



# Analysis of Price Volatility in BIST 100 Index With Time Series: Comparison of Fbprophet and LSTM Model

Yusuf Aker<sup>1\*</sup>

<sup>1\*</sup> Türkiye Finans Katılım Bankası A.Ş., İstanbul, Turkey, (ORCID: 0000-0002-6058-068X), [yusuf\\_aker@yahoo.com](mailto:yusuf_aker@yahoo.com)

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## Abstract

Making predictions about the future based on past datasets is one of the most important issues in analytical finance. Recently developed deep learning approaches and machine learning models have increased the interest in this field. One of these approaches, time series, is trying to predict the changes in a certain frequency. In this study, LSTM (Long Short-Term Memory) and Fbprophet (Facebook Prophet) methods were used to estimate the data of BIST-100 index. Predicting stock market indices with erratic behavior is a complex task, but with the new algorithms developed, price predictions can become more predictable. The research was carried out on the index data between 2021-01-01 and 2021-12-31, which has high volatility. The evaluation criteria of the models we used are MAE (mean absolute error), MSE (mean square error) and RMSE (root mean square error). As a result of the study, it was determined that the LSTM model was more successful than the Fbprophet model with a low error rates.

**Keywords:** BIST 100 Index, Machine Learning, Deep Learning, LSTM, Fbprophet.

## BİST 100 Endeksindeki Volatilitenin Zaman Serileri İle Analizi: Fbprophet ve LSTM Modeli Karşılaştırması

### Öz

Geçmişteki verilere dayanarak gelecek hakkında tahminler yapmak analitik finanstaki en önemli konulardan birisidir. Son dönemde gelişen derin öğrenme yaklaşımları ve makine öğrenmesi modelleri bu alana olan ilgiyi arttırmıştır. Bu yaklaşımlardan birisi olan zaman serileri ile belirli frekanstaki değişimler tahmin edilmeye çalışılmaktadır. Bu çalışmada BIST-100 endeksine ait verileri tahmin edebilmek için LSTM (Long Short-Term Memory) ve Fbprophet (Facebook Prophet) yöntemleri kullanılmıştır. Düzensiz davranışlara sahip borsa endekslerinin tahmin edilmesi karmaşık bir iştir ancak geliştirilen yeni algoritmalar ile fiyat tahminleri daha öngörülebilir hale gelebilmektedir. Araştırma yüksek volatilitelere sahip 2021-01-01 ile 2021-12-31 arasındaki endeks verileri üzerinden gerçekleştirilmiştir. Kullandığımız modellerin değerlendirme kriterleri MAE (ortalama mutlak hata), MSE (ortalama kare hatası) ve RMSE (kök ortalama kare hatası)'dır. Çalışma sonucunda düşük hata oranları ile LSTM modelinin Fbprophet modelinden daha başarılı olduğu tespit edilmiştir.

**Anahtar Kelimeler:** BİST 100 Endeksi, Makine Öğrenmesi, Derin Öğrenme, LSTM, Fbprophet.

\* Corresponding Author: [yusuf\\_aker@yahoo.com](mailto:yusuf_aker@yahoo.com)

# 1. Introduction

Stock exchanges are places that bring investors together in the country where they operate, and where trading transactions are carried out in a safe environment. Borsa İstanbul (BIST) is the only institution operating in this field in Turkey. In some periods, fluctuations that occur with very sharp price movements can cause BIST investors to encounter high gains or losses. Therefore, estimating volatility is a critical issue for BIST investors as well. With this study, the direction of the BIST-100 index which is one of the locomotive indexes of BIST, will be tried to be predicted with developing deep learning and machine learning methods. In this study, which will be conducted with time series analysis, it is aimed to accurately predict future values with measurements ordered over time. LSTM and Fbprophet models were used in the analysis.

In the introduction part of the study, the works in the literature are mentioned, and in the second part, information about the data set and the models used is given. In the third part, the results of the research are given, and in the fourth part, the accuracy measurements are given. The study was finished with the conclusion part.

