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USING LSTM-PREDICTED STOCK PRICES AND RISK-ADJUSTED PERFORMANCE METRICS TO OPTIMIZE PORTFOLIOS IN THE EUROPEAN STOCK MARKET

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ABSTRACT: Long Short-Term Memory (LSTM) neural networks allow to capture long-range dependencies and non-linearities in sequential data and can learn complex patterns and relationships in the data improving the accuracy of future stock price predictions. Since classical portfolio optimization is highly sensitive to the estimated parameters used to construct an optimal portfolio, the purpose of our research is to leverage LSTM abilities to predict the parameters accurately and create portfolios that generate superior results. We predict the prices of the 50 components of the EURO STOXX 50® Index using LSTM and create prediction-based optimal portfolios for ten different investment time horizons. We define the risk as a combination of the standard deviation and the performance of the evaluation metrics obtained testing our model, allowing us to use a measure for the risk based on the level of confidence the model has in the prediction. Our portfolios consistently beat the market over the analyzed investment scenarios from 2021 until the first half of 2022 and are robust for both growing and bear markets. The proposed model achieves an average MAE of 0.01634, an average MSE of 0.00047, and an average accuracy of 95.8% in predicting the direction of the stock movements over the ten proposed periods. Our research contributes to the field of finance by providing an innovative framework for portfolio optimization that leverages the power of LSTM-based stock price prediction and risk-adjusted performance metrics.

KEY WORDS: *Long Short-Term Memory; neural networks; Eurostoxx50; portfolio optimization; risk-adjusted performance metrics.*

1. INTRODUCTION

Anticipating the movements of financial markets is a complex problem that makes it challenging for investors to optimize their portfolios and achieve their investment objectives. Classical portfolio optimization has a significant drawback related to its sensitivity to input parameters. It implies that the weights assigned to the different assets that make up the portfolio will vary depending on the estimation of the returns, variance,

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and covariance (Michaud & Michaud, 2008; Kolm et al., 2014). Consequently, there is a need for advanced techniques that can improve the accuracy and robustness of portfolio optimization methods while mitigating the limitations of classical portfolio optimization methods.

The increasing computing power has facilitated the efficient processing of large amounts of financial data, thereby enabling the use of artificial intelligence algorithms in predicting stock prices and optimizing portfolios.

The purpose of this research is to estimate the returns of the 50 stocks that compose the EURO STOXX 50® Index by using Long Short-Term Memory (LSTM) neural networks to create optimal portfolios based on a blended measure that combines the classical risk-return optimization with evaluation metrics of the model's performance, considering the confidence in the model's predictions during the asset selection process. In other words, we predict the price of the shares and then optimize portfolios based on LSTM-predicted prices. Our portfolios comprise the stocks with a better risk-return-performance, where the estimation errors are considered in the portfolio selection, assessing the problem of estimating the inputs.

This approach has two significant advantages. On the one hand, it allows us to reduce the error in estimating the input parameters of the portfolio optimization problem using advanced techniques such as LSTM neural networks. On the other hand, by including the predictive errors in the objective function to create optimal portfolios, the reliability of the prediction is considered in the selection, reducing the allocation of resources in stocks with less accuracy in the estimation of the parameters.

This paper aims to contribute to the existing literature by exploring the combination of the prediction of the price of the components of the main European market using LSTM and the optimization of prediction-based portfolios using the predictive error covering 2021 and 2022, which implies a period of continued growth but also bear markets.

2. LITERATURE REVIEW

In recent years, the use of machine learning techniques in portfolio optimization has gained significant importance from investment managers and academic researchers in the financial sector.

Portfolios created based on classical mean-variance optimization do not perform well with unknown data. This is caused by the estimation error of the mean and covariance matrix used as inputs, primarily due to the estimation of the sample mean (DeMiguel & Nogales, 2009). Due to the importance of the estimation risk in the creation of optimal portfolios, many authors have considered the incorporation of the estimation errors of the expected returns to create robust portfolios (Ceria & Stubbs, 2006; Gregory et al., 2011; Zymler et al., 2011; Fliege & Werner, 2014).

