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A portfolio construction framework using LSTM-based stock markets forecasting

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Abstract
A novel framework that injects future return predictions into portfolio constructionstrategies is proposed in this study. First, a long–short-term-memory (LSTM) model is trained to learn the monthly closing prices of the stocks. Then these predictions are used in the calculation of portfolio weights. Five different portfolio construction strategies are introduced including modifications to smart-beta strategies. The suggested methods are compared to a number of baseline methods, using the stocks of BIST30 Turkey index. Our strategies yield a very high mean annualized return (25%) which is almost 50% higher than the baseline approaches. The mean Sharpe ratio of our strategies is 0.57, whereas the compared methods' are 0.29 and −0.32. Comprehensive analysis of the results demonstrates that utilizing predicted returns in portfolio construction enables a significant improvement on the performance of the portfolios.

KEYWORDS
BIST30, LSTM, portfolio construction, stock market prediction, stock markets

1 | INTRODUCTION

Financial market analysis is a challenging task since financial markets are complex and evolutionary environments. After the mathematical foundations of portfolio construction had been set by the seminal work of Markowitz (Markowitz, 1952) in 1952, the rapid progress in technology and artificial intelligence has shifted the conception in this field to a new era. Application of machine learning techniques in financial applications has attracted the attention of researchers especially in the last decade, since it enables many opportunities such as forecasting the future stock movements, making optimal investment decisions, and algorithmic trading.

The main purpose of this study is to propose a portfolio construction framework which uses predicted stock prices in the optimal portfolio calculations. For this purpose, we take all the stocks whose data is available in BIST30 Turkey index, which is a market not studied intensively. We first train a long–short-term-memory (LSTM) network to forecast future returns of each stock. Then we insert these predictions into portfolio calculations in different ways. We propose several strategies; each has alternative return and risk performances to address different investor profiles. The experimental results prove the significant improvement in the overall portfolio performance when future predictions are used instead of heuristic approach of using past data while calculating stock weights. The main contributions of this study can be summarized as follows:

- A general framework for integrating stock price predictions into portfolio construction process is proposed.
- Several investment strategies are suggested including variants of smart-beta strategies.
- The proposed framework is very simple and uses a few features (only raw historical stock data).

- It is one of the few studies that use LSTM-based predictions in constructing portfolios including the stocks in BIST30 index.
- The study is done over a large period of time and the number of stocks used are much more than the studies in the literature.
- There is an extensive performance analysis that encompasses comparison to benchmarks and discussion on the results.

The rest of the paper is organized as follows: Section 2 reviews the related work, data, and methodology are explained in Section 3, then a comprehensive performance analysis is done inSections 4 and 5 concludes the paper with possible future directions.

2 | RELATED WORK

In accordance with our methodology, we review the literature in two sections. For a general review on the recent trends in quantitative finance including stock prediction and portfolio construction methods please refer to Emerson, Kennedy, O'Shea, and O'Brien (2019) and Rather, Sastry, and Agarwal (2017).

2.1 | Stock market forecasting

Stock market prediction is an internal stage of this work. Hence, we give a brief summary ofthe related work in this field. Machine learning methods are widely employed in stock marketdirection, price, or return prediction from the historical data (Chong, Han, & Park, 2017).

As a special type of recurrent neural networks, LSTM networks (Hochreiter & Schmidhuber, 1997) are widely used for handling time-series problems since they have the ability to identify long-term patterns in sequential data (Lee & Yoo, 2018). Due to the LSTM cell structure including input, forget, and output gates, LSTM networks can store important past information while they can forget unnecessary information. The recent trend in stock market prediction is also using LSTM networks. There are various applications of LSTM-based stock market prediction such as daily stock return prediction for Chinese market (Chen, Zhou, & Dai, 2015), daily stock movement prediction on CSI300 index companies (Yao, Luo, & Peng, 2018), stock movement prediction in 15-minutes slots on Bovespa Stock Exchange (Brasil) (Nelson, Pereira, & de Oliveira, 2017), and prediction of the directional movements for the constituent stocks of the S&P 500 index (Fischer & Krauss, 2018).

Selvin, Vinayakumar, Gopalakrishnan, Menon, and Soman (2017) compare three deep learning methods recurrent neural networks (RNN), LSTM, and convolutional neural networks (CNN) using minutely data on national stock exchange (India) and they obtain close performances while CNN is slightly better. Another comparative study is done by Hiransha, Gopalakrishnan, Menon, and Soman (2018) to compare the performance of RNN, LSTM, CNN, and multilayer perceptron (MLP) architectures on predicting the daily prices of the companies listed in NSE and NYSE.

