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A portfolio optimization model for return trend rate and risk trend rate based on machine learning

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ABSTRACT

This paper presents a machine learning-based portfolio optimization model alongside a trading strategy algorithm. There are two distinct steps to the approach. Firstly, the long short-term memory (LSTM) neural network model was used to predict the closing price of stocks in the following 4 days. The average rise and fall rate over these four days is then calculated as the stock's return trend rate, which can measure the direction and intensity of the stock's rise and fall. The same method is used to predict the average of the industry index's rise and fall rate over the next four days as the risk trend rate. In the second step, the improved mean–variance model (IMV) model is used to provide customers with the stock portfolio purchasing strategy based on the return trend rate and risk trend rate. The experimental results demonstrate that the approach has a certain application value and outperforms the traditional method in terms of annual returns and Sharpe ratio, using the Shanghai Stock Exchange and the Shenzhen Stock Exchange as study samples. The model shows approximately 1% improvement in prediction accuracy. The latest advancements in machine learning provide substantial prospects for tactics involving the purchase of portfolios.

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1. INTRODUCTION

Portfolio management remains a prominent research field in financial investment, continuously explored by investors and researchers alike. Stock investment has the characteristics of flexible trading, significant risk-return fluctuations, modest initial capital requirements, and transparent market information, stock portfolio management is a hot research issue in securities portfolio management. In recent years, the rapid advancement of machine learning models has spurred the development and application of prediction-based portfolio optimization models in stock management. An excellent stock portfolio optimization model, with identical risk expectations, can potentially yield superior investment returns. Enhancing the performance of prediction-based stock portfolio optimization models thus holds considerable importance. Machine learning models have shown promising results in stock forecasting [1]–[5]. Markowitz introduced the mean-variance (MV) model in 1952 to address portfolio optimization, emphasizing investors' dual objectives of maximizing returns and minimizing risk. This paper divides prediction-based portfolio optimization models into two categories based on investors' decision goals.

One approach to stock return forecasting assumes correctness in the forecast results and focuses solely on enhancing forecast accuracy, disregarding forecast risk. Investment portfolios are then chosen directly based on these forecasted returns [6]–[13]. Specifically, Yang Liu's comparative experiments concluded that long short-term memory (LSTM) recurrent neural networks (RNNs) perform comparably to v-type support vector regression (v-SVR) in predicting long-term volatility and outperform the generalized autoregressive conditional heteroskedasticity (GARCH) model. Liu *et al.* [14] reported a root mean square error (RMSE) of 0.03 for next-day earnings forecasts and 0.049 for three-day forecasts. Song *et al.* [15] introduced the multi graph attention sorting (MGAR) network. This approach employed graph convolution to extract relational features from the relationship graph utilized LSTM networks to capture stock price trends, and subsequently concatenated these features into a fully connected layer for predicting stock return rankings. The model achieved a prediction error mean squared error (MSE) of approximately 0.00037. Lu *et al.* [16] proposed a convolutional neural network (CNN)-LSTM method for predicting stock closing prices, leveraging CNN for feature extraction and LSTM for price prediction. Compared to other models like multi-layer perceptron (MLP), CNN, RNN, LSTM, and CNN-RNN, CNN-LSTM achieved the highest accuracy in predicting the Shanghai Composite Index closing prices. Experimental results of the above researchers indicate that one-day stock return prediction errors translate to a mean absolute percentage error (MAPE) of approximately 2%, increasing with longer prediction time horizons. LSTM methods demonstrate significant advantages in stock predictions despite inherent prediction errors. Ma *et al.* [17] employed metrics like the positive and negative direction predictive performance indicators (HR+, HR-, HR) to assess directional accuracy. Their autoencoder (AE)+LSTM method yielded an average HR accuracy ranging from 47% to 50.42%, indicating the need for further algorithmic refinement to enhance returns.

Another approach focuses on integrating risk measures with enhanced stock prediction accuracy to establish models that combine machine learning and classical portfolio optimization techniques. The primary objective is to compute optimal stock portfolio weights that maximize returns while considering risks [18]–[21]. Markowitz's MV model has long been a cornerstone in this area, optimizing portfolio allocation by minimizing risk for a given expected return or a maximizing expected return given a level of risk. Specifically, Wang *et al.* [22] proposed an LSTM+MV portfolio optimization model where an LSTM network predicts stock returns, selecting stocks with higher predicted returns, followed by applying the MV model to determine portfolio weights. Experimental findings demonstrate significant outperformance over the combination of support vector machine (SVM), random forest (RF), deep neural network (DNN), autoregressive comprehensive moving average model (ARIMA), and MV model in terms of annual cumulative return, Sharpe ratio (SR), and monthly average risk-return. Ma *et al.* [23] recommended RF+mean–variance with forecasting (MVF) model, utilizing RF for return prediction, subsequent portfolio selection based on predicted returns, and the MVF model for final portfolio weight determination. They also explored combining RF, SVR, LSTM, deep multilayer perceptron (DMLP), and CNN models with MV and omega models, identifying RF+MV as superior in the MV combination and SVR+omega in the omega combination. The RF+MV outperforms other combination models. Ma *et al.* [17] proposed an AE+LSTM+omega portfolio optimization model, leveraging autoencoder AE for feature extraction from trading data, LSTM for return prediction, and omega model for portfolio weight confirmation. Their results indicated superiority over equally weighted portfolios and other prediction-based models. While MV models traditionally use predicted return variance as a risk measure, recent advancements introduce additional risk metrics like entropy [24], quantile var [25], and omega ratio [17], which solely rely on stock data without accounting for external factors. Despite achieving promising returns, the enhancing portfolio algorithm performance remains challenging, especially under conditions of significant prediction errors.

