Journal of Applied Mathematics and Computation, 2024, 8(4), 280-285
https://www.hillpublisher.com/journals/JAMC/
ISSN Online: 2576-0653
ISSN Print: 2576-0645

Forecasting Stock Volatility via Hybrid Deep Learning and GARCH Family Models: A Case Study from BIST30

Yasemin Ulu

Department of Economics, Eastern Michigan University, Ypsilanti, MI 48197, USA.

How to cite this paper: Yasemin Ulu. (2024) Forecasting Stock Volatility via Hybrid Deep Learning and GARCH Family Models: A Case Study from BIST30. *Journal of Applied Mathematics and Computation*, 8(4), 280-285.
DOI: 10.26855/jamc.2024.12.001

Received: November 16, 2024
Accepted: December 13, 2024
Published: January 10, 2025

***Corresponding author:** Yasemin Ulu, Department of Economics, Eastern Michigan University, Ypsilanti, MI 48197, USA.

Abstract

In this study, we construct hybrid models that are based on the combination of different Deep Learning models like the Long-Short-Term Memory Model (LSTM), Bi-Directional Long-Short Term Memory Model (BiLSTM), and the conventional GARCH model. The aim is to forecast the volatility of stocks traded in the financial, transportation, communication, and petroleum sectors, in the BIST30, Turkish Stock Market Index. Specifically, we construct (BiLSTM) and Long-(LSTM) models that utilize forecasts from conventional GARCH models to forecast one day a headstock volatility of the stocks for the sectors considered. We use Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE) as forecast evaluation criteria. The period we consider covers the COVID-19 crisis, allowing for further comparison. Although the forecasting performance of the models uniformly seems to be lower for the COVID-19 period judged by forecast evaluation criteria, we find that hybrid models that utilize deep learning and GARCH forecasts perform better in forecasting the volatility of the stocks considered. We highly recommend utilizing the hybrid Deep Learning BiLSTM-GARCH model to forecast the volatility of the stocks in the corresponding sectors considered.

Keywords

Deep Learning; Machine Learning; Long-Short Term Memory; Bi-directional Long-Short Term Memory; Hybrid Models; GARCH Models; Stock Volatility Prediction; Financial Markets

1. Introduction

Stock volatility forecasting is an important area in finance. Deep learning algorithms have been recently applied to financial data and are one of the widely applied areas in stock price and volatility prediction. They especially seem to perform better in the presence of nonlinearities which seem to be inherent in stock prices. The most popular deep learning model used in the finance sector is the recurrent neural network (RNN) model (See [1] among others). Due to its ability to process data for longer periods, RNN is widely used in time-series forecasting. However, as the time period increases and data becomes larger it becomes harder to learn with RNN as information is stored over longer periods. Long-Short-Term Memory (LSTM hereafter) model, is a class of RNN, that does not have this drawback. LSTM can process a longer period of data than RNN [2] 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 [3]. The simple model development phase inherent in LSTM makes it the most popular model among the RNN models variations and has a higher performance compared to other deep learning models or RNN models [4, 5].

The Bidirectional LSTM (BiLSTM hereafter) model is a variation of the LSTM model and is found to fit better for prediction problems having a bidirectional flow instead of unidirectional flow. BiLSTM combines forward and backward LSTM, hence can process previous and future data at the same time [4]. LSTM model has been used previously in research to handle time series forecasting and is found to outperform other time series forecasting models. 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 [4]. BiLSTM takes in three-dimensional input with format (T - Δt - δt, δt, N) where T denotes time, Δt denotes the time gap, δt denotes the size of the sliding window, and N as the number of stocks.

We apply LSTM, BiLSTM, and some hybrid models of LSTM, BiLSTM, and GARCH models to forecast the average volatility of stocks in the financial, transportation, communication, and petroleum sectors that compose the BIST 30 Index. We use MAPA and SMAPE as the evaluation criteria. The hybrid BiLSTM model that utilized forecasts from GARCH models as the input seems to perform better overall compared to other models, and its performance is specifically more pronounced after the onset of the COVID-19 crisis period, for the stocks considered. We conclude that a hybrid deep learning algorithm—BiLSTM-GARCH model would be the preferred model to forecast the volatility of the stocks considered for the BIST30 Index.

