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Forecasting Stock Prices via Deep Learning During COVID-19: A Case Study from an Emerging Economy

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Abstract:

In this study we apply a Deep Learning Technique to predict stock prices for the 30 stocks that compose the BIST30, Turkish Stock Market Index before and after the onset of Covid-19 crises. Specifically, we utilize the Bi-Directional Long-Short Term Memory (BiLSTM) model which is a variation of the Long-Short-Term Memory (LSTM) model to predict stock prices for the BIST30 stocks. We compare the performance of the model to other commonly used machine learning models like decision tree, bagging, random forest, adaptive boosting (Adaboost), gradient boosting, and eXtreme gradient boosting (XGBoost), artificial neural networks (ANN), and other deep Leaning models like recurrent neural network (RNN), and the Long-Short-Term Memory (LSTM) model. The BiLSTM model seems to have better performance compared to conventional models used for predicting stock prices and continues to have superior performance in the Covid19 period. The LSTM model seems to have a good overall performance and is the next best model.

Keywords: *Deep Learning, Machine Learning, Long-Short Term Memory, Bi-Directional Long-Short Memory, Recurrent Neural Networks, Gradient Boosting, Extreme Gradient Boosting, Stock Price Prediction, Financial Markets.*

Introduction

Based on random walk theory asset prices follow a random walk, hence stock prices are not forecastable. Despite this, stock price predictability is an important area in applied finance. After the onset of Covid-19 many stock markets experienced turmoil. The S&P 500 index fell by more than 34% between its peak in February 2020 and its low point in March 2020, the Dow Jones Industrial Average index decreased by 29% from the beginning of February 2020 to early March 2020 (International Monetary Fund, 2020). The emerging markets were hit more drastically during the Covid-19 crises as foreign investment leaves these markets quicker compared to the advanced economies. Singh (2020) notes that, although stock markets in emerging markets are popular, they are subject to significant capital outflow during uncertain times and financial crises. During the crises, some emerging markets were affected more than the others. Topcu and Gulal (2020), found that the impact of Covid-19 was more pronounced on the Asian emerging markets compared to emerging markets in Europe. Stock market of Turkey was one of the highly affected ones and plummeted during the pandemic. Aside from the diverse impact on different markets, there was also a significant variation in how different sectors were impacted; Shen et al. (2020) found that the tourism, catering, and transportation industries were hit the worst compared to other industries. He et al. (2020), found that COVID-19 affected transportation, mining, electricity and heating, and environment industries more adversely compared to manufacturing, information technology, education, and health-care industries in China. This emphasizes the importance of stock price prediction further for investment strategies, diversification and for better picking the winning and losing sectors.

During the pandemic, predicting stock price movements became more important but also more difficult due to increased uncertainty. Recently, aside from conventional models used to predict stock market dynamics, deep learning algorithms have been applied to financial data and started to be widely used in stock price prediction. They are especially found to perform better in the presence of nonlinearities which seem to be inherent in stock prices.

In this study, we utilize deep learning methods that seem to outperform conventional time series methods, to forecast stock prices for the 30 stocks that compose the BIST30 index. Specifically, we utilize the Bi-Directional Long-Short Term Memory (BiLSTM) model which is a variation of the Long-Short-Term Memory (LSTM) model to predict stock prices for the BIST30 stocks and compare its predictive performance to the rest of the models. Although there are a few studies that concentrate on the stock price prediction for some of the stocks that compose the BIST30 index utilizing deep learning methods, see for example Kalyoncu at. al. (2020) who utilize LSTM model to predict price of five stocks traded in BIST30 and Raso and Demirci (2019) who utilize a deep learning model fed with technical indicators and oscillators calculated from historical index price data, this is the first study that applies the BiSTLM model. Our study is also distinct as it is the only study that applies deep learning techniques to all the stocks that compose the BIST-30 index. Moreover, this is the only study that covers the Covid-19 period for the BIST30 index that utilizes deep learning techniques. Comparing the predictive ability of BiSTLM model to the rest of the models is important because it is found to have better predictive ability applied to other stock market data. Analyzing the predictive performance of this model and comparing it with the rest of machine learning and deep learning methods for the Turkish stock market index BIST 30 is important to see if the results found for some other markets would carry over to the Turkish stock market which is known to have some different dynamics compared to the other markets. Moreover, Turkish stock market experienced great turmoil during the Covid-19 period and investigating the predictive performance of BiLSTM model is important during and after the Covid-19 period to study if it conserves its robustness during high volatile periods.

