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Comparative Analysis of SVR and LSTM in Stock Price Forecasting Across Market Cycles

Weimeng Liu[1,a,*]

[1]*SWUFE-UD Insitute of Data Science at SWUFE, Southwestern University of Finance and Economics, Chengdu, China*
a. 42153039@smail.swufe.edu.cn
**corresponding author*

Abstract: This study investigates the predictive capabilities of Support Vector Regression and Long Short-Term Memory networks on stock price trends across different market conditions—bear, bumpy, and bull markets. With the ongoing evolution of machine learning technologies, their application in financial forecasting has shown substantial potential for capturing complex patterns in vast datasets, which traditional models often fail to process efficiently. This study particularly focuses on the performance of these models in forecasting stock prices from the S&P 500 index, evaluated through the lens of Modern Portfolio Theory (MPT). The models are assessed based on their ability to forecast trends and their implications when applied to constructing investment portfolios, evaluating key financial metrics such as expected returns, standard deviation, Sharpe ratio, and maximum drawdown. The findings indicate that while both SVR and LSTM exhibit competence in trend prediction, especially in bull markets, their predictions diverge from actual market performance when applied to portfolio construction under MPT. This discrepancy underscores the need for further refinement in modeling approaches to enhance accuracy and reliability in real-world investment scenarios. This research contributes to the empirical literature by demonstrating the practical implications of deploying advanced machine learning and deep learning models in dynamic market environments and suggests directions for future enhancements.

Keywords: Stock price prediction, SVR, LSTM, MPT

1. Introduction

The prediction of stock market trends has been a prominent subject in the field of finance due to the strong interconnection between the stock market and the economy. This has significant consequences for individual investors, financial institutions, and policymakers involved in economic matters [1]. Accurate stock price forecasts can help investors make informed investment decisions, support financial institutions' asset management, and help policymakers understand and predict market trends. Extracting valuable information from the market and making accurate stock price forecasts is extremely challenging due to the market's complexity, the uncertainty of the external economic environment, and the volatility of investor behaviour [2].

Over the years, scholars have developed many forecasting models trying to reveal the underlying patterns of price movements from historical data. Due to the progress in machine learning and deep learning techniques, especially their extensive application in time series forecasting, the focus of research has gradually moved from traditional statistical models to these advanced forecasting methods [3].

In 1952, with the introduction of Markowitz's mean-variance theory, which provided the theoretical basis for a series of subsequent studies on quantitative investing [4], it followed that a series of predicted stock prices were applied to his theory in pursuit of ideal investment returns.

Extensive research has shown that machine learning has been successfully applied in financial forecasting. For example, Cortes and Vapnik made significant contributions to the theory of Support Vector Regression (SVR) in 1995, and subsequent studies have confirmed its effectiveness in predicting stock prices [5]. SVR utilises the principle of structural risk minimization and the kernel trick to enable the model to effectively perform nonlinear regression in high-dimensional spaces. This capability is especially valuable when dealing with non-stationary and highly noisy financial data. This is especially beneficial in financial data that is not stable and contains a high level of noise.

On the other hand, LSTM was proposed by Hochreiter and Schmidhuber and has rapidly become one of the mainstream techniques for processing sequence data in 1997, especially in forecasting complex financial time series. LSTM models, due to their unique gating mechanism, are able to efficiently capture long term dependencies in time series, which is often difficult to realize.

Existing literature also points out that although SVR and LSTM have improved in prediction accuracy compared to traditional models, there are still challenges. For example, the choice of hyperparameters for the models, the risk of overfitting, and their applicability in a variable market environment are all topical issues in current research. Moreover, the performance of these models is significantly affected by market efficiency and external economic factors, which are difficult to be fully accounted for in the models.