These two research directions aim to enhance the performance of stock portfolio optimization models from different perspectives. To effectively utilize these findings, this study explores improving stock direction prediction accuracy and identifying new risk indicators closely linked to stocks, thereby expanding relevant research. Currently, limited research has focused on these aspects. On the one hand, the LSTM network has achieved satisfactory performance in stock return prediction [26], [27], so this paper chooses LSTM to forecast stock return. Given the T+1 trading system on Shanghai and Shenzhen stock exchanges, where shares bought one day can only be sold the next, significant forecast errors can increase trading risks. Thus, the paper introduces an index return trend rate to gauge the direction and strength of stock returns, aiming to enhance prediction accuracy and reduce forecasting errors. Four LSTM networks predict the next four days' closing prices, averaging these forecasts to determine directional changes. Additionally, traditional risk metrics like variance, entropy, mean-var, and omega ratio rely solely on stock data without considering inter-stock correlations within industries. Hence, this paper proposes a novel risk measure, the risk trend rate, calculated similarly to the return trend rate, to factor industry correlations into stock risk assessment. The return trend rate and risk trend rate lay the basis for optimizing stock portfolio allocation using an improved mean–variance (IMV) model to maximize portfolio returns, prioritizing robust stocks in strong industries. In summary, this paper presents a machine learning-based portfolio optimization model integrating return and risk trend rates, alongside a strategic trading algorithm. Specifically, the model utilizes LSTM for short-term stock price prediction, computes return and risk trend rates, applies an IMV model for portfolio allocation, and outlines a trading strategy for implementation. Emphasis is placed on optimizing purchase weights post-stock selection to maximize portfolio returns rather than the initial stock screening process.

This paper contributes to existing literature in several ways. Firstly, it introduces the return trend rate as the expected rate of return. Compared to using a single LSTM model to directly forecast fourth-day price, this approach reduces forecast errors and improves directional accuracy by approximately 1%. Through experimental analysis, it identifies a 4-day holding period as optimal for maximizing annual returns (AR). This discovery reduces trading frequency while increasing AR and prolonging the holding period of investment portfolios. Notably, literature is scarce addressing portfolio holding cycles. Secondly, we propose the innovation of risk trend rate as a measure of risk. It is utilized to formulate an objective function and establish a linear programming model aimed at determining the optimal purchase ratio for investment portfolios. Experimental findings demonstrate that the proposed model significantly enhances AR rates, SR, and overall portfolio profitability. Thirdly, this paper outlines a comprehensive trading strategy algorithm, detailing optimal buying time, purchase proportions, and selling time. An error correction mechanism is also integrated into the algorithm execution process to mitigate potential losses from prediction errors. Third, this paper puts forward a complete trading strategy algorithm, and gives a clear trading strategy from the buying time, buying proportion, and selling time. At the same time, the error correction mechanism is introduced in the execution process of the algorithm to avoid the heavy loss caused by the prediction error. Additionally, the study focuses on 45 constituent stocks across 5 industry indexes of Shanghai and Shenzhen stock exchanges, using daily trading data from 2010 to 2023, and evaluates the proposed portfolio model based on the most recent three years' data. In summary, the trading strategy algorithm proposed herein notably enhances investment portfolio profitability and holds practical value.

The structure of the remainder of this article is as follows: section 2 introduces some utilized models. Section 3 gives the experimental process in detail. Experimental results are discussed in section 4. Finally, the conclusion is drawn in section 5.

2. METHODOLOGY

This section begins by introducing the LSTM network and its application parameters. It then presents the LSTM4 network developed in this paper, detailing how it calculates the return trend rate and risk trend rate based on LSTM4's predictions. Following this, the MV model is discussed. Finally, the paper introduces the enhanced IMV model and the LSTM4-IMV algorithm proposed in this study.

2.1. Long short-term memory model

LSTM model represents a sophisticated type of RNN distinguished by three gate control mechanisms: forgetting gate, input gate, and output gate. These mechanisms enable it to retain information over extended periods, making it particularly suitable for processing time-series input data [27]. Compared to other models such as SVM, RF, DNN, and ARIMA models, LSTM networks demonstrate superior performance in predicting stock prices using daily trading data [22], [28]. The LSTM network constructed in this study comprises an input layer with LSTM neurons, multiple LSTM neurons in a hidden layer, and fully connected layers within a DNN framework, culminating in an output layer. Training involves stochastic gradient descent with overfitting mitigation through early stopping techniques. Key hyperparameters considered include the number of hidden layers, nodes per layer, learning rate, iterations, dropout rate, loss function, optimizer, and activation function. The input feature data series length ranges from 1 to 10 days based on recommendations by Wang *et al.* [22], utilizing the rectified linear unit (ReLU) activation function. Hyperparameter optimization employs grid search, with specifics detailed in Table 1.

Table 1. Parameters of LSTM network

Parameters	Values
LSTM layer	1, 2, 3
LSTM nodes	10, 20, 32, 64
Learning rate	0.001, 0.01, 0.1
Batch size	50, 100, 150
Dropout rate	0.1, 0.2, ..., 0.5
Loss function	Mean absolute error
Optimizer	SGD, RMSprop, Adam
Active function	ReLu
Time series	1, 2, 3, ..., 10

2.2. LSTM4 network

The error of a single LSTM neural network model in predicting the stock price direction and the forecast values is insufficient for achieving stable profitability, as stock direction fluctuates bidirectionally. To address this, this paper introduces the return trend rate to signify the strength and direction of stock return forecasts. The return trend rate is derived using four LSTM networks to predict the closing price over the next four days. It calculates the average forecast value and evaluates the rise and fall based on this average (1). In this study, this model is referred to as the LSTM4 network. The return trend rate of the i-th stock is expressed using TP_i.

$$TP_i = \frac{\frac{\sum_{k=1}^{d} predictP_{i,k}}{d} - P_i}{P_i} \tag{1}$$

Where $predictP_{i,k}$ represents the predicted value of the i-th stock on day k, P_i indicates the current closing price of the i-th stock, d is the number of days. In subsection 4.1, this paper determines through experiments that the AR rate performance is better when d is 4 days.