Machine learning algorithms can provide more accurate predictions than conventional techniques. Several studies have investigated the use of different artificial intelligence techniques, such as support vector machines, genetic algorithms, or neural networks, to predict stock prices (Alizadeh et al., 2011; Huang, 2012; Ticknor, 2013; Patel et al., 2015; Ma et al., 2021). Also, some authors have compared machine learning algorithms with traditional techniques, showing that recurrent neural networks outperform traditional methods, such as ARIMA, AR, or MA, in the prediction of time series (Ruis et al., 1998; Ghiassi et al., 2005; Adebiyi et al., 2014).

In addition, other authors have combined and compared artificial intelligence algorithms with conventional models. For instance, Kim & Won (2018) combined LSTM neural networks with GARCH models. Then they compared the result with GARCH models, which evidenced that the hybrid model performed better regarding the error metrics.

LSTM neural networks have demonstrated the ability to learn patterns and make predictions when using time series or sequential data as inputs, overcoming some of the drawbacks presented by recurrent neural networks (RNN), such as exploding or vanishing gradients or the ability to model long-term dependencies in sequences (Hochreiter & Schmidhuber, 1997; Hochreiter, 1998; Hochreiter et al., 2001). A comparison between LSTM and RRN was published by Lee & Yoo (2020). Their study, conducted on a specific set of 10 stocks from the S&P500, revealed that the LSTM model demonstrated superior performance compared to the RNN model regarding the hit ratio of 1-month ahead forecast.

Du (2022) conducted a study that focused on the S&P500 and CSI 300, where he applied several machine learning algorithms to predict the return of stocks. The LSTM presented the best performance in terms of predictive errors compared to the rest of the algorithms. The author constructs a portfolio that includes estimation errors in the objective function.

3. METHODOLOGY

3.1 Data and data treatment

This study focuses on the 50 stocks that compose the EURO STOXX 50® Index, representing the 50 largest companies in the Eurozone in terms of free-float market cap. Our research uses the data available from Yahoo! Finance. Specifically, we use daily closing prices from 2015 until the first half of 2022, implying 1903 trading days.

Considering that the EURO STOXX 50® Index comprises companies from several countries and not all of them entered the index on the same date, the trading days are not homogeneous, and the stock components present some missing values. These missing values are dropped before training the LSTM. In addition, before starting the training process, we use Min-Max Scaler to transform the values between 0 and 1 and apply a rolling window of 42 days. Therefore, the model is trained considering that the

42 consecutive trading days used as input have the 43rd day as output, representing around two months of trading. We trained the model using several rolling window sizes, but a window of 42 days provided better results than the others.

Table 1 illustrates the rolling window input-output sequence used (Jansen, 2020).

Table 1. Rolling window sequence.

Input	Output
(x1, x2,…,x41, x42)	(x43)
(x2, x3,…,x42, x43)	(x44)
⋮	⋮
(xT-42, xT-41,…,xT-2, xT-1)	(xT)

We split the resulting dataset into training and test data based on the year. The model is trained with closing prices that cover until the end of 2020 and tested with closing prices from 2021 until the 30th of June. This split allows us to test the ability to predict prices unknown by the model.

3.2 Long Short-Term Memory

We use Long Short-Term Memory neural networks since their ability to capture long-range dependencies and non-linearities in sequential data improves the results in the prediction of stock prices.

The LSTM was trained during 500 epochs using early stopping to avoid overfitting, with a batch size of 50 and a learning rate of 0.001, and the hyperparameters were fine-tuned. The resulting architecture of the LSTM is composed of two layers. The first layer contains 40 hidden units; the second layer is a regular dense layer of 1 unit. Despite training with other topologies that are more complex, the results did not improve significantly.

To avoid vanishing gradients, we use tanh as the activation function, sigmoid as the recurrent activation function, and RMSprop as the optimizer (Hinton et al., 2012). Also, the loss function, the function that the model will try to minimize during the training, that we use is Mean Squared Error (MSE) since it is widely used for regression problems (Hastie et al., 2009).