The most popular deep learning model used in time-series forecasting in finance is the recurrent neural network (RNN) model [See Sezer et al., 2020 among others] due to its ability to process data for longer periods of time. However, as the time period increases and data becomes larger it becomes harder to learn with RNN as information is stored over longer periods. A class of RNN that does not have this drawback is the Long-Short-term Memory (LSTM hereafter). LSTM can process a longer period of data than RNN (Wang et al., 2020) and can handle both short and long-term data and is able to handle the problem that exists in the RNN model such as the vanishing-gradient (Gao and Chai, 2018). Simple model development phase inherent in LSTM makes it the most popular model among the RNN models variations and allows for a higher performance compared to other deep learning models or RNN models (Vo et al., 2019), (Sambas et al., 2020).

The Bidirectional LSTM (BiLSTM hereafter) model is a variation of the LSTM model and is found to fit better for prediction problems because it has a bidirectional flow instead of unidirectional flow. BiLSTM combines forward and backward LSTM, hence can process previous and future data at the same time (Vo et al., 2019). BiLSTM model has been applied in time series forecasting and is found to outperform other time series forecasting models (Ivasaki and Chen, 2018), (Khaled et al., 2018). Different from the univariate LSTM model which only preserves information from the past, the BiLSTM model can preserve information from the past and the future (Vo et al., 2019).

We apply BiLSTM model to forecast the closing prices of the stocks that compose the BIST 30 Index. For brevity we group stocks based on sectors as financial, metallic, transportation, communication and nutrition related. We also consider other commonly used models in machine learning like decision tree, bagging, random forest, adaptive boosting (Adaboost), gradient boosting, and eXtreme gradient boosting (XGBoost), artificial neural networks (ANN). We use MAPA and SMAPE as the evaluation criteria. Although BiLSTM seems to perform better overall compared to other models, its performance is specifically more pronounced after the onset of Covid-19 for the stocks considered. We conclude that a deep learning algorithm – BiLSTM model would be the best model to use to predict closing stock prices for the stocks of the BIST30 Index.

Methodology

Data used in this study is obtained from Borsa Istanbul. The data runs from 2000 to 2022 and has a daily frequency. The Borsa Istanbul 30 Index, also referred to as BIST30 is a capitalization-weighted index of top 30 companies listed in the Istanbul Stock Exchange with the highest market value. The list of the stocks in the BIST30 index are presented in Table 1.

Table 1. List of Stocks in the BIST 30

1	AKBNK	22	KOZAL
2	ARCLK	23	KRDMD
3	ASELS	24	PETKM
4	BIMAS	25	PGSUS
5	BRMEN	26	QNBFB
6	DENGE	27	QNBFL
7	EKGYO	28	SAHOL
8	EREGL	29	SASA
9	FROTO	30	SISET
10	GARAN	31	SNKRN
11	GUBRF	32	TAVHL
12	HALKB	33	TBORG
13	HEKTS	34	TCELL
14	ISBI	35	THYAO
15	ISCTR	36	TKFEN
16	ISYAT	37	TOASO
17	IZINVI	38	TTKOM
18	KCHOL	39	TUPRS
19	KENT	40	UTPYA
20	KLNMA	41	VESTL
21	KOZAA	42	YKBNK

We employ different machine learning and Deep Learning Algorithms to predict the closing stock prices of the stocks that compose the BIST30 index. Among the models we consider are tree-based models like; bagging, boosting, gradient boosting, XGBoost, Neural Network models like; ANN and Deep Learning Methods like RNN, LSTM and BiLSTM. For brevity, we refer the reader to literature on Machine Learning and Deep Learning for the details, features and drawbacks of each model and describe the data process below.

Following conventional practice in this area, we split the data into training and test samples in the ratio of 80:20. BILSTM model consists of 50 neurons with two BILSTM neurons. We used adam optimizer with mean squared error loss optimizer.

Evaluation Criteria

The evaluation criteria used for the stock prediction are Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE). The MAPE and SMAPE values are the average values for the stocks that are considered for that sector.

Results and Discussion

Table 2 presents the average results for the stocks related to the financial sector for immediate one-day ahead price forecasts: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next. Deep learning models (aside from RNN) seem to perform better than the other methods, BiLSTM seems to be the best model.

Table 2. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Financial Sector

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	2.29	2.29
Random Forest	2.88	2.86
Adaboost	2.84	2.82
Gradient Boosting	2.50	2.52
XGBoos	2.56	2.57
ANN	4.02	4.09
RNN	1.89	1.91
LSTM	1.26	1.27
BILSTM	1.02	1.12

Table 3 presents the average results for the stocks related to communication sector for immediate one-day a-head price forecasts: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next. BiLSTM seems to be the best model for this group of stocks as well.

Table 3. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Communication Sector

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	1.99	1.99
Random Forest	1.88	1.87
Adaboost	1.84	1.84
Gradient Boosting	1.50	1.52
XGBoos	1.56	1.57
ANN	3.02	3.02
RNN	1.49	1.5
LSTM	1.10	1.11
BILSTM	0.98	0.987

Table 4 presents the average results for the stocks related to transportation for immediate one-day a-head forecasts: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next. BiLSTM seems to be the best model for this group of stocks as well.