2.2 | Portfolio construction

Portfolio construction is the second and main stage of our study. Therefore, we also review the literature in this field. We will focus more on the studies that utilize deep learning methods in portfolio construction applications. Heaton, Polson, and Witte (2016) propose deep portfolio theory which introduces a framework for constructing portfolios with the objective of outperforming a benchmark strategy by a certain amount, using auto-encoders.

There are also several studies that integrate future return predictions in the portfolio construction process. The general approach in these studies is to predict future returns from past data using a machine learning algorithm, then using a threshold value to determine up or down movement and assigning equal weights to the assets whose direction is predicted as up. In one of these studies, support vector machine (SVM) and artificial neural networks (ANN) are used to predict daily stock returns of the selected stocks in S&P500 index (Huang, 2019). Based on these predictions, a threshold limited equally weighted portfolio (EWP) construction is suggested. Similarly, Lee and Yoo (2018) investigate the effect of different threshold values on the risk of the portfolios constructed based on LSTM predictions. Zhang, Huang, Zhang, and Chen (2018) also use LSTM stock return predictions during the calculation of monthly portfolio weights, with a predetermined threshold value. Obeidat, Shapiro, Lemay, Macpherson, and Bolic (2018) propose a framework for determining the asset weights in a diverse portfolio including different types of assets; by first performing principle components analysis (PCA) dimensionality reduction on the features and predicting the future returns using LSTM network, followed by a mean–variance portfolio optimization.

Although there are studies that integrate future stock predictions into portfolio construction in the literature, this topic is far from saturated. First of all, they are tested on specific indices and stocks such as CSI, S&P500, or NSE and their test periods and data are limited. More importantly, the general approach does not go beyond a threshold limited EWP. Therefore, a more complex strategy with a more comprehensive performance analysis is required.

3 | DATA AND METHODOLOGY

3.1 | Data

In this study, we have used the stocks existing in Turkey BIST30 index by 2019/Q2. We have obtained the data from Yahoo Finance.[1] Eight of the stocks in the index are excluded from the study since their data is incomplete or insufficient. 22 stocks used in this study along with their date intervals are listed in Appendix Table A1. The overall study period is 230 months from May 2000 to July 2019. However, the starting dates differ for several stocks as shown in the table due to the data unavailability. Regardless of the starting date, the last 60 months (August 2014–July 2019) are used as test period for each stock, to keep consistency. We have used monthly historical data of each stock. Five features we have used are monthly *opening*, *high*, *low* and *closing prices*, and *volume*. All the features are rescaled to 0–1 range, using min–max normalization with respect to the data of training period. In addition, during the calculations of Sharpe ratio (SR), we use Turkish two-year bond yield as risk-free rate obtained from investing.com.

3.2 | Methodology

In this study, we calculate the weights of the stocks in the portfolio according to several strategies, using the predicted monthly closing prices of each stock from past data. Figure 1 illustrates the overall process. Input to the system is the monthly historical data (open, high, low, close, and volume) for each stock and the output is a 22-dimensional vector including the weights of each stock in the portfolio. The method consists of two main stages. First of all, a LSTM network model is trained for each stock to predict the monthly closing prices and then using these predictions, expected stock returns and movements are calculated (Section 3.2.1). These future predictions are used for constructing an optimal portfolio based on several strategies (Section 3.2.2). All these steps are explained in detail in the subsequent sections.

3.2.1 | Stock price forecasting

The main purpose of this stage is to predict future returns and directions of each stock based on past data. For this purpose, we construct a LSTM network, using the LSTM cell structure depicted in Appendix Figure A1, for each stock to predict the future closing prices. For background information on LSTM, see Appendix. The network consists of a single LSTM layer with 100 units and a dropout layer with rate of 0.2 to avoid overfitting. The last layer is a fully connected layer. Mean squared error (MSE) is used as loss function and the model is fitted using Adam optimizer. For each stock, the model was trained for 100 epochs and five simulations were run.

During the training of the model, we use a rolling-window approach as in many time-series applications. According to this approach, data is sorted in ascending order with respect to date and divided into train and test sets. While training, a rolling-window of size W is used. In other words, first W months' data is used to learn the closing price of $(W+1)^{\text{th}}$ month. This process is repeated for all records in the training set by shifting the window 1 month ahead. We use $W = 60$ (5 years) as the rolling-window size. Then the test set is used for measuring the prediction accuracy.