In the literature review, it is seen that the LSTM model is used to predict the future in different fields. Ma et al., [1] used the LSTM model to predict the covid 19 epidemic trend. However, it has been observed that LSTM is used in many different areas such as supply chain management, soil stress behavior modeling, and traffic flow estimation ([1]; [2]; [3]). There are many studies that use the LSTM model to predict cryptocurrencies ([4]; [5]; [6]). Baek and Kim [7] compared SP500 and Korea Composite Stock Price Index 200 and obtained successful results by using two different LSTM models for preventing overfitting and index estimation.

In the Fbprophet model, which is another widely used model in time series analysis, it is seen that studies are carried out on very different subjects such as the future course of covid 19, the prediction of traffic density, the future course of currency movements, the expected tourism activity and the future estimated values of cryptocurrencies ([8]; [9]; [10]; [11]). Durairaj and Mohan [12] tried to predict the future values of the Nifty 50 stock market index with a hybrid model including the Fbprophet model. As a result of the study, the superiority of the hybrid model over models such as ARIMA, LSTM and Chaos+LSTM has been proven.

## 2. Material and Method

### 2.1. Data set

In this study, the year 2021, which is the period with the highest volatility, was chosen. The opening, closing, highest and lowest volume values of the BIST-100 index between January 1, 2021 and December 31, 2021 were chosen as primary data. Python programming language was used in the research and the data set was obtained from the yahoo finance platform with the web.Datareader library. The data other than the date and closing values were removed and the study continued with 248 days of observation.

Table 1. BIST 100 Index Data Set Values

	Date	Open	High	Low	Close	Volume
0	2021-01-04	1482.199951	1500.000000	1478.699951	1495.400024	5172334300
1	2021-01-05	1492.199951	1506.900024	1474.800049	1489.599976	6659180300
2	2021-01-06	1501.599976	1509.500000	1497.099976	1505.400024	5330873300
3	2021-01-07	1511.599976	1522.699951	1505.699951	1522.199951	6175892400
4	2021-01-08	1526.500000	1542.800049	1519.800049	1540.599976	5500828100
...	...	...	...	...	...	...
243	2021-12-27	1898.699951	1942.500000	1873.300049	1897.099976	3014802700
244	2021-12-28	1913.300049	1916.199951	1830.900024	1850.500000	2584687100
245	2021-12-29	1847.300049	1901.500000	1828.599976	1895.500000	2570994300
246	2021-12-30	1916.300049	1923.699951	1860.699951	1863.699951	2341048300
247	2021-12-31	1867.699951	1885.199951	1845.599976	1857.699951	1586782500

### 2.2. Long Short-Term Memort (LSTM)

LSTM, a deep learning algorithm, was developed by Hochreiter and Schmidhuber in 1997 to eliminate the disadvantages of the RNN algorithm [13]. It is this pattern that is similar to RNN networks. However, RNN networks cannot keep information for a long time and may encounter significant information losses at the beginning of the network. The disadvantages of this model, which is also encountered with the gradient disappearance problem in the backpropagation process, can be solved by the LSTM method. The short-term memory problem in LSTM cell structures is solved by gates that regulate and control the information flow [14]. LSTM architecture consists of input, output, forget gates and memory cells. It is a frequently used algorithm in time series, and it has given successful results in chaotic time series, text processing, speech and classification applications [15].

### 2.3. Facebook Prophet (Fbprophet)

Developed by the Facebook company. It is extremely good at handling long-term volatile trends, non-seasonal data, or incomplete data. This algorithm, which is used to predict time series, can be used with both R and Python programming languages. It provides intuitive parameters that are easy to set. Using time as a regressor, Prophet tries to fit many linear and non-linear functions of time as components. It is an algorithm that is also used in time series problems after parameter changes are made [16].

The Prophet model includes three main components [11]. These are seasonality, holidays and “predict y”. Its mathematical formula can be shown as (1);

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

$\epsilon_t$  represents the expected error term. Takes into account unusual changes not covered by the model,

$g(t)$  represents a piecewise linear or logistic growth curve for modeling non-periodic changes in time series,

$s(t)$  represents periodic changes (seasonal, annual, weekly),

$h(t)$  represents the effects of holidays with irregular schedules.