Table 4. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Transportation Sector

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	2.99	2.89
Random Forest	2.88	2.86
Adaboost	2.84	1.83
Gradient Boosting	2.50	1.51
XGBoos	1.56	1.57
ANN	3.98	3.99
RNN	2.00	2.01
LSTM	1.87	1.88
BILSTM	1.12	1.13

Table 5 presents the average results for the stocks related to petroleum for immediate one-day a-head: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next.

When we consider all the groups, and all the models BiLSTM model seems to outperform all other models uniformly followed by the LSTM model.

Table 5. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Petroleum Sector

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	2.79	2.799
Random Forest	2.68	2.69
Adaboost	2.54	2.556
Gradient Boosting	2.40	2.402
XGBoos	1.36	1.37
ANN	4.98	4.99
RNN	1.94	1.95
LSTM	1.67	1.68
BILSTM	1.04	1.045

Table 6 presents the average results for the stocks related to financial sector for immediate one-day a-head after the onset of Covid19: Both MAPE and SMAPE criteria are still the lowest for the BiLSTM and LSTM next.

Table 6. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Financial Sector After the Onset of Covid-19

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	3.25	3.29
Random Forest	2.91	2.93
Adaboost	2.96	2.97
Gradient Boosting	3.00	3.01
XGBoos	3.25	3.27
ANN	5.02	5.07
RNN	2.87	2.89
LSTM	1.97	1.98
BILSTM	1.90	1.91

Table 7 presents the average results for the stocks related to communication sector for immediate one-day a-head the onset of Covid-19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next.

Table 7. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Communication Sector After the Onset of Covid-19

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	2.99	2.998
Random Forest	2.87	2.88
Adaboost	2.95	2.97
Gradient Boosting	3.50	3.51
XGBoos	3.56	3.57
ANN	5.20	5.21
RNN	2.79	2.8
LSTM	1.98	1.99
BILSTM	1.96	1.97

Table 8 presents the average results for the stocks related to transportation for immediate one-day a-head the onset of Covid19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next. BiLSTM seems to be the best model for this group of stocks as well.

Table 8. Average MAPE, SMAPE Values from One-Day-Ahead Stock Price Prediction for Stocks Related to Transportation Sector After the Onset of Covid-19

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	3.06	3.07
Random Forest	3.01	3.03
Adaboost	2.96	2.97
Gradient Boosting	2.94	2.95
XGBoos	2.56	2.56
ANN	4.93	4.94
RNN	2.83	2.84
LSTM	2.17	2.18
BILSTM	2.06	2.08

Table 9 presents the average results for the stocks related to petroleum for immediate one-day a-head the onset of Covid19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM and LSTM next. BiLSTM seems to be the best model for this group of stocks as well.

Table 9. Average MAPE, SMAPE values from one-day-ahead stock price prediction for stocks related to petroleum sector after the onset of Covid-19.

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	2.79	2.799
Random Forest	2.68	2.69
Adaboost	2.54	2.556
Gradient Boosting	2.40	2.402
XGBoos	1.36	1.37
ANN	4.98	4.99
RNN	1.94	1.95
LSTM	1.67	1.68
BILSTM	1.04	1.05

Table 10. Results for Stocks Related to Transportation Sector for Immediate One-Day A-Head After the Onset of Covid-19

Model	Evaluation Criteria	
Decision Tree	MAPE	SMAPE
Bagging	3.95	3.96
Random Forest	3.87	3.88
Adaboost	2.98	2.99
Gradient Boosting	2.85	2.87

XGBoos	2.75	2.76
ANN	4.85	4.87
RNN	2.98	2.98
LSTM	2.19	2.20
BILSTM	2.17	2.18

When we consider all the stock groups, and all the models BiLSTM model still seems to outperform all other models followed by the LSTM model in the Covid-19 era as well. When we compare the MAPE values pre and post Covid period although we see a drop in the overall performance of all the models both the BiLSTM and LSTM models continue to outperform the other models having more distinction in the MAPE values compared to the pre -Covid period.

Conclusion

In this study we employ Deep Learning algorithms like BiLSTM, LSTM to predict stock prices for the 30 stocks that compose the Borsa Istanbul30; BIST30-Turkish Stock Market Index, before and after the onset of Covid-19 crises. We compare the performance of the models to other commonly used machine learning models like decision tree-based models, Neural Network Based Models. The BiLSTM model seems to have better performance compared to conventional models used for predicting stock prices and continues to have superior power during the Covid-19 period. The LSTM model seems to have a good overall performance and is found to be the next best model.

Based on our findings we highly recommend utilizing the Deep Learning algorithms like BiLSTM type models for stock price prediction for the stocks in the BIST 30 index. Our findings have implications interms of stock price prediction, investment strategies and diversifications in emerging markets, Turkey BIST30 index being a special case.

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