The network outputs the predicted monthly closing prices for each stock. Then we calculate the expected monthly returns using Equation (1), where r^t is the expected monthly return for month t, c^t is the predicted closing price for month t, and c^{t-1} is the predicted closing price for month $t-1$.

$$r^t = \left(c^t - c^{t-1}\right)/c^{t-1}. \tag{1}$$

Lastly, stock price movements are also calculated to be used during portfolio construction. Here, we categorize the stock movement direction as *UP*, *DOWN*, or *NEUTRAL*; from the predicted returns using the strategy in Equation (2). Since the predicted data may contain noise, we use a threshold value (th) to improve the accuracy of forecasting. Put differently, if the expected monthly return is between $-th\%$ and $th\%$, stock movement is assumed to be *NEUTRAL*. We take $th = 0.35\%$ in this study, which is the variance of the predicted returns.

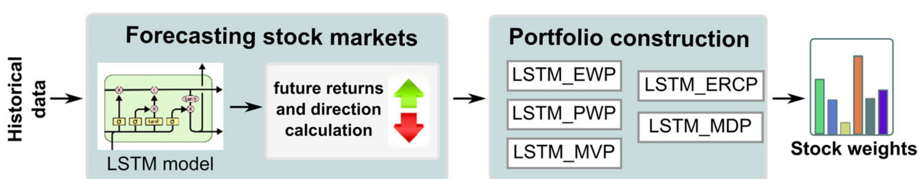

FIGURE 1 Method overview [Colour figure can be viewed at wileyonlinelibrary.com]

$$dir^t = \begin{cases} UP, & \text{if } r^t > th \\ DOWN, & \text{if } r^t < -th. \\ NEUTRAL, & \text{otherwise} \end{cases} \quad (2)$$

3.2.2 | Portfolio construction

In portfolio construction step of our method, we suggest to use predicted stock returns and directions, instead of the conventional approach of using past data. Here, we propose five different strategies, which are abbreviated in Figure 1:

1. *LSTM_EWP* (LSTM predictions-based equally weighted portfolio): Equal weights are assigned to the stocks whose directions are predicted as *UP* by Equation (2), for each month of the test period. Other weights are assumed to be zero. Equation (3) summarizes the strategy, where R_{UP}^t is the set of returns of the stocks whose directions are *UP*, and w_t^i is the weight of the i^{th} stock in the portfolio in month t.

$$count^t = |R_{UP}^t|$$

$$w_t^i = \begin{cases} 0, & \text{if } dir_t^i = NEUTRAL \text{ or } DOWN \\ \dfrac{r_t^i}{count^t}, & \text{otherwise} \end{cases} . \quad (3)$$

2. *LSTM_PWP* (LSTM predictions-based proportional weight portfolio [PWP]): Weights of the stocks are determined in proportion to the predicted returns (Equation (1)), among the stocks whose directions are predicted as *UP* by Equation (2), for each month of the test period. The weights of the stocks whose directions are determined as *NEUTRAL* or *DOWN* are zero again. This strategy is summarized in Equation (4)

$$sum^t = \sum_{r_t^i \in R_{UP}^t} r_t^i$$

$$w_t^i = \begin{cases} 0, & \text{if } dir_t^i = NEUTRAL \text{ or } DOWN \\ \dfrac{r_t^i}{sum^t}, & \text{otherwise} \end{cases} . \quad (4)$$

3. *LSTM_MVP* (LSTM predictions-based minimum variance portfolio [MVP]): The main objective of MVP strategy is to minimize the overall variance and has the form in Equation (5), where Σ is the covariance matrix, w is the weight vector, and lb and ub are lower and upper bounds respectively (Clarke, De Silva, & Thorley, 2011; Hitaj & Zambruno, 2016). However, as distinct from conventional MVP method, instead of using past data during calculations, predicted returns (Equation (1)) of the test period are used in this method.

$$\underset{\boldsymbol{w}}{\text{minimize}} \ \sigma_p^2 = \boldsymbol{w}'\Sigma\boldsymbol{w}$$

$$\text{subject to } \begin{array}{c} \sum w = 1 \\ lb \le w_i \le ub \end{array} . \quad (5)$$