The industry index initially categorizes stocks by sector and then employs a specific weighting algorithm to aggregate stocks within each category, generating daily trading data similar to individual stock indices. When the industry index shows an upward trend, the majority of stocks within that sector also tend to rise, and conversely for a downward trend. Fluctuations in the industry index reflect the overall condition of the sector and investor sentiment, synchronized with stock movements, thereby offering a more accurate representation of stock risk. Accordingly, this paper introduces a novel indicator, the risk trend rate, to assess stock risk. This index applies a similar methodology as the return trend rate to analyze the industry index, formulated as shown in (2). The risk trend rate for the ith stock is denoted as $\mathrm{TR_i}$.

$$TR_i = -\frac{\frac{\sum_{k=1}^{d} predictPR_{i,k}}{d} - PR_i}{PR_i} \tag{2}$$

Where $predictPR_{i,k}$ represents the predicted value of the i-th industry index on day k, PR_i indicates the current closing price of the i-th industry index, *d* is the number of days. *d* is the same value 4 as the return trend rate.

2.3. Mean-variance model

Markowitz developed the MV model to mathematically calculate portfolio optimization ratios. This development direction has been widely adopted in the field of portfolio optimization [29]–[34]. This approach not only identifies portfolios with the lowest risk given a specific expected return, but it also targets portfolios with the highest return at a predetermined risk threshold. The model efficiently manages the risk by diversifying investments among equities within the portfolio. In (3) outlines the calculation formula of the MV model utilized in this paper's experimental procedures.

$$\begin{cases} max(E) \\ E = \sum_{i=1}^{n} k_i * \mathrm{TP_i} \ , \mathrm{TP_i} \in [c_1, c_2] \\ D = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[k_i * \mathrm{TP_i} - \frac{E}{n}\right]^2} \\ \sum_{i=1}^{n} k_i = 1 \ , \quad k_i > 0 \\ D < td \end{cases} \tag{3}$$

Where *n* is the number of stocks in the portfolio, k_i means the purchase proportion of the i-th stock, $\mathrm{TP_i}$ represents the predicted return trend rate of the i-th stock, c_1 and c_2 are the left and right boundary values of $\mathrm{TP_i}$, respectively, and *td* denotes the threshold value of investors' acceptable loss risk, which is between c_1 and c_2.

2.4. Proposed improved mean–variance model

This study proposes incorporating the return and risk trend rates into the MV model to create a new linear programming model, IMV, that can be solved to determine the stock portfolio's purchase proportion. The IMV model can better fulfill the general trading strategy of buying increasing trend stocks in the rising industry index, greatly improving the portfolio return. At the same time, the risk trend rate is not determined by the return trend rate, it can spread some of the return forecast risk. The IMV model is calculated using (4).

$$\begin{cases} max(E) \\ E = \sum_{i=1}^{n} k_i * \mathrm{TP_i} \ , \quad \mathrm{TP_i} \in [c_1, c_2] \\ D = \sum_{i=1}^{n} k_i * \mathrm{TR}_i \ , \quad \mathrm{TR}_i \in [c_3, c_4] \\ \sum_{i=1}^{n} k_i = 1 \ , \quad k_i > 0 \\ D < td \end{cases} \tag{4}$$

Where *n* is the number of stocks in the portfolio, k_i means the purchase proportion of stock *i*, $\mathrm{TP_i}$ represents the predicted trend rate of stock *i*, c_1 and c_2 are the left and right boundary values of $\mathrm{TP_i}$, respectively, TR_i is the predicted risk value of stock *i*, c_3 and c_4 are the left and right boundary values of TR_i, respectively, and *td* denotes the threshold value of investors' acceptable loss risk, which is between c_1 and c_2.

In order to mitigate the risks arising from extended holding periods and prediction errors, this paper introduces a return threshold value *trd* for error correction. If the stock yield falls below *trd* during the holding cycle, the stock is sold preemptively; otherwise, it is retained. Integrating the LSTM4 model and IMV model with this error correction mechanism constitutes the LSTM4-IMV algorithm proposed in this paper, illustrated in Figure 1. The algorithm takes as inputs the selected portfolio stock code array ListSC, industry index name array ListII, trading date *d1*, and executes a trading strategy. First, it iterates through ListSC, predicting the next four days' closing price $predictP_{i,k}$ (*k*=1,2,3,4) for each stock using the LSTM4 network, then calculates the stock's return trend rate by using (1), yielding the return trend rate vector TP. Second, it traverses ListII to predict the next four days' closing price $predictPR_{i,k}$ (*k*=1,2,3,4) of each industry index using LSTM4, computes the risk trend rate of each index with (2), yielding risk trend rate vector *TR*. In the third step, *TP* and *TR* are inputted into (4) to determine the portfolio's stock purchase proportions. The fourth step executes the stock purchase strategy if the purchase ratio and predicted return trend rate are positive; otherwise, it skips purchasing. The fifth step monitors daily stock returns during the holding period, selling stocks preemptively if their return rate drops below *trd*; otherwise, they are held. Finally, on the fourth day, all remaining stocks are sold, concluding the trading cycle.