The aim of this study is to assess the predictive abilities of SVR and LSTM models in forecasting stock prices across various market cycles. Additionally, it seeks to evaluate the accuracy of these predictions using modern portfolio theory. The study aims to provide new empirical evidence in this field and test the practicality of modern investment theories in real-world market predictions. This study aims to determine the model that can accurately capture market trends in conditions of high market volatility and limited data. It will compare actual market data with forecast data and categorize the market's cycle into bear market, bumpy market, and bull market phases. By doing so, it will validate and assess which model can serve as a reliable reference for future stock price forecasting in various market environments.

2. Methodology

2.1. Segmentation of data sets and market cycles

Forecasting equity index prices is of utmost importance as it forms the foundation for making strategic decisions in the financial sector [6]. It improves risk management and helps in effectively diversifying investment portfolios. Precise predictions of indices offer crucial understanding of market patterns and economic prospects, which are vital for investors aiming to optimize their asset allocations. Investors can strategically mitigate their risk exposure, safeguard against potential downturns, and align their investment strategies with prevailing economic conditions by anticipating potential market movements. Moreover, regulators and financial institutions employ these predictions to oversee and uphold market stability, guaranteeing adherence to regulations and taking proactive steps to mitigate market fluctuations. Therefore, the capacity to forecast equity index prices not only aids in making individual investment choices but also strengthens the overall resilience and efficiency of the financial ecosystem. The dataset used in this study is historical price data for the S&P 500 index for the period January 1, 2021 to January 1, 2024 in Figure 1. The data is provided by Yahoo Finance and obtained through the yfinance interface program library. Daily closing prices are the main basis of the analysis and are used to identify market cycles and as base data for model training.

The identification of market cycles is achieved by visually analyzing the historical closing price trends of the S&P 500 index. This study employs a time-series decomposition methodology to classify price trends during the specified time period into three distinct market conditions: bear markets, bumpy markets, and bull markets, as shown in table 1. This categorization allows us to perform specialized analysis and model forecasts for different market conditions.

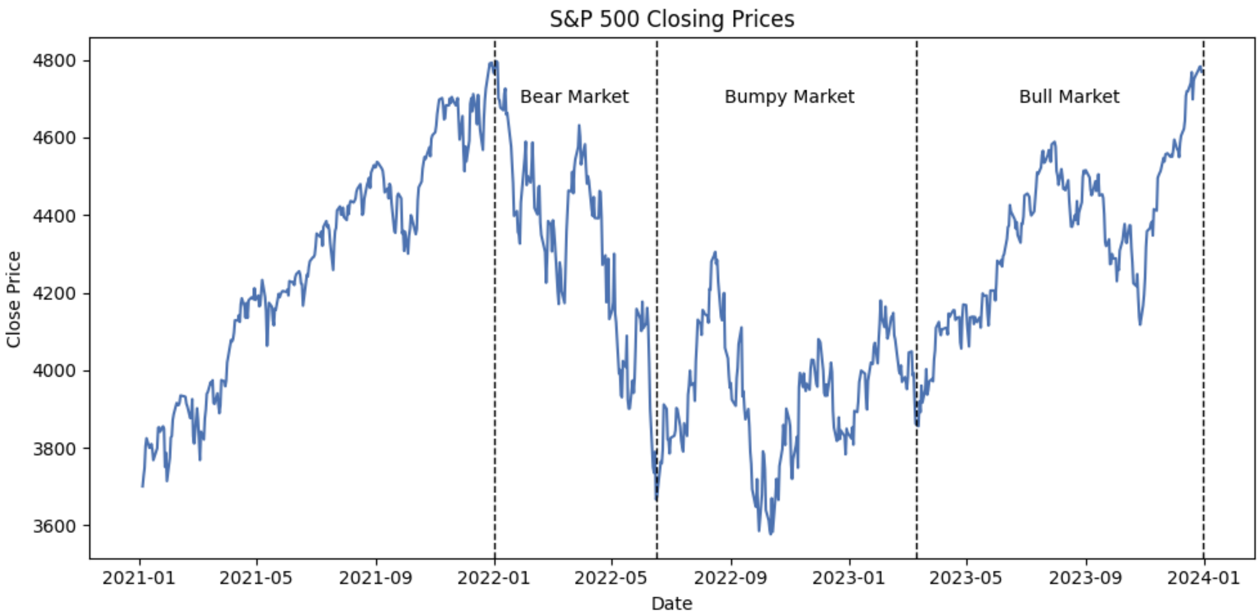

Figure 1: S&P 500 Closing Price Chart.