4. *LSTM_ERCP* (LSTM predictions-based equal risk contribution portfolio [ERCP]): According to the classical ERCP strategy, weights are determined in such a way that each asset contributes to the portfolio risk equally (Hitaj & Zambruno, 2016; Maillard, Roncalli, & Teiletche, 2010), using Equation (6). Instead of using past data during ERCP calculation, predicted returns (Equation (1)) of the test period are used in LSTM_ERCP, too.

$$\underset{\boldsymbol{w} \in A_0}{\text{minimize}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(w_i (\Sigma w)_i - w_j (\Sigma w)_j \right)^2$$

$$\text{subject to } \begin{array}{c} \sum w = 1 \\ lb \le w_i \le ub \end{array} . \quad (6)$$

5. *LSTM_MDP* (LSTM predictions-based maximum diversified portfolio [MDP]): The objective of this strategy is to maximize the benefits from diversification and it uses a diversification ratio calculated as in Equation (7) (Choueifaty & Coignard, 2008; Hitaj & Zambruno, 2016). Similar to the previous methods, past data is used in traditional MDP calculations. Instead of using past data, predicted returns (Equation (1)) of the test period are used in LSTM_MDP.

$$\underset{\boldsymbol{w} \in A_0}{\text{maximize}} \ DR = \frac{\sum_{i=1}^{n} w_i \sigma_i}{\sqrt{\boldsymbol{w}'\Sigma\boldsymbol{w}}}$$

$$\text{subject to } \sum w = 1 \atop lb \le w_i \le ub. \quad (7)$$

First two of these strategies are adaptive since they generate different weightings for different months. On the other hand, the last three strategies, which are variants of *risk-based weighting methods* (a.k.a. *smart-beta strategies*), calculate the weights of each stock once and use the same weights for the other months.

Assumptions during portfolio construction:

- Stocks are bought at the first trading day and sold at the last trading day of the month. Short sales are not allowed, so the weights are nonnegative.
- During the calculation of LSTM_MVP, LSTM_ERCP, and LSTM_MDP methods, we set maximum 10% limit for each stock to avoid over-concentration.
- The sum of the weights is always 1.
- Transaction costs are ignored.

4 | RESULTS

4.1 | Stock price forecasting

In this section, we show the results of stock price forecasting step, although forecasting is anintermediate step that is not the main focus of the paper. Table 1 includes average, minimum, maximum, and standard deviation of root-mean-squared (RMS) errors and direction prediction accuracy (DPA) of all stocks. DPA measures how accurate the model is in predicting the direction of the stock, in percentages. It is calculated as the ratio of the number of correctly predicted monthly directions over the total number of predicted months, for each stock. While calculating directions of the stock movements, we assume three classes: up, down, and neutral. In the table, RMS-C denotes the RMS error calculated based on closing prices directly, since our model forecasts closing prices. Although RMS errors on closing prices give an idea about how accurate the predictions are for a given stock; closing prices vary in a quite different range for different stocks. Therefore calculating the RMS error on monthly returns would be more decent to have fair comparison of different stocks. The table also includes RMS errors denoted by RMS-R, which is calculated based on monthly returns, thus changes in the same range across the stocks. Predicted versus true closing prices for each stock are also plotted in Appendix Figure A2, along with their RMS-R, RMS-C, and DPA values. These plots show that our model produces near-accurate results, but it is not able to perfectly predict abrupt changes in real stock market movements.

According to the results, average DPA value is about 50% and DPA values change between 38% (KCHOL) and 70% (ARCLK). These results are on par with the results of the studies for stock movement prediction of BIST30 companies in the literature (Filiz & Öz, 2017; Özçalıcı, 2016). The results also show that our prediction model predicts monthly returns with an average RMS-R value of 0.12; while the best RMS-R value is 0.07 (ARCLK) and the worst RMS-R value is 0.32 (BIMAS). Note that we have used the same network model and parameters for each stock, for convenience. Constructing a different model and performing hyper-parameter tuning per stock would further improve the prediction performance.

The results show that even though average DPA is about 50%, average RMS error is quite low. One can observe that DPA and RMS values are not directly correlated; for example, DPA is the lowest (38%) for the stock KCHOL but its RMS-R value is 0.09 which is close to the best RMS-R value. Similarly, BIMAS has the worst RMS-R value (0.32), although its DPA is medial. We hypothesize that using these predictions while constructing a portfolio will yield a high return. On the grounds that predicted prices are very close to the true values, the loss will not be much in cases of false direction prediction.