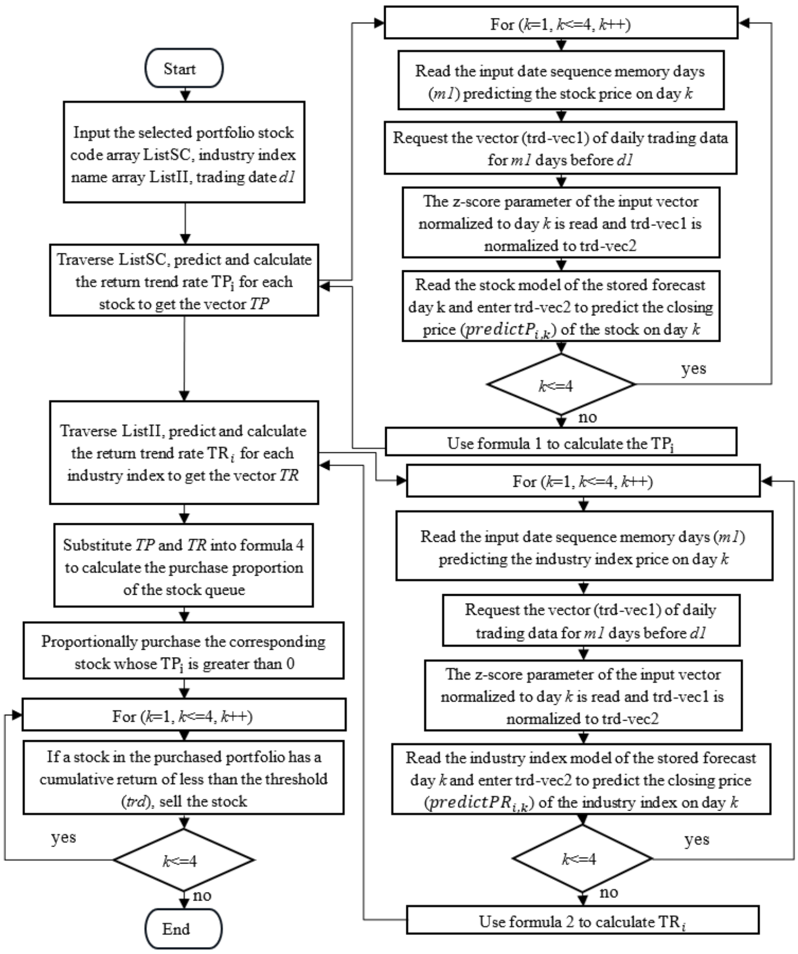

Figure 1. Flowchart of the LSTM4-IMV algorithm

3. EXPERIMENT

This section describes the experimental process and outlines the main parameters employed. This study focuses on five industries in the Shanghai and Shenzhen stock markets: computer equipment, home appliances, coal, communication services, and general equipment. Nine stocks were randomly selected from each sector, resulting in a total of 45 stocks. Following common investor strategies, industries were first chosen for investment, followed by a selection of individual stocks within those industries. Diversification across sectors and stocks reduces portfolio risk. Hence, the 45 stocks were divided into 9 groups, each encompassing one stock from each of 5 industries, as illustrated in Table 2. The first column of Table 2 denotes the group name, while the subsequent five columns list the stock codes of the industry indexes represented in each group.

Table 2. Stock grouping

Group	Computer equipment	Home appliance industry	Coal industry	Communication services	General equipment
Group1	000066	000016	000552	000063	000039
Group2	000977	000541	000723	000561	000410
Group3	002152	000921	000937	002148	000816
Group4	002180	600261	000983	002383	002122
Group5	002308	000333	600188	600050	300083
Group6	002415	000651	600348	002123	300091
Group7	002512	600839	601225	600804	300145
Group8	600100	002429	601699	002093	601369
Group9	603019	600690	601918	002467	002426

This paper focuses on simulating transaction data for the years 2021, 2022, and 2023. As trading hours increase, stock price fluctuations also widen. A short training sample period may not capture the full range of these fluctuations. Therefore, for simulating stock trading in 2021, daily trading data from January 1, 2010 to December 31, 2020, is used to train the LSTM network. Subsequently, daily trading data from January 1, 2021 to December 31, 2021, is employed for conducting the trading simulation. For the simulation of 2022 stock trading, daily trading data spanning from January 1, 2010 to December 31, 2021, is used for LSTM training, and data from January 1, 2022 to December 31, 2022, is used for simulation. Likewise, for the 2023 stock trading simulation, data from January 1, 2010 to December 31, 2022, is used for training, and data from January 1, 2023 to December 31, 2023, is used for simulation. This study utilizes daily trading data of industry indexes obtained from the akshare platform provided by the China Oriental Wealth Securities Company. Training and testing sessions for industry indexes correspond to the stocks they encompass.

When training and predicting stock closing prices, this paper employs daily trading data input features that include: opening price, the highest price, the lowest price, closing price, trading volume, price change, amplitude, turnover, turnover rate, and ten other daily trading indicators. The daily data for a single day encompassing these indicators is denoted as $\{D_{1,t}, D_{2,t}, D_{3,t}, D_{4,t}, D_{5,t}, D_{6,t}, D_{7,t}, D_{8,t}, D_{9,t}, D_{10,t}\}$, where t signifies the day within the input date sequence. In this paper, by using the super parameters shown in Table 1, the LSTM network used to predict the closing price of 45 stocks and 5 industry indexes in the next 4 days is independently trained to obtain the prediction network and input time series memory days *T*. The input feature data for the prediction network is represented as $\{\{D_{1,1}, D_{2,1}, D_{3,1}, D_{4,1}, D_{5,1}, D_{6,1}, D_{7,1}, D_{8,1}, D_{9,1}, D_{10,1}\}, \{D_{1,2}, D_{2,2}, D_{3,2}, D_{4,2}, D_{5,2}, D_{6,2}, D_{7,2}, D_{8,2}, D_{9,2}, D_{10,2}\}\ldots\{D_{1,t}, D_{2,t}, D_{3,t}, D_{4,t}, D_{5,t}, D_{6,t}, D_{7,t}, D_{8,t}, D_{9,t}, D_{10,t}\}\}$, where $t \in [1, T]$. Given the varying value ranges of each indicator, this study employs the Z-score algorithm to standardize the input feature data. The Z-score transformation involves calculating the mean and standard deviation of each indicator's original data, and normalizing it using (5). This method ensures that the data conforms to a standard normal distribution, facilitating comparability across different measures.