Table 1: Bear Market, Bumpy Market, Bull Market Divided in Time

Period	Time	Exponential change
Bear Market	2022.1.1-2022.6.16	-20.99%
Bumpy Market	2022.6.16-2023.3.11	5.31%
Bull Market	2023.3.11-2024.1.1	23.71%

Diversification is critical when selecting stocks in the S&P500 for forecasting and portfolio purposes. Diversification can help to diversify the unsystematic risk posed by a particular stock or sector [7]. A total of 25 stocks from various sectors including Energy, Materials, Industrials, Consumer Discretionary, Consumer Necessities, Healthcare, Financials, Information Technology, Communication Services, Utilities, Real Estate, and others were chosen for this study. The companies listed are Exxon Mobil (XOM), Chevron (CVX), Linde (LIN), Ecolab (ECL), Honeywell (HON), Boeing (BA), Amazon (AMZN), Tesla (TSLA), Procter & Gamble (PG), Coca-Cola (KO), Johnson & Johnson (JNJ), Pfizer (PFE), Merck (MRK), JPMorgan Chase (JPM), Bank of America (BAC), Goldman Sachs (GS), Apple (AAPL), Microsoft (MSFT), Nvidia (NVDA), AT&T (T), Verizon (VZ), NextEra Energy (NEE), Duke Energy (DUK), American Tower (AMT), and Prologis (PLD).

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2.2. SVR

SVR is a regression technique that is derived from the principles of Support Vector Machines (SVMs), aiming to find an optimal regression function in a given dataset. SVR is well suited for analyzing data in high-dimensional spaces and has good robustness to points outside the data.

The fundamental concept behind Support Vector Regression (SVR) is to identify a function within the dataset that can accurately forecast the true target value, while adhering to a predetermined tolerance ε. This is achieved by minimising the complexity of the model to improve its ability to generalise. The core of this approach lies in the construction of a maximally spaced plane that is capable of handling not only linear problems but also nonlinear problems by introducing kernel tricks.

For a linear SVR, the model can be expressed as:

$$f(x) = w^T x + b \tag{1}$$

where w is the weight vector, x is the feature vector, and b is the deviation term.

The goal of the model is to minimize the following objective function:

$$min \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} \xi_i \tag{2}$$

d the following conditions are met:

$$\begin{aligned} &y_i - w^T x_i - b \leq \epsilon + \xi_i \\ &w^T x_i + b - y_i \leq \epsilon + \xi_i \\ &\xi_i \geq 0 \end{aligned} \tag{3}$$

Here ξ_i is the slack variable to handle the case where the data points do not fall exactly within the ε tolerance band. The parameter C serves as a regularisation parameter, allowing for the adjustment of the balance between the error term and the complexity of the model.

2.3. LSTM

LSTM is a specialised variant of Recurrent Neural Network (RNN) that is specifically engineered to tackle the challenges faced by conventional RNNs when handling long-term dependencies. LSTM can efficiently capture dependencies over long time intervals in sequential data through its unique internal structure, which makes it very useful in financial time series analysis, language processing, and other applications that need to take temporal information into account.

The LSTM is primarily characterised by its cellular architecture, which consists of individual cells that incorporate three primary gating mechanisms: forgetting gates, input gates, and output gates.

Forget Gate - Determines which data to eliminate from the cellular state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f \tag{4}$$

Input Gate - Determines which additional data to incorporate into the cell state.

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{5}$$

Module status updates - Updates the cell state by combining the old state and new information.