4.2 | Portfolio construction

In this section, we compare the performance of our portfolio construction strategies which are already explained in Section 3.2.2 to several methods and BIST30 index funds that are used as benchmark. We consider our proposed strategies as the first category and broadly categorize other benchmark strategies into two groups. The first benchmark category consists of the following market capitalization and risk-based weighting methods:

6. *BIST30*: A common strategy in portfolio construction is to calculate the weights based on market capitalization. Therefore, we compare our method to BIST30 index, which consists of 30 most traded stocks on the Turkish stock exchange, weighted by their market capitalization.
7. *EWP*: This is the simplest strategy in which weights of the 22 stocks used in the study are equal every month.
8. *MVP*: Using the past returns of the stocks, a minimum variance portfolio is constructed using Equation (5). A rolling-window approach with 60 months window size is used.
9. *ERCP*: Using the past returns of the stocks, an ERC portfolio is constructed using Equation (6). A rolling-

TABLE 1 Results of stock price forecasting step

	Average	Minimum	Maximum	Standard deviation
RMS-R	0.12	0.07	0.32	0.06
RMS-C	1.91	0.12	10.38	2.26
DPA (%)	50.15	38.33	70	6.96

Abbreviations: DPA, direction prediction accuracy; RMS-C, root-mean-squared error of closing prices; RMS-R, root-mean-squared error of monthly returns.

window approach with 60 months window size is used.

10. *MDP*: Using the past returns of the stocks, a maximum diversified portfolio is constructed using Equation (7). A rolling-window approach with 60 months window size is used.

Note that in accordance with the constituents of BIST30, we use upper weight limit as 10% both in our LSTM_MVP, LSTM_ERCP, and LSTM_MDP methods and their counterparts MVP, ERCP, and MDP methods.

Other than these strategies, there are also several common BIST30 index funds as listed below. These data are gathered from Tefas.[2] Through Tefas, only the last 5 years' data is available, which is the reason for us to set the test period as the 60 months from August 2014 to July 2019.

11. *ZIRAAT*: ZIRAAT PORTFOLIO BIST30 INDEX FUND.
12. *GARANTI*: GARANTI PORTFOLIO BIST30 INDEX FUND.
13. *YKB*: YAPI KREDI PORTFOLIO BIST30 INDEX FUND.
14. *IS*: IS PORTFOLIO BIST 30 INDEX FUND.
15. *AK*: AK PORTFOLIO BIST 30 INDEX FUND.

The most common method to measure the performance of a portfolio is SR (Sharpe, 1994). It is defined by Equation (8), where R_f is the risk-free rate, and R_p and σ_p are return and risk of portfolio p, respectively. It basically corresponds to the return in excess of the risk-free rate per unit of risk

$$\mathrm{SR} = \frac{R_\mathrm{p} - R_\mathrm{f}}{\sigma_\mathrm{p}}. \tag{8}$$

Table 2 lists annualized return, annualized risk, SR, maximum drawdown (MDD), and conditional value at risk (CVaR) values for each method. The best values for each column and category average are marked with bold font in the table. From the table, it is seen that our methods, risk-based strategies and EWP have positive SR; while BIST30 index and other index funds all have negative SR since their returns remain under risk-free rate (annualized risk-free return is 12.67%).

When we sort the methods according to their SRs, we see that LSTM_MDP method is the best performing method and MDP follows it. This shows that MDP-based strategies outperform the other strategies in their own categories. Another result observed from the table is that LSTM-based methods outperform their conventional counterparts (i.e., LSTM_EWP is better than EWP, and so on). The highest annualized return is obtained by LSTM_PWP strategy and the lowest annualized risk is given by MVP. Although the SR of LSTM_EWP method is slightly higher than LSTM_PWP method's, annualized return of LSTM_PWP method is much greater. Hence, risk-seeking investors may prefer LSTM_PWP over LSTM_EWP. Furthermore, in their own categories, MVP-based methods are the least risky methods, in accordance with the main objective of MVPs.

MDD measures the greatest fall from a peak to a low point, before another peak occurs. In other words, it shows the greatest loss. From the table, we see that LSTM_MDP strategy produces the lowest MDD value. Yet the average MDD value for Category 1 is higher than that of Category 2. This is reasonable because Category 1 includes more risky strategies. Note that although MDD measures the value of the greatest loss, it does not consider the frequency of losses. Hence it is not a general performance measure for portfolios.