The organization of the paper is as follows. Section 2 describes the data. Section 3 provides some background information on the techniques used and presents the results. Section 4 concludes.

2. Data

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

Table 1. List of Stocks in the BIST 30

Stocks in BIST 30
AKBNK
ARCLK
ASELS
BIMAS
BRMEN
DENGE
EKGYO
EREGL
FROTO
GARAN
GUBRF
HALKB
HEKTS
ISBI
ISCTR
ISYAT
IZINVI
KCHOL
KENT
KLNMA
KOZAA
KOZAL
KRDMD
PETKM
PGSUS
QNBFB

Table 1 Continued

QNBFL
SAHOL
SASA
SISET
SNKRN
TAVHL
TBORG
TCELL
THYAO
TKFEN
TOASO
TTKOM
TUPRS
UTPYA
VESTL
YKBNK

3. Methodology and Results

We employ two common Deep Learning Algorithms; LSTM and BiLSTM to predict the volatility of the stocks in the above groups that compose the BIST 30 index. For brevity, we refer the reader to literature on Machine Learning and Deep Learning for the details, features, and drawbacks of each model.

3.1 Evaluation Criteria

The evaluation criteria used for the stock prediction are Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE).

Table 2 presents the average volatility forecast results for the stocks related to the financial sector for immediately one day ahead: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH and the LSTM-GARCH next. Among the homogeneous deep learning models, BiLSTM seems to be the best model.

Table 2. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Financial Sector

	Evaluation Criteria	
Model	MAPE	SMAPE
LSTM	2.88	2.80
BILSTM	1.89	1.72
LSTM-GARCH	1.20	1.16
BILSTM-GARCH	1.02	1.12

Table 3. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Communication Sector

	Evaluation Criteria	
Model	MAPE	SMAPE
LSTM	1.47	1.36
BILSTM	1.38	1.24
LSTM-GARCH	1.15	1.10
BILSTM-GARCH	0.95	0.88

Table 3 presents the average volatility forecast results for the stocks related to the communication sector immediately one day ahead: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH followed by the LSTM-GARCH model next. BiLSTM-GARCH seems to be the best model for this group of stocks as well.

Table 4 presents the average volatility forecast results for the stocks related to transportation for immediate one-day ahead: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH, followed by the LSTM-GARCH model. BiLSTM-GARCH seems to be the best model for this group of stocks as well.

Table 4. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Transportation Sector

	Evaluation Criteria	
Model	MAPE	SMAPE
LSTM	2.01	2.00
BILSTM	1.86	1.85
LSTM-GARCH	1.37	1.28
BILSTM-GARCH	1.25	1.24

Table 5 presents the volatility average forecast results for the stocks related to petroleum immediately one day ahead: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH, followed by the LSTM-GARCH next.

Table 5. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Petroleum Sector

	Evaluation Criteria	
Model	MAPE	SMAPE
LSTM	2.06	1.98
BILSTM	1.97	1.94
LSTM-GARCH	1.69	1.62
BILSTM-GARCH	1.04	1.01

When we consider all the groups and all the models BiLSTM-GARCH models seem to outperform all other models uniformly followed by the LSTM-GARCH models. Their homogenous counterparts follow the same order; i.e. the BILSTM models outperform the LSTM models.

Table 6 presents the average volatility forecast results for the stocks related to the financial sector immediately one day ahead after the onset of COVID-19: Both MAPE and SMAPE criteria are still the lowest for the BiLSTM-GARCH and the LSTM-GARCH next.

Table 6. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Financial Sector after the onset of COVID-19

	Evaluation Criteria	
Model	MAPE	SMAPE
LSTM	2.96	2.01
BILSTM	2.76	1.94
LSTM-GARCH	1.95	1.67
BILSTM-GARCH	1.89	1.04

Table 7 presents the average volatility forecast results for the stocks related to the communication sector immediately one day ahead of the onset of COVID-19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH and the LSTM-GARCH next.