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$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

Output Gate - Calculates the subsequent concealed state, which encompasses data derived from the revised cell state.

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t * \tanh\,(C_t) \end{aligned} \tag{7}$$

The output gate controls what information will be output as the activation value h_t for this cell, or the output of this step.

2.4. Ledoit-Wolf Shrinkage Estimation

Ledoit-Wolf shrinkage estimation is an improved covariance matrix estimation method proposed by Olivier Ledoit and Michael Wolf. This approach is particularly suitable for scenarios in which the sample size is relatively limited in comparison to the number of variables. It is commonly used in the examination of financial market data, specifically in predicting stock prices, especially when the time period of the data is short or there are only a few data points available [8]. The fundamental concept is to merge the empirical covariance matrix (a sample covariance matrix) with a more reliable target covariance matrix in a linear manner. The objective is to minimise the estimation error and enhance the accuracy of estimating the covariance matrix.

The formula can be expressed as:

$$\hat{\Sigma} = \rho \cdot F + (1 - \rho) \cdot S \tag{8}$$

The contracted covariance matrix, $\hat{\Sigma}$, is determined by optimising the intensity of contraction, ρ, which is a constant between 0 and 1. The optimisation aims to minimise the mean-square error between the estimated covariance matrix, S, and the target covariance matrix, F, in order to accurately estimate the true covariance matrix.

3. Empirical Analysis

3.1. Data Preprocessing

Prior to constructing the prediction model, data preprocessing was conducted. This study utilises the yfinance library to acquire the historical trading data of the chosen stocks within a defined timeframe. The data includes the opening price (Open), the highest price (High), the lowest price (Low), the trading volume (Volume), and the adjusted closing price (Adj Close) [9]. In order to optimise the efficiency of model training and testing, the dataset is divided into two segments. The training set, which accounts for 80% of the dataset, is utilised to facilitate the learning process of the model. The remaining 20% of the dataset is allocated as the test set, which is employed to assess the model's predictive capabilities. The target variable for analysis and prediction in this study is the adjusted closing price, which is a crucial indicator that represents the change in the market capitalization of a stock.

Normalizing the feature data is a critical step before making predictions. During this stage, the data features are adjusted to a standardised range, typically with an average of 0 and a standard deviation of 1. The purpose of the normalisation process is to mitigate the influence of variations in feature magnitudes, expedite the convergence rate of the algorithm, and augment the model's capacity to generalise to novel data [10]. The training set features were adjusted and converted using the

StandardScaler class. The same adjustment process was also applied to the test set to maintain data consistency.

3.2. Performance Indicator

The mean squared error (MSE) is a commonly employed measure in machine learning and statistical modelling for assessing the predictive accuracy of models [11]. It has undergone thorough validation and has been conclusively demonstrated to be highly effective. The Mean Squared Error (MSE) is a metric that quantifies the average of the squared differences between the predicted values of a model and the actual observed values. Specifically, for a given data point, MSE is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{9}$$

n represents the total number of data points. y_i refers to the ith true observation, while $\hat{y}_i$ represents the ith predicted value.

In this study, MSE is used as an evaluation metric to measure the accuracy of SVR model and LSTM model on stock price prediction.

3.3. SVR

3.3.1. Model Building

When constructing SVR model, the choice of parameters has a decisive impact on the model performance. To systematically explore the parameter space and find the optimal parameter combinations, this study adopts a grid search (GridSearchCV) combined with five-fold cross-validation.

Grid search is a method of optimizing model parameters by traversing a given parameter grid. In this analysis, the parameter grid is set to contain multiple preset values of the regularization parameter C at different levels, the kernel function coefficient gamma, and the error term epsilon. The parameter C determines the model's sensitivity to errors; higher values of C can result in overfitting, while lower values can lead to underfitting. The parameter gamma determines the distribution of the data after the radial basis function (RBF) kernel transformation, which directly affects the model's capture of the data features. epsilon controls the width of the intervals in the SVR, which affects the model's fitting accuracy to the training data.