We calculate the returns for ten different investment strategies covering 2021 and the first half of 2022 using the predicted prices. First, we focus on 2021, when the market experienced continuous growth, where we define five different investment strategies based on the time the stock is held, being approximately 1, 3, 6, 9, and 12 months holding the stocks. Second, we cover the first half of 2022, the worst first half of the market in the last 50 years. For this period, we define five strategies of 25, 50, 75, 100, 127 days holding the stocks. We assume that the investor buys the stocks on the first day of the year for both periods, implying a fixed starting point for the different holding periods. Equation (1) presents how the predicted returns ($\hat{r}_t$) are calculated, where $\hat{P}_t$ and $\hat{P}_{t-1}$ are the predicted price at time t and t-1, respectively.

$$\hat{r}_t = \frac{\hat{P}_t - \hat{P}_{t-1}}{\hat{P}_{t-1}} * 100 \tag{1}$$

The metrics considered to evaluate the prediction are the MSE and the Mean Absolute Error (MAE), both shown in equations (2) and (3), respectively, and where r_t is the real return. In addition, the accuracy of the model predicting the direction of the movement of the stock price is calculated following equation (4), where TP, TN, FP, and FN are the true positive, true negative, false positive, and false negative values, respectively.

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (r_t - \hat{r}_t)^2 \tag{2}$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |(r_t - \hat{r}_t)| \tag{3}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

3.3 Risk-Adjusted Performance Metrics Portfolio Optimization

In order to perform the portfolio optimization problem, we need to calculate the portfolio's expected return and the risk, which are based on the prices predicted by the LSTM. The expected return of the portfolio with N stocks is the weighted average of each stock and is presented in equation (5), where $\hat{r}_i$ is the LSTM predicted return of the stock i and W_i is the percentage of available resources allocated to stock i.

$$\hat{r}_p = \sum_{i=1}^{N} \hat{r}_i \times W_i \tag{5}$$

In the calculation of the risk of the portfolio, we propose the blended Error-Risk measure that combines the Mean Squared Error obtained by the model for each stock as a performance metric and the volatility calculated as the classical risk measure in portfolio optimization. The calculation is shown in equation (6), where MSE_i is the Mean Squared Error of the stock i, W_i and W_j are the stocks i and j weights, and γ_{ij} is the covariance. *Metrics_Weight* and *Classical_Risk_Weight* are used to weigh the two components in the equation.

$$\widehat{ER}_p = Metrics\_Weight \times \left(\sum_{i=1}^{N} MSE_i \times W_i \right) + Classical\_Risk\_Weight \times \sqrt{\sum_{i,j=1}^{N} W_i \, W_j \, \gamma_{ij}} \tag{6}$$

In the portfolio optimization model, we aim to maximize the Sharpe Ratio, calculated using the metrics mentioned above, and the risk-free rate r_f, which is 0.0106 due to the value of the 3-month US Treasury bill as of May 2022.

The portfolio optimization model that we proposed is presented below. The objective function (7) is the predicted Sharpe Ratio, with the Error-Risk adjusted performance metric considered as the denominator. The model is subject to several constraints. Equation (8) guarantees that the return is higher or equal to the return of the risk-free investment. Equation (9) guarantees that the sum of all the individual weights allocated to the stocks equals 1, meaning that all the available budget is invested. Equation (10) ensures that individual weights of the stocks are non-negative to avoid the possibility to short-sell assets and represent less than 45% of the portfolio to guarantee that at least three stocks should be selected.

$$\text{Maximize} \quad \widehat{SR} = \frac{\hat{r}_p - r_f}{\widehat{ER}_p} \tag{7}$$

$$\text{Subject to} \quad \sum_{i=0}^{N} \hat{r}_i \times W_i \geq r_f \tag{8}$$

$$\sum_{i=1}^{N} W_i = 1 \tag{9}$$

$$0.45 \geq W_i \geq 0, \qquad i = 1, 2, \dots, N \tag{10}$$

The portfolios are constructed for the ten holding periods considered in the prediction of prices and compared against the EURO STOXX 50® Index, which is used as the benchmark, allowing us to have an objective reference of the performance of the portfolios created and to evaluate if active is worth it compared to passive investment.

4. FINDINGS AND VALUE OF THE PAPER

The results of our research shed light on the effectiveness of the proposed approach in portfolio optimization. We can achieve several milestones using Long Short-Term Memory neural networks to predict stock prices and the posterior incorporation of predictive errors in the objective function.