Figure 1. LSTM Data Visualization



### 3. Results

#### 3.1. Prediction with LSTM

The model was started by training 139x6 matrices. In order to better train the data in the LSTM model, the training data is divided into 50 clusters (Cross-Validation=50). For validation last 2 months were selected. The epoch value of the model is set to 10.

Epoch 1/10	139/139 [=====]	- 4s 16ms/step	- loss: 0.0012
Epoch 2/10	139/139 [=====]	- 2s 16ms/step	- loss: 9.4459e-04
Epoch 3/10	139/139 [=====]	- 2s 16ms/step	- loss: 6.7852e-04
Epoch 4/10	139/139 [=====]	- 2s 17ms/step	- loss: 5.8298e-04
Epoch 5/10	139/139 [=====]	- 3s 20ms/step	- loss: 5.4020e-04
Epoch 6/10	139/139 [=====]	- 3s 24ms/step	- loss: 4.9332e-04
Epoch 7/10	139/139 [=====]	- 2s 17ms/step	- loss: 5.0639e-04
Epoch 8/10	139/139 [=====]	- 2s 16ms/step	- loss: 4.7374e-04
Epoch 9/10	139/139 [=====]	- 2s 16ms/step	- loss: 4.8612e-04
Epoch 10/10	139/139 [=====]	- 2s 16ms/step	- loss: 3.8621e-04

Figure 2. LSTM Epoch Structure

The LSTM model structure is composed of 50 neurons with 4 hidden layers. There is only one output in the output layer. The predicted values of the model are shown in figure 2. It has been observed that the forecast values follow the closing values successfully. The data is divided into 80 percent training and 20 percent testing. The last 60 days are validation part, and although the volatility is high, it is seen that the model has a very successful predictive power.

#### 3.2. Prediction with Fbprophet

In the analysis made with Facebook prophet, the data was divided into two as training and testing. The predictions made with Prophet are very easy to analyze.

In the model, the date (“ds”) and the numerical value (“y”) that we want to predict, that is, the closing prices of the index are used. In the analysis made with the Python program, a model was created with the fit function, and future price predictions were made with the predict function.

### 4. Performance Measures

The performances of the models were measured with three parameters. Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). Equations of the parameters are shown in 1, 2 and 3;

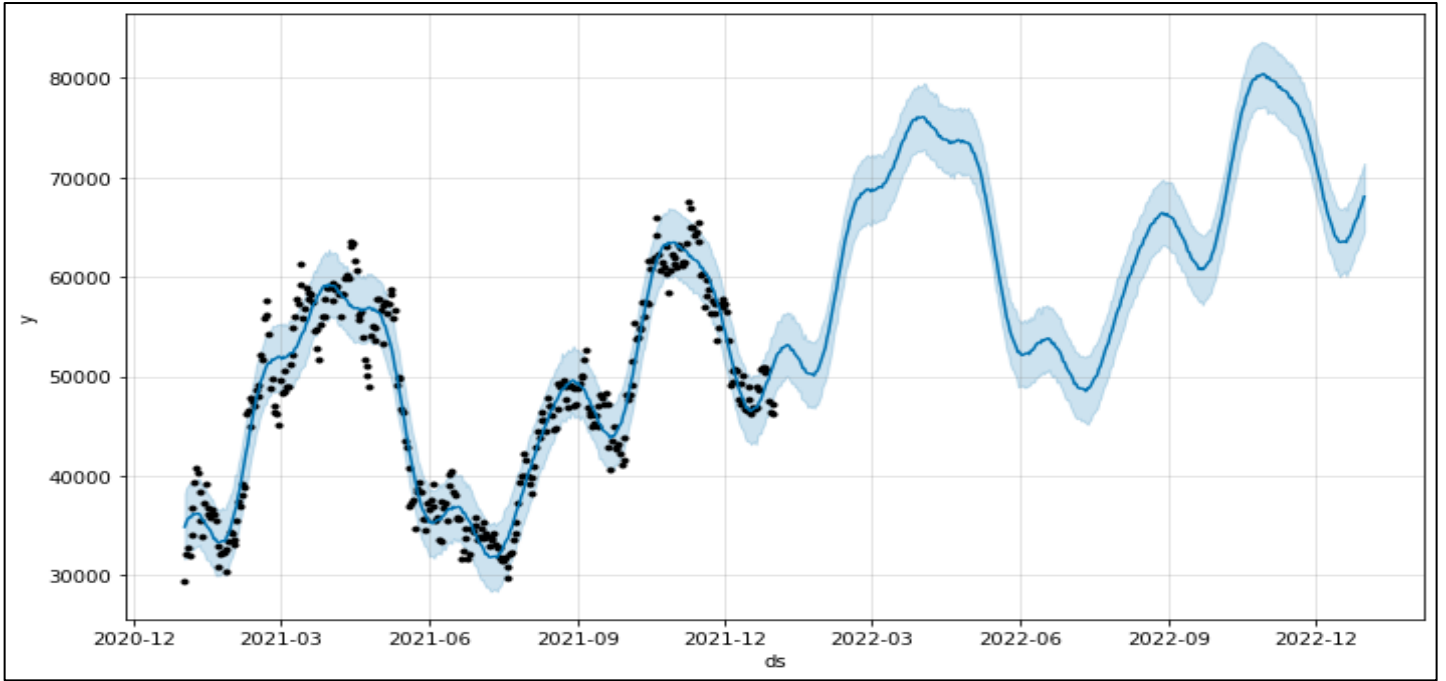
$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (1)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (3)$$