$$STvalue_{i,t} = \frac{D_{i,t} - mean_{i,t}}{std_{i,t}} \quad (5)$$

Where $D_{i,t}$ is the daily trading data indicator *i* on day *t*, $mean_{i,t}$ denotes the average of the daily trading data indicator *i* on day *t*, $std_{i,t}$ means the variance of the daily trading data indicator *i* on day *t*, $STvalue_{i,t}$ is the standardized value of the daily trading data indicator *i* on day *t*.

Because daily trading data, such as stock prices and volumes for each stock and industry index, vary significantly in value range, LSTM models identified by each forecasting model are suboptimal. Consequently, each prediction model requires independent training, storing essential data such as parameters normalized with Z-score, suboptimal LSTM model parameters, and the memory duration of its input sequences. When implementing the LSTM4-IMV4 algorithm to calculate the portfolio purchase ratios, several critical parameters are employed. The selected 45 stocks in this study have a daily fluctuation limit of

±10%, while the cumulative 4-day fluctuation boundaries for the return rates in (4) are set as c_1=c_3=-0.271 and c_2=c_4=0.331. Additionally, the value of td in (4) takes the value of 40% of the principal amount that investors can bear to lose, td=0.09. Within the LSTM4-IMV4 algorithm, trd is defined as -0.05. During the execution of the trading strategy, parameters include a trading commission rate of 0.0003, a selling stamp duty rate of 0.001, and an initial investment of 1 million yuan. For simulation purposes, it is assumed that stock trading activities are completed 1 second before the market closes each day. The study does not currently account for temporary stock suspensions; if any stocks are suspended within the next 4 trading days, trading for those stocks will be skipped, the trading day will reset to the following day, and the strategy recalculated.

4. EXPERIMENTAL RESULTS

This section begins by examining the selection of prediction days d in the LSTM4 network. Subsequently, it evaluates the prediction accuracy achieved by the LSTM4 network. The performance of the IMV model proposed in this paper is then analyzed in terms of profitability. Lastly, to assess the practical effectiveness of the LSTM4-IMV algorithm, this section compares it with established models such as LSTM4-MV, AE+LSTM+OMEGA, and RF+MVF.

4.1. Select the predicted days d in the LSTM4 network

This section examines how the forecast horizon of the LSTM4 network and the holding period of the portfolio influence its earnings performance. Take 1-5 days for d in (1) and (2) to calculate the return trend rate and risk trend rate respectively. Concurrently, set the portfolio's holding period to d. Subsequently, the LSTM4-IMV algorithm was employed to conduct experimental simulations on the 2023 data for portfolios categorized as group1 to group3. The experimental results are detailed in Table 3. When d is set to 4 days, the AR rates for all three groups of stocks either surpassed or closely approached those for d=1,2, and 3, achieving a positive return of over 10%. However, with d=5, the AR decreased for groups 1 and 3, with only group 2 showing a slight increase. Therefore, it is concluded in this paper that setting d=4 achieves the optimal balance between prediction accuracy and investment return. Consequently, d in (1) and (2) is fixed at (4), and the portfolio's holding period is also set to 4 days.

Table 3. The average value error of future stock prediction

Group	Index value	d=1 (%)	d=2 (%)	d=3 (%)	d=4 (%)	d=5 (%)
group1	annualized returns	-17.02	0.85	17.48	12.31	-5.04
	maximum drawdown (MD)	26.18	14.78	11.32	11.56	13.34
group2	annualized returns	-41.16	-25.85	-27.59	25.70	26.82
	MD	46.51	31.17	34.64	25.25	8.83
group3	annualized returns	-21.28	-9.99	16.72	28.11	1.48
	MD	29.36	20.75	14.84	11.72	13.32

4.2. The prediction accuracy of LSTM4 network

Four indices, namely MAPE, trend accuracy (HR), negative trend accuracy (HR-), and positive trend accuracy (HR+), were utilized to evaluate the predictive performance and validate the strength and directional accuracy of the LSTM4 model proposed in this study. HR, HR-, and HR+ were employed to assess the accuracy of trend prediction direction [17], [35], while MAPE was used to gauge prediction accuracy [29]. These metrics are computed using (6) to (9).

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\widehat{tr}_k - tr_k}{tr_k}\right| * 100\% \tag{6}$$

$$HR = \frac{Count_{k=1}^{N}(\widehat{tr}_k * tr_k > 0)}{Count_{k=1}^{N}(\widehat{tr}_k * tr_k \neq 0)} \tag{7}$$

$$HR- = \frac{Count_{k=1}^{N}(\widehat{tr}_k < 0 \ AND \ tr_k < 0)}{Count_{k=1}^{N}(tr_k < 0)} \tag{8}$$

$$HR+ = \frac{Count_{k=1}^{N}(\widehat{tr}_k > 0 \ AND \ tr_k > 0)}{Count_{k=1}^{N}(tr_k > 0)} \tag{9}$$

where $\widehat{tr}_k$ and tr_k represent the predicted value and the actual value on day *k*, *N* indicates the total number of days.