First, using Long Short-Term Memory neural networks, we can accurately predict the stock price of EURO STOXX 50® Index components. The prediction is tested for the ten investment strategies for 2021 and the first half of 2022. The predictive errors are displayed in Tables 2 and 3. The average MSE and MAE of the considered holding periods are 0.00047 and 0.01634, respectively. The average accuracy is 95.8% in predicting the direction of the stock's movements.

These findings regarding the predicted returns align with the existing literature in the field. We achieve comparable or even superior results compared to other studies (Sadaei et al., 2016; Weng et al., 2018; Wang et al., 2020; Ma et al., 2021; Du, 2022).

Table 2. Predictive performance for the different holding periods – Year 2021.

Performance metric	Holding period (days)				
	20	63	125	191	255
Mean Squared Error	0.000282	0.000315	0.000567	0.000506	0.000607
Mean Average Error	0.014035	0.011952	0.016857	0.017717	0.016256
Accuracy (%)	92	96	94	96	98

Table 3. Predictive performance for the different holding periods – Year 2022.

Performance metric	Holding periods (days)				
	25	50	75	100	127
Mean Squared Error	0.000733	0.000274	0.000296	0.000539	0.000541
Mean Average Error	0.023118	0.013162	0.013619	0.018037	0.018692
Accuracy (%)	90	100	98	94	100

Second, constructed portfolios based on LSTM-predicted data and optimized using the blended Error-Risk measure are tested using real data. We use the weights allocated to the different stocks selected in the portfolio based on predicted returns to calculate the real returns of the portfolio. The results show that our optimized portfolios can obtain positive returns and persistently beat the benchmark. These results are consistent for both analyzed periods, showing that our results are robust and independent of the direction of the market. Despite that the EURO STOXX 50® Index went down by more than 20% in the first half of 2022, our portfolio achieved almost 15% of return. These results are presented in Figure 1, where the analyzed holding periods are compared against the benchmark.

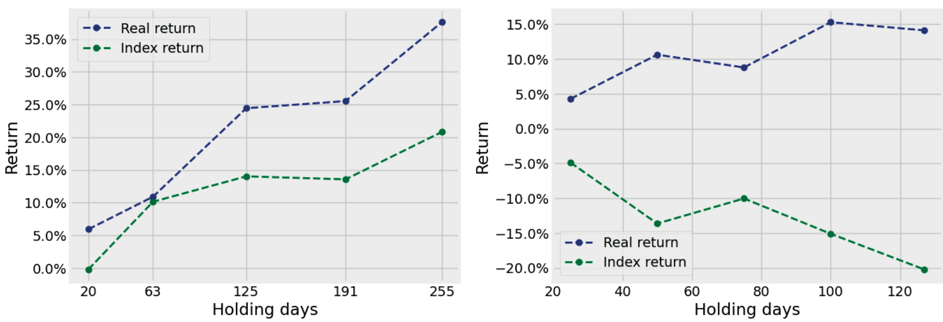

Figure 1. Real return of the portfolio compared to the return of EURO STOXX 50® Index – Year 2021 (left) and 2022 (right).

5. RESEARCH LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Even with the achieved results, this paper has certain limitations. The prediction relies only on historical prices, disregarding news, macroeconomic aspects, or fundamental indicators. Our approach considers a strictly technical perspective, assuming prices comprehensively reflect all relevant information.

For future research, we could consider fundamental or technical indicators to complement the input of the neural network and use transformers to improve the performance of the predictions. Also, other techniques could be used to optimize the portfolios, such as reinforcement learning or quantum-inspired algorithms.

6. PRACTICAL IMPLICATIONS

Since we focus on European public markets, asset and portfolio managers or individual investors could use the current research to support them in making investment decisions or automating their investments. In addition, using algorithms to select assets reduces the subjective factor and avoids decisions driven by irrational emotions.

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CONFLICT OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AUTHOR CONTRIBUTIONS

Martínez-Barbero, X. Conceptualization, Methodology, Software, Writing - Original Draft, Writing - Review & Editing. Cervelló-Royo, R. Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision. Ribal, J. Conceptualization, Writing - Original Draft, Writing - Review & Editing, Supervision.

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