Cross-validation is a statistical technique employed to assess and enhance a model's capacity to generalise to independent data sets. Five-fold cross-validation involves partitioning the original data into subsets of equal size. During this procedure, four of these subsets are utilised as training data for each iteration, while the remaining subset is used to assess and validate the model's performance. This process is iterated 5 times, with a distinct validation set chosen for each iteration to ensure that each subset is given a single opportunity to be utilised as validation data. The result of cross-validation is usually the average of the five scores, which helps to minimize model performance bias on a particular sample set.

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3.3.2. Diversity Analysis of the Ledoit-Wolf Covariance Matrix

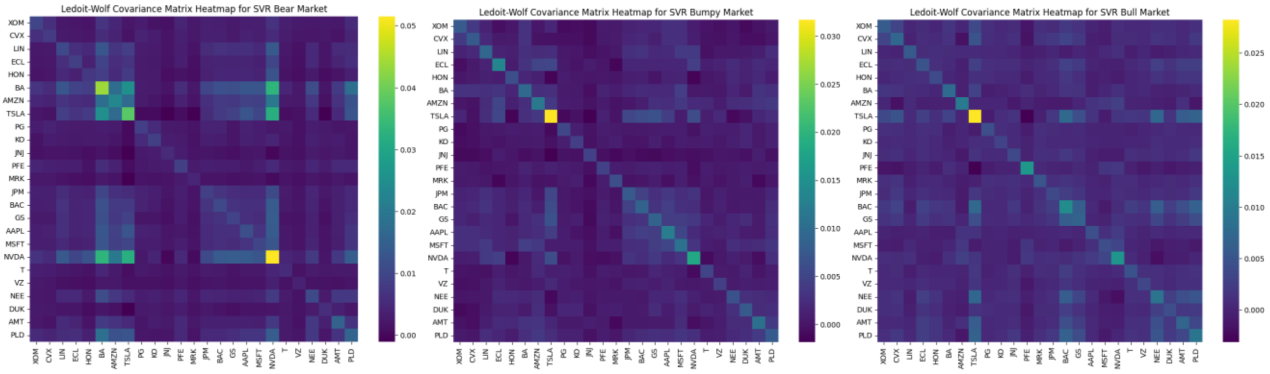

Figure 2: Heat map of Ledoit-Wolf covariance matrix for three periods of SVR.

In exploring the relationship between stock price movements in three different market cycles: bear market, bumpy market and bull market, the heat map visualization analysis (Figure 2) reveals the low covariance values properties. The generally low covariance values observed for most stock pairs in the covariance matrix are suggestive of a low degree of correlation between different stocks. This is consistently reflected even across market cycles. The stocks selected were from different sectors of the S&P 500 Index, and the prevalence of low covariance values is consistent with the desired effect of portfolio diversification. This cross-industry selection reduces the impact of a single market factor on the portfolio as a whole and helps to diversify the risk of specific industry or market events. And no significant increase in the covariance value is observed in the covariance matrix for all three market cycles, implying that the price volatility of the selected stocks remains independent even under drastic changes in market conditions. This phenomenon suggests that the distribution of assets within the portfolio is able to provide stable risk exposure under different market conditions.