Table 4 presents the statistical averages of the four indicators for 45 stocks listed in Table 1 when *d*=4 for the return trend rate, specifically predicting stock closing prices four days into the future. It is evident from Table 4 that all four indicators of LSTM4 outperform those of a single LSTM prediction model across the 2021-2023 simulation data, showing improvements of approximately 1%. Additionally, the proposed method in this paper demonstrates comparable MAPE to the AE+LSTM algorithm used by Ma *et al.* [17] for predicting stock prices one day ahead, with slight enhancements in HR, HR+, and HR-. This suggests that compared to the benchmark model, the algorithm proposed in this paper marginally improves overall prediction accuracy and positively impacts higher returns for investment portfolios. However, Table 4 also indicates an average MAPE above 4% and fluctuating trend accuracy indicators (HR, HR+, and HR-) around 50%, indicating substantial prediction errors and low model stability, thereby suggesting susceptibility to significant losses when trading based on predicted return trend rates.

Table 4. The statistical average of 45 stocks on 4 indicators

Year	Model	MAPE (%)	HR (%)	HR+ (%)	HR- (%)
2021	LSTM	4.14	51.02	52.09	50.82
2021	LSTM4	4.08	52.12	52.89	51.62
2022	LSTM	5.34	47.82	48.62	47.19
2022	LSTM4	5.27	48.52	49.12	48.23
2023	LSTM	4.32	50.12	51.39	49.62
2023	LSTM4	4.27	51.03	52.49	50.22

4.3. Profit performance of IMV model

In this section, the enhanced IMV model is compared with the benchmark MV model in terms of profitability performance and frequency of trading strategy execution. Figure 2 illustrates the simulation results for group 1, group 2, group 3, and group 4 using LSTM4-IMV and LSTM4-MV algorithms over the years 2021, 2022, and 2023. The y-axis in Figure 2 represents the total funds after executing the trading strategy. Analysis of Figure 2 reveals distinct patterns: subgraphs numbered 1, 3, 4, 9, 10, and 11 demonstrate that the LSTM4-IMV algorithm achieves significantly higher cumulative profits compared to the LSTM4-MV algorithm. Conversely, in subgraphs numbered 5, 6, 7, 8, and 12, the cumulative profits of the LSTM4-IMV algorithm are generally comparable to those of the LSTM4-MV algorithm. Only subgraph number 2 indicates that the LSTM4-IMV algorithm yields notably lower cumulative returns than the LSTM4-MV algorithm. Figure 2 also highlights that the transaction frequency of the LSTM4-IMV algorithm is considerably lower than that of the LSTM4-MV algorithm, indicating fewer trades executed. Despite this, the LSTM4-IMV algorithm achieves superior cumulative returns compared to LSTM4-MV. In conclusion, the proposed LSTM4-IMV algorithm significantly enhances portfolio profitability when incorporating the risk trend rate index, thereby mitigating prediction errors by reducing transaction frequency.

4.4. Model comparison

To further validate the profitability of the LSTM4-IMV algorithm proposed in this study, we compare its performance with the benchmark LSTM4-MV algorithm, as well as with the state-of-the-art AE+LSTM+OMEGA algorithm [17] and RF+MVF algorithm [23] in simulation experiments involving nine investment portfolio groups from 2021 to 2023. Three metrics-AR, SR, and MD-are employed to assess the profitability of trading strategies. The AR measures the profit performance of the portfolio after executing the trading strategy for one year. A higher AR indicates better performance. The SR evaluates the profit performance of an investment portfolio after deducting risk-free investment returns. A higher SR indicates better performance, reflecting higher returns per unit of risk. The paper computes the SR using the monthly variance of portfolio returns and a risk-free rate of 0.02. MD represents the maximum historical decline in net asset value, indicating the peak-to-trough decline. A lower MD suggests lower risk, while a higher drawdown signifies higher risk. The formulas for calculating these metrics are detailed as follows.

$$AR = \frac{IVend - IVstart}{IVstart} \tag{10}$$

$$SR = \frac{AR - RF}{\sigma_P} \tag{11}$$

$$MD = \max\left(\frac{M_i - M_j}{M_i}\right) \tag{12}$$

Where $IVend$ is the total investment funds at the end of the year, and $IVstart$ means the initial investment funds at the beginning of the year. RF is the fixed return on treasury bonds, and σ_P represents the standard deviation of the portfolio's monthly return every month. M_i indicates the maximum value of the current investment funds in the upward trend, and M_j is the minimum value of the current investment funds that do not exceed M_i after the reversal of the current upward trend.

