data can refer to data from sources different from the original data source, such as other relevant stock indices, macroeconomic data, news events, social media data, etc. They can provide additional information related to stock prices, thereby enriching the feature representation capabilities of the model and alleviating data sparsity, thereby helping the model better understand market dynamics and predict trends.

4.3.4. Combining Multiple Models

Combining multiple models can improve the performance and resilience of machine learning and deep learning models. Through stacking integration, promotion integration, model fusion and other integration methods, the advantages of each model are utilized to complement each other between different models, thereby improving the accuracy and robustness of prediction and obtaining better prediction results. We can select the best model and ensemble method through cross-validation and model evaluation, as well as perform appropriate parameter tuning to maximize the effectiveness of the algorithm model in predicting stocks.

4.3.5. Model Evaluation and Tuning

Model evaluation and tuning can help us evaluate the model's performance and improve the accuracy and generalization ability of predictions by adjusting the model's parameters and structure. Model evaluation is the process of measuring a model's performance on given data. Common model evaluation indicators include accuracy, precision, recall, F1-score, ROC curve, root mean square error (RMSE), mean absolute percentage error (MAPE), and others. Choosing an appropriate evaluation metric depends on the task type and specific application scenario. Model tuning is to adjust the parameters and structure of the model to improve the performance of the model through methods such as grid search, random search, and adaptive optimization algorithms, so that the model can better adapt to the training data and perform better in stock prediction.

5. Conclusion

Machine learning and deep learning each have their own strengths and weaknesses in the field of stock prediction. In order to help investors obtain greater benefits from the stock market, it is hoped that this research can provide new ideas for stock prediction. However, due to the limitations of current algorithms, the current performance of the model and the prediction results obtained may not be entirely satisfactory. Future research must continue to refine algorithms and develop more efficient and accurate prediction models in order to improve the predictability of results.

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