CVaR, also known as expected shortfall, gives the expected loss on the portfolio in the worst q% of the cases. In this study, we take $q = 5$. Similar to the MDD results, CVaR is also minimum in LSTM_MDP method. This indicates that expected shortfall in 5% level is minimal in LSTM_MDP method. However, the overall performance of Category 1 is low in terms of CVaR, because of the risky methods LSTM_PWP and LSTM_EWP.

Among Category 1 methods, adaptive methods (LSTM_PWP and LSTM_EWP) produce very high returns but also they increase the risk. This is also indicated by MDD and CVaR values. The overall performance of the variants of risk-based methods (LSTM_MVP, LSTM_ERCP, and LSTM_MDP) can be considered as the best among all the methods. Nevertheless, for risk-seeking investors, our proposed adaptive methods are

TABLE 2 Results of each portfolio construction strategy

	Strategy	Return (%)	Risk (%)	SR	MDD (%)	CVaR (%)
Category 1	LSTM_PWP	**30.74**	35.28	0.5123	34.53	18.28
	LSTM_EWP	26.54	24.21	0.5732	22.08	10.37
	LSTM_MVP	21.18	17.88	0.4759	12.69	7.45
	LSTM_ERCP	22.16	18.38	0.5166	12.56	7.79
	LSTM_MDP	26.48	19.04	**0.7254**	**11.22**	**6.12**
	Average	**25.42**	19.88	**0.5728**	18.62	10.00
Category 2	BIST30	4.83	19.96	−0.3926	23.25	9.51
	EWP	18.31	18.08	0.3124	16.31	8.44
	MVP	19.56	**15.96**	0.4323	13.27	6.79
	ERCP	19.95	16.28	0.4473	11.72	6.83
	MDP	23.35	16.86	0.6337	16.61	7.01
	Average	17.20	**17.43**	0.2866	**16.23**	**7.72**
Category 3	ZIRAAT	7.16	18.82	−0.2926	20.34	8.42
	GARANTI	6.24	18.81	−0.3414	18.98	8.64
	YKB	6.90	18.54	−0.3110	21.02	8.56
	IS	6.24	19.01	−0.3380	20.51	8.76
	AK	7.19	18.46	−0.2967	18.19	8.44
	Average	6.75	18.73	−0.3160	19.81	8.56

Abbreviations: CVaR, conditional value at risk; MDD, maximum drawdown; SR, Sharpe ratio.
Bold values indicate the best values for the columns. The best values for the average rows of each column are also shown in bold.

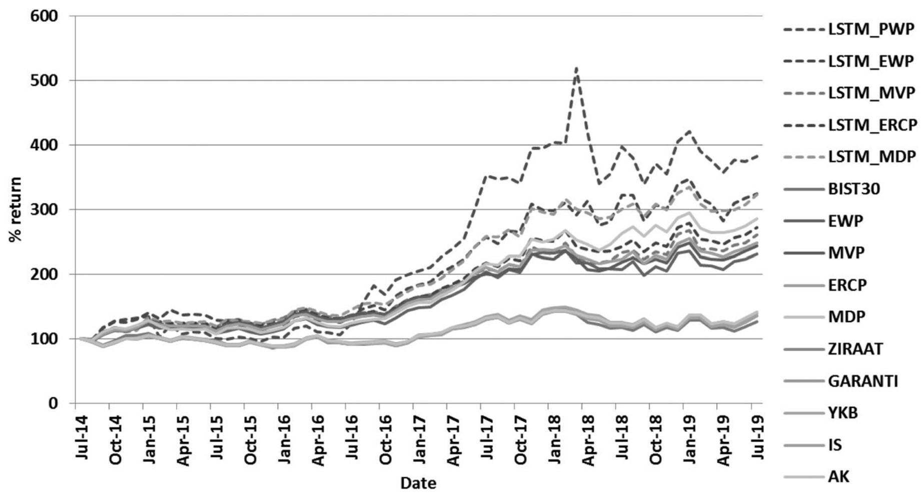

FIGURE 2 Percentage return comparison of each method over the test period [Colour figure can be viewed at wileyonlinelibrary.com]

good alternatives since their return is high at the expense of higher risk.

Last and most prominent observation is that injecting future predictions into portfolio construction strategies improves the performance of the portfolios. Figure 2 demonstrates the growth of portfolios for each strategy during the test period. In the figure, base values are set to the same value (100%) for each strategy and the cumulative returns are plotted through the test months. Our proposed strategies (Category 1) are displayed with dashed lines in the graph. LSTM_PWP strategy yields the highest return at the end of the test period, but its volatility is also high. LSTM_EWP and LSTM_MDP strategies also produce high profits with lower risk. The plot verifies the superior performance of Category 1 strategies in terms of return, compared to the reference strategies in general. According to the plot, the returns of the best performing strategies for each category (LSTM_PWP in Category 1, MDP in Category 2, AK in Category 3) are 282%, 186%, and 42% respectively, at the end of the test period.