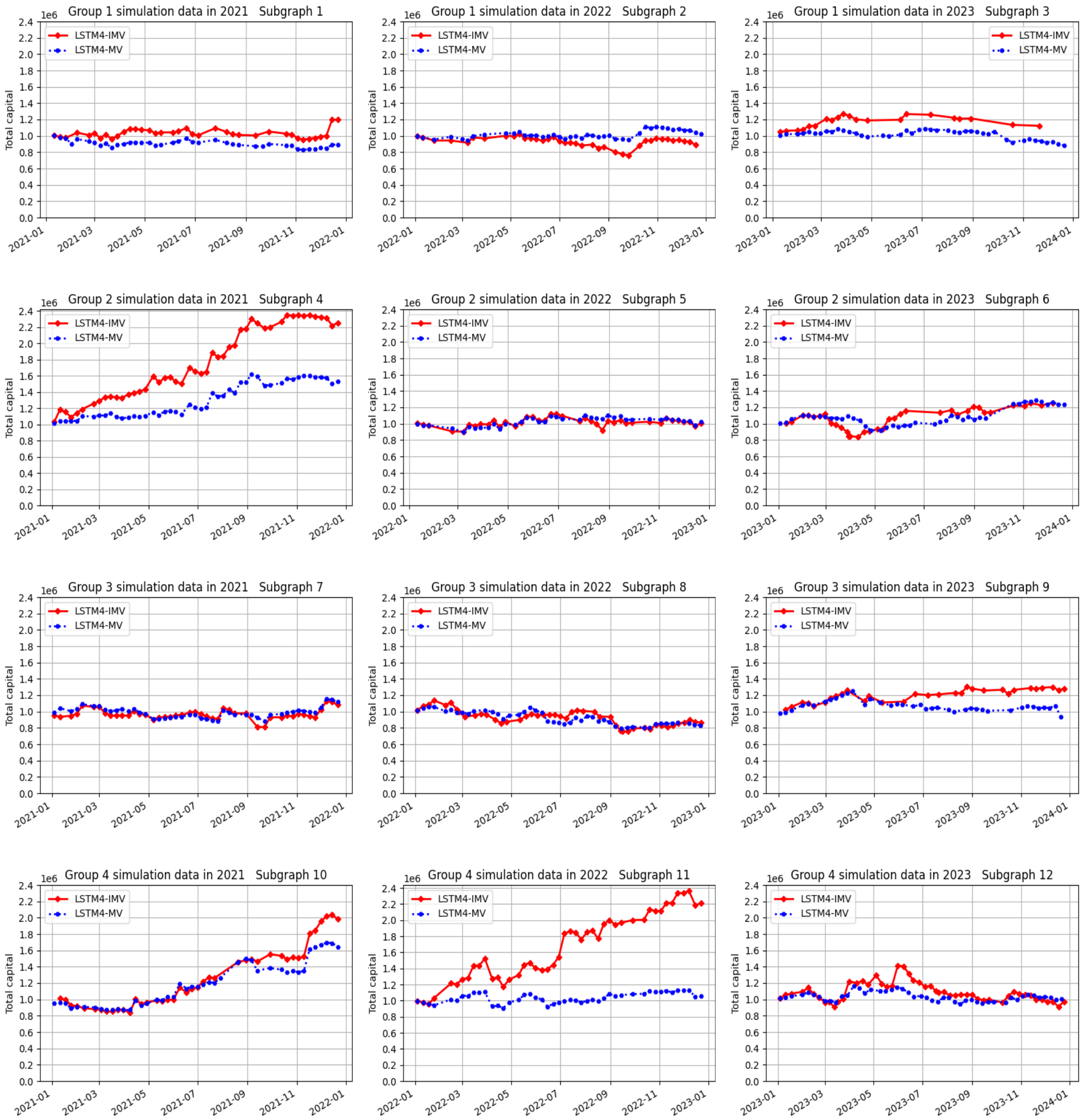

Figure 2. The return trend chart of group 1-4 after trading strategy simulation on 2021-2023

As shown in Tables 5 to 7, the LSTM4-IMV algorithm exhibits a notably higher average AR rate compared to the other three models, consistently exceeding 18%. Moreover, this algorithm achieved positive returns in 8 groups in 2021, 5 groups in 2022, and 7 groups in 2023, surpassing the performance of the other algorithms. Therefore, the LSTM4-IMV algorithm clearly outperforms the other models in terms of profitability. The average AR of all algorithms in 2022 are lower than those in 2021 and 2023, which is largely affected by the worst economic situation before China's COVID-19 was announced to open up in December 2022, leading to significant fluctuations in China's stock market and an overall downward trend before the opening up, affecting the prediction accuracy. In terms of the SR, the LSTM4-IMV algorithm demonstrates a significantly higher average SR in 2021 and 2023 compared to the other three algorithms, albeit slightly lower than the AE+LSTM+OMEGA algorithm in 2022. Hence, the LSTM4-IMV algorithm exhibits superior profitability stability. Finally, regarding maximum retracement, the LSTM4-MV algorithm records the lowest average maximum retracement value, while the LSTM4-IMV algorithm shows a slightly higher average maximum retracement value. This difference arises because the LSTM4-IMV algorithm concentrates portfolio investments on strong stocks within robust industry indices, resulting in larger pullbacks in case of forecast failures. Overall, the LSTM4-IMV algorithm demonstrates superior profitability and stability compared to LSTM4-MV, AE+LSTM+OMEGA, and RF+MVF models, thereby enhancing the performance of forecast-based portfolio optimization models.

Table 5. Four algorithms simulation results in 2021

Group	LSTM4-IMV (%)			LSTM4-MV (%)			AE+LSTM+OMEGA (%)			RF+MVF (%)		
	SR	AR	MD	SR	AR	MD	SR	AR	MD	SR	AR	MD
Group1	102.6	19.6	13.1	-103.3	-10.7	17.6	1.9	2.2	13.1	-105.2	-16.9	34.2
Group2	619.3	125.5	6.0	311.7	53.1	8.8	347.8	70.2	19.7	649.0	117.1	13.2
Group3	25.7	8.2	24.8	53.6	12.1	19.2	-9.7	-1.1	19.9	-63.7	-18.0	32.5
Group4	290.1	98.2	17.2	171.1	64.5	12.9	109.0	32.1	10.6	293.8	93.6	10.2
Group5	-44.6	-13.8	32.8	106.9	23.4	14.0	30.0	7.3	20.2	-67.2	-25.6	33.5
Group6	216.1	36.0	17.2	-45.6	-5.0	24.9	-60.9	-9.9	25.1	-21.6	-4.1	22.2
Group7	59.7	29.1	19.4	173.5	56.3	8.9	55.1	19.0	17.2	48.5	15.3	24.6
Group8	182.7	66.6	15.5	130.5	32.9	15.4	-4.1	0.9	27.2	44.4	9.4	17.7
Group9	0.5	2.2	18.1	-32.1	-6.9	20.3	-170.4	-28.3	28.9	-41.2	-16.7	34.5
Average	161.3	41.3	18.3	85.1	24.4	15.8	33.2	10.3	20.2	81.9	17.1	24.7