3.3.3. Overview of projected effects

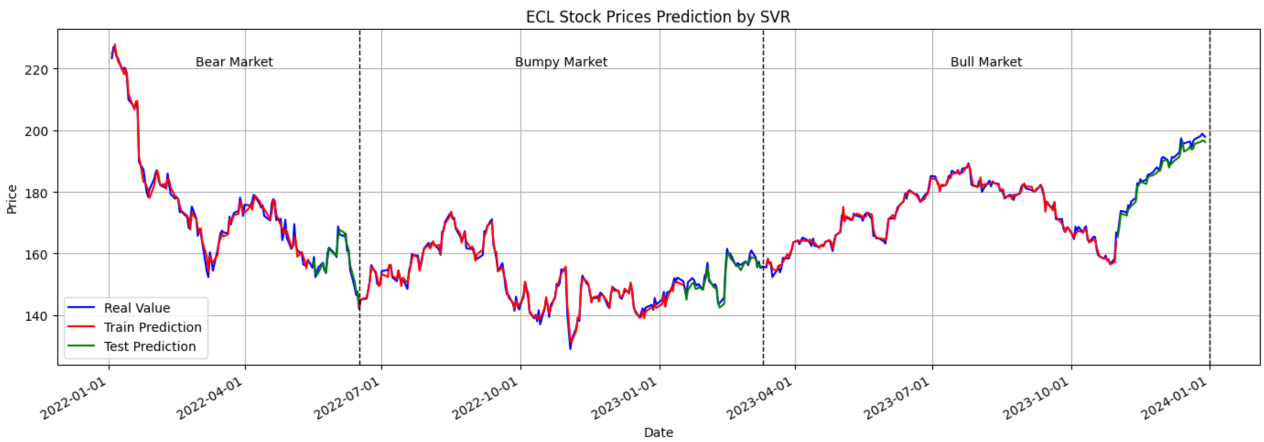

Figure 3: SVR's Stock Price Forecast Chart for Ecolab, Inc.

This study utilises the SVR model to predict stock prices during various market cycles and generates corresponding forecast charts. These charts show the model's predicted performance for each stock during three phases: bear market, oscillator market and bull market. The Figure 3 displays the prediction results of SVR for Ecolab over three time periods, including both the training and test sets.

By synthesizing the forecast charts, the SVR model is able to accurately capture and follow the trend of actual stock prices in most cases. During both bear and bull markets, the model is able to demonstrate responsiveness to changes in market trends despite high market volatility. Irrespective of the data used for training or testing, the SVR model exhibits a high level of accuracy in predicting outcomes and maintains consistent performance across various time periods.

3.4. LSTM

3.4.1. Model Building

To train the LSTM model, a dataset containing a specific time window is first constructed. The time window is defined as a span of five consecutive days. This implies that the model will utilise data from the present day and the preceding four days to forecast the stock price for the subsequent day. The method is implemented through the function create_dataset, which accepts the original feature set with labels, and then outputs a new feature set, where each element contains five days of historical data, and the corresponding price of the next day as a label.

The chosen LSTM model contains two layers with 30 cells each and uses the ReLU activation function. In addition, two fully connected layers and a Dropout layer to prevent overfitting were included. The model is trained for 50 training cycles (epochs) and uses small batch gradient descent with a batch size of 32. The validation process involves reserving a fraction (10%) of the training data to monitor and prevent overfitting. During the training process, the training loss decreases as the number of iterations increases, indicating that the model is gaining knowledge about the characteristics and inherent relationships within the dataset.