5 | CONCLUSIONS

In this paper, we propose a framework that replaces the traditional approach of using historical data during portfolio construction with using predicted values of the stocks. According to this approach, we first predict the future stock prices using a LSTM model from the historical stock data. Then we propose several portfolio construction strategies including modified smart-beta strategies.

We have performed an extensive performance analysis on the results by comparing our methods to the baseline methods including common index funds. We have tested our strategies on the stocks of BIST30 index and constructed monthly portfolios. We have obtained about 25% average annualized return with 0.57 mean SR using our strategies; where the two opponents' mean annualized returns are 17% and 7% and mean SRs are 0.29 and −0.32, respectively. Although the annualized risk is slightly higher than the compared methods, the return is significantly greater than those to the extent that this risk is worth taking. We have also performed MDD and expected shortfall analysis on the portfolios and discuss the advantages and drawbacks of the methods. The results clearly indicate that incorporating future return predictions into portfolio construction strategies ameliorates the performance of the portfolios.

The future research directions may be two-folds: improving the stock market forecasting accuracy and developing more sophisticated portfolio construction algorithms. Forecasting accuracy may be improved by considering additional features such as macroeconomic data and financial news. Moreover, LSTM architecture and model parameters should be fine-tuned. Also, a comparative study should be performed to identify the best forecasting method in portfolio construction. Other than improving the forecasting step, more advanced and probabilistic portfolio construction methods based on predicted returns should be developed. Lastly, a similar approach can be applied on other markets and for different asset types.

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DATA AVAILABILITY STATEMENT

Data available on request from the authors

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ENDNOTES

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APPENDIX

See Table A1.

Long–short-term-memory (LSTM) networks

Figure A1 illustrates a simple LSTM cell. In the figure, red circles represent the pointwise vector operations, green matrices are the learned network layer, x is the input vector, c is the carry state, and h is the output vector. The equations for the memory block in the figure are given in Equation (A1); where f_t, i_t, o_t, c_t, and h_t are forget gate, input gate, output gate, memory cell state, and output vector respectively. For detailed information about LSTM, one can refer to Goodfellow, Bengio, and Courville (2016)

Stock	Study period	Stock	Study period
AKBNK	May 2000–July 2019	KOZAA	Mar 2003–July 2019
ARCLK	May 2000–July 2019	PETKM	May 2000–July 2019
ASELS	May 2000–July 2019	SAHOL	May 2000–July 2019
BIMAS	July 2005–July 2019	SISE	May 2000–July 2019
DOHOL	May 2000–July 2019	SODA	May 2001–July 2019
EREGL	May 2000–July 2019	TCELL	July 2000–July 2019
FROTO	May 2000–July 2019	THYAO	May 2000–July 2019
GARAN	May 2000–July 2019	TOASO	May 2000–July 2019
ISCTR	May 2000–July 2019	TUPRS	May 2000–July 2019
KARDMD	May 2000–July 2019	VAKBN	Nov 2005–July 2019
KCHOL	May 2000–July 2019	YKBNK	May 2000–July 2019

TABLE A1 Ticker symbols and study periods of the stocks used in this study

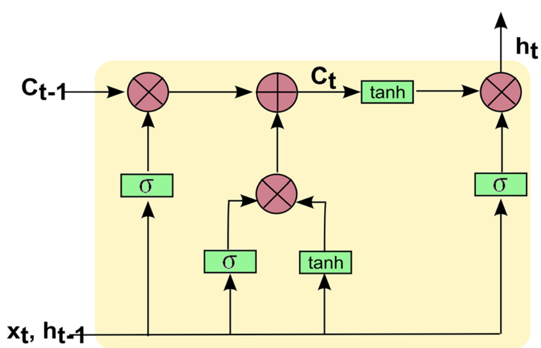

FIGURE A1 A simple LSTM cell structure. *Source:* Adapted from Lee and Yoo (2018) [Colour figure can be viewed at wileyonlinelibrary.com]

$$
\begin{aligned}
f_t &= \sigma(W_f h_{t-1} + W_f x_t + b_f)\\
i_t &= \sigma(W_i h_{t-1} + W_i x_t + b_i)\\
c_t &= \tanh(W_c h_{t-1} + W_c x_t + b_c).\\
o_t &= \sigma(W_o h_{t-1} + W_o x_t + b_o)\\
h_t &= o_t * \tanh(c_t)
\end{aligned}
\tag{A1}
$$

See Figure A2.