Table 6. Four algorithms simulation results in 2022

Group	LSTM4-IMV (%)			LSTM4-MV (%)			AE+LSTM+OMEGA (%)			RF+MVF (%)		
	SR	AR	MD	SR	AR	MD	SR	AR	MD	SR	AR	MD
Group1	-36.9	-11.1	25.2	3.6	2.8	9.8	50.9	17.0	13.0	-90.8	-26.2	35.0
Group2	-6.3	0.9	18.0	-0.5	1.9	11.7	29.0	5.9	15.6	-160.3	-25.4	33.2
Group3	-47.9	-13.7	33.4	-78.4	-16.6	24.7	-146.2	-29.7	34.0	-110.2	-14.3	24.8
Group4	312.6	121.5	23.0	16.1	5.9	18.0	109.3	26.2	7.8	149.0	79.0	31.6
Group5	8.0	4.6	31.5	-0.5	1.9	15.9	-67.6	-18.5	26.9	49.7	11.7	17.1
Group6	66.2	33.8	23.3	55.8	11.6	9.7	110.8	26.2	12.9	19.4	6.1	17.1
Group7	-46.4	-16.7	29.6	-77.8	-15.7	20.8	-53.4	-12.5	22.0	-83.9	-12.2	24.4
Group8	-13.6	-2.4	30.5	-63.6	-12.3	18.5	118.4	32.5	11.9	-28.1	-0.8	9.2
Group9	113.0	48.9	34.3	-1.5	1.7	16.7	297.9	33.9	6.9	135.5	23.5	8.9
Average	38.7	18.4	27.7	-16.3	-2.1	16.2	49.9	9.0	16.8	-13.3	4.6	22.4

Table 7. Four algorithms simulation results in 2023

Group	LSTM4-IMV (%)			LSTM4-MV (%)			AE+LSTM+OMEGA (%)			RF+MVF (%)		
	SR	AR	MD	SR	AR	MD	SR	AR	MD	SR	AR	MD
Group1	49.1	12.3	11.6	-74.4	-11.9	19.0	22.8	5.7	11.0	-29.0	-5.9	25.6
Group2	63.3	25.7	25.3	76.5	23.4	17.0	8.1	3.7	15.6	0.7	2.3	28.7
Group3	110.1	28.1	11.7	-51.0	-6.6	25.2	-97.0	-16.3	25.0	45.4	16.1	18.3
Group4	-11.6	-2.6	35.4	-10.5	0.4	19.3	-132.2	-14.2	20.1	-30.6	-0.8	6.9
Group5	27.2	10.8	26.4	-9.6	-0.2	20.6	-114.7	-19.1	25.8	-106.0	-27.7	42.6
Group6	-63.8	-6.0	12.6	-63.7	-5.8	13.0	-72.6	-6.4	17.0	41.8	13.8	30.0
Group7	129.3	50.6	18.4	279.9	103.2	11.6	281.5	101.1	18.7	147.4	29.1	18.1
Group8	115.5	51.4	28.6	97.0	35.1	19.5	175.5	91.3	15.6	23.0	11.4	33.6
Group9	65.2	19.1	15.6	66.4	14.1	12.0	219.9	40.2	13.4	95.6	57.3	28.7
Average	53.8	21.1	20.6	34.5	16.9	17.5	32.4	20.7	18.0	20.9	10.6	25.9

5. CONCLUSION

This paper presented a portfolio optimization model based on the machine learning to predict return trend rate and risk trend rate, and designs a portfolio trading strategy algorithm based on this model, namely LSTM4-IMV. The prediction accuracy of the LSTM4 network is evaluated and compared with state-of-the-art algorithms. Findings indicate several key outcomes. Firstly, the LSTM4 model shows an overall improvement of approximately 1% across four prediction accuracy metrics: MAPE, HR, HR-, and HR+. This improvement slightly outperforms the LSTM model. Higher forecast accuracy correlates with increased portfolio returns. Secondly, accounting for transaction costs, taxes, and the initial capital, the LSTM4-IMV algorithm outperforms current advanced models-LSTM4-MV, AE+LSTM+OMEGA, and RF+MVF-in two profitability indicators: AR and SR. However, it exhibits a slightly higher risk as indicated by the maximum retracement rate. Lastly, experiments demonstrate that a holding period of 4 days achieves an optimal balance between forecast accuracy and portfolio return. The introduced return trend rate and risk trend rates play pivotal roles in this portfolio optimization model, expanding the current literature on prediction-based portfolio models. The model effectively identifies rising stocks in rising industry indices, significantly enhancing profitability over benchmark LSTM4-MV and other advanced models, thereby advancing portfolio optimization based on prediction. Despite valuable conclusions, this study acknowledges certain limitations. In future research, three aspects can be explored further. Firstly, this paper only focuses on the pre-selected stock portfolio, so the selected portfolio may not be the optimal portfolio, and the algorithm for selecting the optimal stock portfolio can be further studied. Secondly, despite the LSTM4 model's proposal, the prediction error remains significant, indicating a need for enhanced prediction accuracy. Lastly, while this paper establishes a correlation between the risk trend rate and the stock, future studies could delve into additional risk indicators influencing short-term stock price trends, such as news dynamics, investor sentiment, economic conditions, and financial data.

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