3.4.2. Diversity Analysis of the Ledoit-Wolf Covariance Matrix

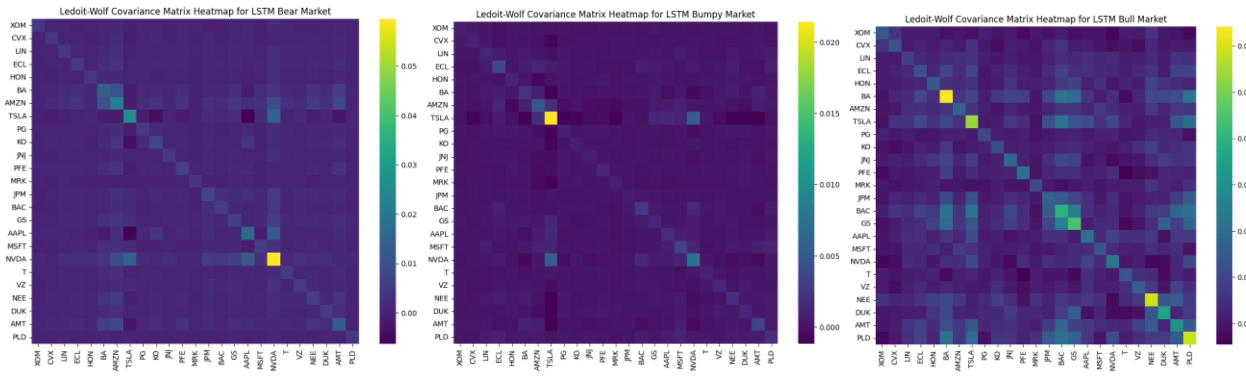

Figure 4: Heat map of Ledoit-Wolf covariance matrix for three periods of LSTM.

Similar to the SVR model, the LSTM model yields generally low covariance values throughout the analysis period (Figure 4), reflecting the low correlation of assets across sectors. This result supports the validity of the stock selection strategy, which is to reduce portfolio risk through diversification. The heat map of the covariance matrix over the periods shows relatively consistent low correlations among stocks, indicating that the selected stock portfolios maintain a robust diversification effect regardless of changes in market conditions. In addition, the covariance distribution pattern in the heat map further validates the stability of the predictive ability of the LSTM model across market environments.

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3.4.3. Overview of projected effects

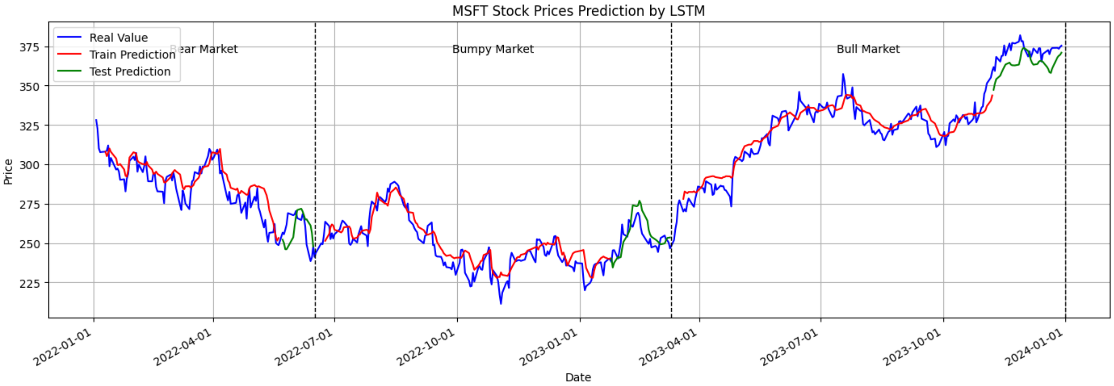

Figure 5: SVR's Stock Price Forecast Chart for Microsoft, Inc.

This study utilises the LSTM model to predict stock prices across various market cycles. This section aims to evaluate the overall predictive effectiveness of the LSTM model by comparing its generated predictions with the actual market prices. The Figure 5 depicts the graphs that demonstrate the forecast outcomes of LSTM for Microsoft across three distinct time intervals, encompassing both the training and test datasets. The LSTM model demonstrates a notable level of competence in monitoring and tracking stock price patterns. The model accurately captured the volatility patterns of stock prices and faithfully reflected the upward and downward trends of the market across different time periods. However, there is a gap in the numerical prediction accuracy compared to the SVR model. This may indicate that the LSTM model needs to be improved in handling absolute values of prices, especially during cycles of more intense market volatility. On the test set, the predictions of the LSTM deviate at some specific points, especially at market turning points or high volatility regions. This may be related to the model's limitations in learning about long-term dependencies.

4. Analysis of Result

When comparing and analyzing the prediction results of SVR and LSTM under different market cycles, we can comprehensively evaluate them in terms of four dimensions: expected return, standard deviation (risk), Sharpe ratio, and maximum drawdown [12].