Table 8 presents the average volatility forecast results for the stocks related to transportation immediately one day ahead of the onset of COVID-19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH and LSTM-GARCH next. Hybrid BiLSTM seems to be the best model for this group of stocks as well.

Table 7. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Communication Sector after the onset of COVID-19

Evaluation Criteria		
Model	MAPE	SMAPE
LSTM	2.73	2.00
BILSTM	2.47	1.94
LSTM-GARCH	2.17	1.67
BILSTM-GARCH	2.05	1.04

Table 8. Average MAPE and SMAPE Values from one-day-ahead volatility prediction for stocks related to the Transportation Sector after the onset of COVID-19

Evaluation Criteria		
Model	MAPE	SMAPE
LSTM	2.86	2.36
BILSTM	2.53	2.14
LSTM-GARCH	2.27	2.07
BILSTM-GARCH	2.09	1.98

Table 9 presents the average volatility forecast results for the stocks related to petroleum immediately one day ahead of the onset of COVID-19: Both MAPE and SMAPE criteria are the lowest for the BiLSTM-GARCH and LSTM-GARCH next. BiLSTM-GARCH seems to be the best model for this group of stocks as well.

Table 9. Average MAPE and SMAPE Values from one -day -a head volatility prediction for stocks related to the Petroleum Sector after the onset of COVID-19

Evaluation Criteria		
Model	MAPE	SMAPE
LSTM	2.06	1.98
BILSTM	1.93	1.87
LSTM-GARCH	1.27	1.17
BILSTM-GARCH	1.09	1.04

When we consider all the stock groups and all the models BiLSTM-GARCH models still seem to outperform all other models followed by the LSTM-GARCH models in the Covid-19 era as well. When we compare the MAPE and SMAPE values from the pre- and post-Covid periods, we observe a decline in the overall performance of all models. However, both the BiLSTM-GARCH and LSTM-GARCH models continue to outperform the other models.

4. Conclusion

In this study, we employ Deep Learning algorithms like BiLSTM, LSTM, and hybrid models that utilize BILSTM, LSTM, and GARCH models to predict stock volatility for the stocks in the Financial, transportation, communication, and petroleum sectors in the BIST30 Index before and after Covid-19 crises. The BiLSTM-GARCH models seem to have the best out-of-sample forecasting performance in both the pre and COVID-19 periods. The LSTM-GARCH models seem to have a good overall performance and are found to be the next best class of models.

Based on our findings we highly recommend utilizing the hybrid Deep Learning algorithms like LSTM and BILSTM with GARCH forecasts for volatility forecasting for the stocks in the Financial, transportation, communication, and petroleum sectors that are traded in the BIST 30 index.

References

[1] Sezer OB, Gudelek MU, Ozbayoglu AM. Financial time series forecasting with deep learning: A systematic literature review: 2005-2019. Applied Soft Computing. 2020;90:106181.

[2] Wang W, Li W, Zhang N, Liu K. Portfolio formation with preselection using deep learning from long-term financial data. Expert Systems with Applications. 2019.

[3] Gao T, Chai Y. Improving Stock Closing Price Prediction Using Recurrent Neural Network and Technical Indicators. Neural Computation. 2018;30(10):2833-2854.

[4] Vo NN, He X, Liu S, Xu G. Deep learning for decision making and the optimization of socially responsible investments and portfolio. Decision Support Systems. 2019;124:113097.

[5] Sambas A, He S, Liu H, Vaidyanathan S, Hidayat Y, Saputra J. Dynamical analysis and adaptive fuzzy control for the fractional-order financial risk chaotic system. Advances in Difference Equations. 2020;674(1):1-12.

[6] Min HP, Dongyan N, Yerin K, Jang HK. CBOE Volatility Index Forecasting under COVID-19: An Integrated BiLSTM-ARIMA-GARCH Model. Computer Systems Science and Engineering. 2023;47(1).

[7] Duan Y, Liu L., Wang Z. COVID-19 sentiment and the Chinese stock market: Evidence from the official news media and Sina Weibo. Research in International Business and Finance. 2021;58(4):101432.

[8] Kim HY, Won C. H. Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. Expert Systems with Applications. 2018;103(1):25-37.