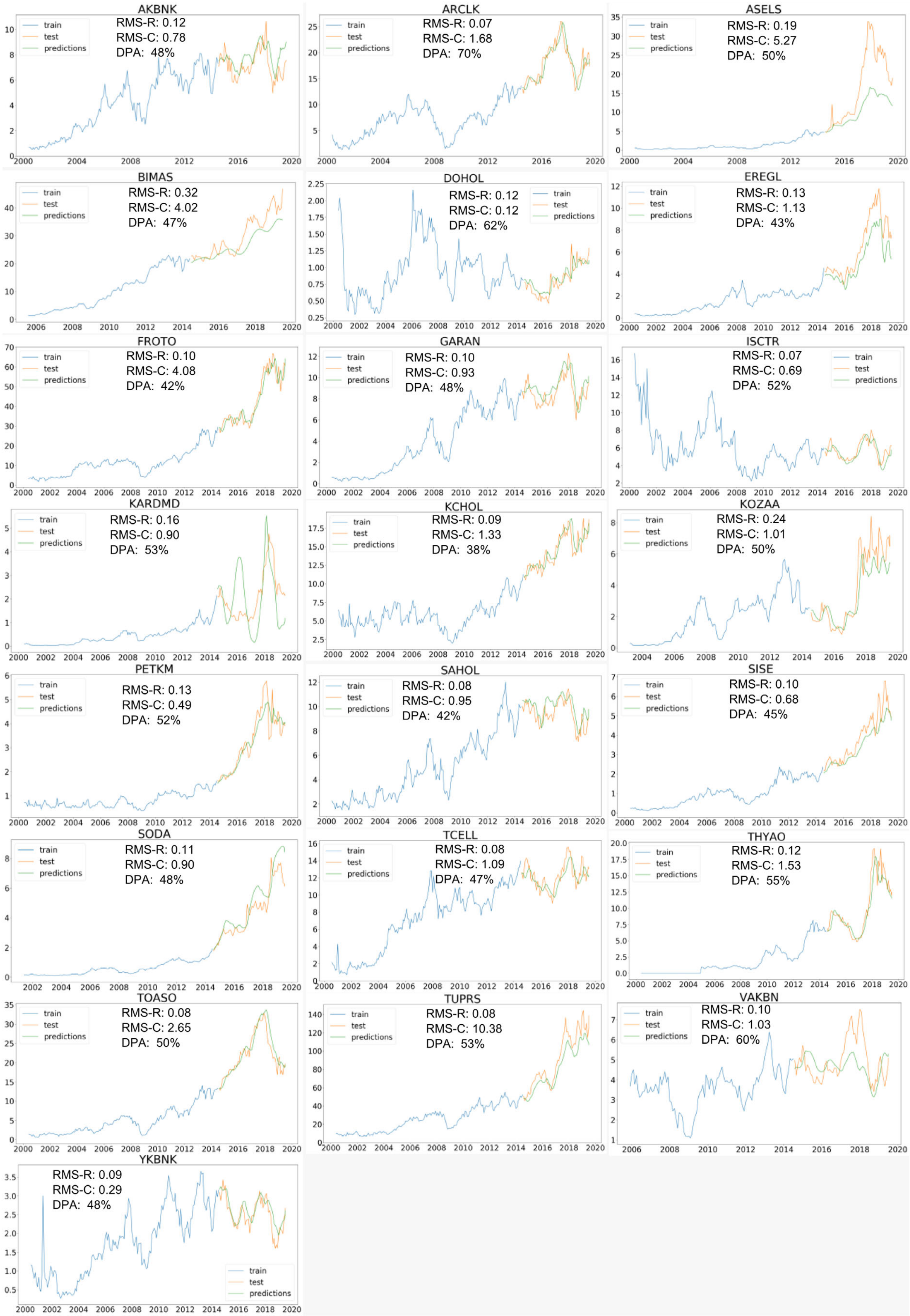

FIGURE A2 Predicted versus true closing price plots for each stock. RMS (root-mean-squared) errors and direction prediction accuracy (DPA) values are also given [Colour figure can be viewed at wileyonlinelibrary.com]