Table 2: The performance of each model in different periods.

	S&P 500	Real Value	SVR	LSTM
Expected Return	-8.66%, -2.21%, 18.19%	-3.24%, -7.57%, 10.76%	8.74%, 7.51%, 20.77%	13.47%, 5.29%, 18.59%
Standard Deviation	11.03%, 7.64%, 5.11%	5.28%, 4.54%, 3.24%	9.95%, 7.50%, 3.39%	7.19%, 6.53%, 1.72%
Sharpe Ratio	-1.15, -0.81, 2.77	-1.37, -2.55, 2.08	0.48, 0.46, 4.94	1.32, 0.19, 8.48
Maximum Drawdown	-10.57%, -7.61%, -1.47%	-6.36%, -6.35%, -1.14%	-12.56%, -17.39%, -0.41%	-2.87%, -2.17%, -0.01%

In the Table 2, the "Real Value" represent the results fitted with Markowitz's Modern Investment Theory using the real values of the period of the test set, and the three numbers in each table represent the corresponding results for each of the three time periods.

The projected anticipated yields of both SVR and LSTM surpass the actual performance of the S&P 500 in bear and volatile market cycles, indicating that the models may exhibit excessive optimism regarding favourable shifts in market trends. In particular, during the bear market, the actual market showed negative growth, while the forecasts showed positive growth. The standard deviations of the SVR and LSTM forecasts, on the other hand, remain relatively consistent with the S&P 500 and the standard deviations of the true value fits over the three economic cycles. Compared to the actual market, SVR and LSTM show higher Sharpe ratios in all cycles, with LSTM in particular showing unusually high Sharpe ratios during the bull market. This indicates a significant difference in the risk-adjusted returns of the models compared to the actual market, possibly because the models did not accurately evaluate risk.

In terms of maximum drawdown, both SVR and LSTM show lower values than the actual market. SVR's maximum drawdown is particularly significant during bear markets, while LSTM maintains lower maximum drawdown values throughout all cycles, which may indicate that LSTM performs better in controlling market downside risk. Overall, SVR and LSTM perform best in predicting economic cycles in bull markets, with SVR being the best predictor of bull markets. In this study, SVR is relatively accurate in predicting the price trend of each stock in the market, which affirms to some extent the feasibility of SVR in stock price prediction.

However, both SVR and LSTM models fail to numerically match the actual market performance accurately, which is not uncommon when forecasting financial time series, as market prices are not only influenced by historical price data, but also by macroeconomics, market sentiment and external events. Both models tend to be optimistic in assessing positive market movements, while showing conservatism in risk estimation, resulting in high Sharpe ratio calculations. This suggests that the models need to be further adjusted and optimized to improve their ability to capture market volatility and reflect the risk-return relationship more accurately.

5. Conclusion

This study provides valuable insights into the accuracy of SVR and LSTM models in predicting stock price trends during bear markets, bumpy markets, and bull markets. Advanced machine learning and deep learning models can accurately detect and monitor market price trends in all types of market conditions. They exhibit the capacity to forecast future price trends by analysing past data.

However, while trend forecasts for a single stock are important from an investor's perspective, the actual investment decision usually involves constructing a diversified portfolio of stocks. In this regard, by evaluating these forecasting models using modern investment theory, there is a discrepancy between key investment metrics fitted based on the model's forecasting results (e.g., expected return, standard deviation, Sharpe ratio, and maximum drawdown) and metrics fitted based on actual market data. This disparity highlights the limitations of predictive models in modeling real market conditions and actual investor experience.

Therefore, although SVR and LSTM models have shown some effectiveness in predicting market trends, their model accuracy and parameters still need further refinement and adjustment when being used for actual portfolio management and optimization. Future research endeavours should prioritise model optimisation in order to enhance the precision of their predictions and ensure that the predictions more accurately capture the intricate dynamics of markets.

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