In the equations, the sample set is represented by  $N$ , while  $y_i$  represents the observed value and  $\hat{y}_i$  represents the predicted value. MAE measures the difference between two continuous variables. MAE is the average horizontal distance of the line that best fits the data points. MSE is always positive and shows how close the regression curve is to the set of points. RMSE, on the other hand, can be defined as a quadratic metric that measures the magnitude of the error [17]. The smaller the MAE, MSE and RMSE values, the higher the success of the model [18].

Figure 3. FbProphet Data Visualization



Models/Measures	MAE	MSE	RMSE
Fbprophet	324	155653	395
LSTM	106	15845	126

Table 2. Metric Measurements

As it can be seen in table 2, MAE, MSE and RMSE values are higher than the LSTM algorithm values in the estimations made with the Fbprophet algorithm, so it is seen that the LSTM algorithm gives better results.

## 5. Conclusions

Estimating the price of a financial asset while making an investment decision and measuring the relationship between risk and expected return has become one of the important problems that today's finance and information sector make joint efforts. Deep neural networks have recently become one of the common methods used in the field of finance. Software and hardware developing with today's technology can make very successful predictions about the unknown by making inferences from the existing data with mathematical and statistical methods. With the help of models, even the most hidden relationships between data structures can be trained with datasets called training. Model algorithms that learn by training can make very successful new inferences and predictions with the test dataset they have never seen before.

Today, making predictions for the future in the field of analytical finance is an extremely important issue for successful investments. Deep learning approaches have started to offer new methods to those who are interested in this subject. Time series, which is one of these approaches, is used to make estimations of changes in a known frequency and period. In this study, LSTM and Fbprophet methods were used to estimate the data of BIST-100 index. Predicting stock market indices with erratic behavior is a complex task, but with the new algorithms developed, price

predictions can become more predictable. The research was carried out on the BIST-100 index data between 2021-01-01 and 2021-12-31, which has high volatility. The evaluation criteria of the models we use are MAE, MSE and RMSE. In the Fbprophet model, MAE, MSE and RMSE ratios were determined as 324, 155653 and 395, respectively, while in the LSTM it was determined as 106, 15845 and 126, respectively. As a result of the study, it was determined that the LSTM model was more successful than the Fbprophet model with low error rate in all three parameters.

In the literature review, although there are many studies showing that the LSTM model is a very useful model in time series problems, it has been observed that less research has been done in this area with the Fbprophet model. Alpay (2020), researching on USD/TRY price prediction, compared the LSTM and Fbprophet method and concluded that the LSTM model is a more successful time series estimator with a lower error rate. Likewise, Mata (2020) in his study on the S&P 500 price index estimation concluded that the LSTM model is more successful than the Fbprophet model. It is seen that the results of both studies support this paper's result. In future studies, it is recommended to add more variables such as inflation, interest and exchange rates, and more variables at the national and international level that can affect price indices in order to achieve higher accuracy and less margin of error.

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