

BIST 100 Index Prediction

Alaattin Burak Koçer
040210262

Depertment of Electrics and Electronics
Istanbul Technical University
kocera21@itu.edu.tr

Necati Vural
040220264

Depertment of Electrics and Electronics
Istanbul Technical University
vuraln22@itu.edu.tr

Yiğit Yılmaz Yanç
040210044

Depertment of Electrics and Electronics
Istanbul Technical University
yanc21@itu.edu.tr

Abstract—Forecasting stocks in the stock market is a very serious challenge in financial analysis due to the non-linear changes in financial data dynamics and the high volatility of financial data over time. In this project, LSTM, GRU and finally a polynomial regression will be used to compare these data for the 1-day and 15-day prediction of the BIST 100 index. In the dataset, a wide range of features which explain the price movements, volatility, long term and short term trends, macroeconomic metrics and inter-market relations are used. Daily data from February 19, 2021 to May 6, 2025 were collected and combined into a single data set and models were built on this data set. The models are finally evaluated with various performance metrics such as RMSE, MSE, MAPE, R² and accuracy. At the same time, this study contributes to the forecasting and comparison studies of market indices with artificial neural networks and different regression techniques and provides short-term practical solutions for investors who want and aim to closely follow the Turkish financial market in the short term.

Index Terms—BIST 100, Artificial Neural Networks, LSTM, GRU, Polynomial Regression, Time Series Forecasting, Recurrent Neural Networks

I. INTRODUCTION

A. The Importance of Financial Forecasting and the Role of BIST 100

Financial exchanges and financial markets are complex and dynamic systems shaped by political, economic, and even psychological factors [1]. The complexity of these markets and their forecasting has been the focus of attention of investors and academia who are interested in developing specific models and methods using these markets. The frequent uncertainty in emerging markets has made the forecasting of these markets even more critical. In Turkey, one of the emerging countries, the BIST 100 index, which indexes the performance of the 100 largest/significant companies traded on Borsa Istanbul, lies at the center of investors' focus on the Turkish stock market. There is no doubt that this index, which is also an indicator of economic stability in the country, will provide micro and macroeconomic benefits if it can be accurately estimated.

B. Challenges of Financial Series and ANN Approach

Financial indices and time series are characterized by high variability, non-linearity and, as mentioned, sensitivity to exogenous factors. For this reason, Traditional models, such as linear regression or ARIMA, often fall short in capturing nonlinear dependencies and sudden shifts in financial markets [2]. In this case, the use of Artificial Neural Networks is

inevitable. Artificial neural networks offer an alternative to this complexity by providing flexible, data-driven modeling that is less reliant on statistical assumptions [3]. The ANNs used appropriately for the problem are prominent in financial analysis and forecasting because they can even show performance improvement in increasing the data set, adapt to the new pattern and learn the hidden relationships between the data.

C. Deep Learning Models: LSTM and GRU

Although recurrent neural networks (RNNs) play an important role in traditional models of time series forecasting, due to their long-term dependencies and inadequacy in the learning phase, more advanced models such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) are preferred and used in the forecasting and learning phase. While LSTM can store both long-term and short-term data patterns through cell states and gate mechanisms, GRU is much simpler and can achieve similar performance with much less computational burden. These models have a higher ability to learn factors such as temporal deviations, sudden jumps and falls, and trend reversals in the stock market.

D. Current Requirements for the Turkish Economy and the BIST 100 Prediction

Turkey is a developing country and Turkey's financial structure is highly sensitive to both domestic political developments and global economic shifts, a characteristic shared by many emerging markets [4]. For example, macroeconomic factors such as sudden changes in exchange rates, interest rates and inflationary pressures affect the short-term movement of the BIST100 and make it hard to analyze the data. Besides these factors, interactions between the BIST 100 and important international stock market indices such as the S&P 500, NASDAQ and DAX have been found. At the same time, local macroeconomic variables such as the unemployment rate in Turkey, the 10-year and 2-year government bond yields in Turkey are also among the factors affecting the BIST 100. These data are also included in this project. The dataset used in this study covers the period between February 19, 2021 and May 6, 2025, which provides an important context for understanding how events such as COVID-19, global interest rate hikes and regional political developments affect the BIST-100 index and the dynamic direction of financial markets. In

this framework, Multiple deep learning and machine learning models will be used to compare their accuracy and error performance, especially in modeling long-term dependencies on this complex structure [5].

E. The Intersection of Data Science and Financial Prediction

Today, data science is no longer just a tool to support the analysis of financial markets, but a component that directly affects investors' decision-making processes. Areas such as big data, machine learning (especially artificial neural network models) and artificial intelligence are increasingly revolutionizing the analysis and prediction of stock market data. Based on this, it is a fact that financial analysis today is not only an economic analysis but also a multidimensional data processing, analysis and modeling process. Investment firms and even leading financial institutions such as central banks are actively using these models in their decision-making processes. Data science specific processes such as feature engineering, hyperparameter optimization and cross-validation are important data science processes that improve the generalization of forecasting models. Based on this, in this study, not only model selection but also data processing, and data transformation are addressed and emphasized. In addition to the statistical success of these models, their predictive capability in application is also evaluated.

F. Contributions of This Study

As explained earlier, this study aims to make four main contributions to BIST 100 forecasting:

1. Use a dataset that covers a wide time period (February 19, 2021 - May 6, 2025) and includes a wide range of features that describe price movements and the economic environment,
2. This study compares multiple deep learning and regression approaches over a long-term dataset and evaluates their forecasting performance with detailed error metrics
3. Provide two options for the forecast, such as 1 and 15 days using the walk-forward analysis,
4. Systematic application of deep learning models such as LSTM and GRU as well as classical polynomial regression model on BIST 100,
5. Obtaining objective results by measuring the success of the model with different evaluation metrics and plots namely RMSE, MAE, MAPE, R², accuracy, actual vs. prediction plot, and residual plot.

These contributions aim to fill the gaps in the literature by utilizing existing work and offer innovations at both theoretical and applied levels. The use LSTM and GRU reduces errors due to feature redundancy, and the use and testing of multiple models allows for a comparative demonstration of their strengths and weaknesses. In these aspects, the project involves extensive preparation and work, and finalizes its results under their influence.

II. LITERATURE REVIEW

In this section, we review past studies on the BIST 100 index and examine the artificial intelligence methods utilized in these studies and explain where the current approaches are located and where they are positioned.

A. Evolution of Artificial Neural Networks in Financial Forecasting

Artificial neural networks are among the most widely used methods in stock market forecasting due to their superior ability to model non-linear and high-dimensional data in recent years [6]. The main reason for this is that they overcome the limits of linear learning and approaches and follow a different path thanks to their ability to learn. As mentioned earlier, financial time series contain multivariate structures and attempts to analyze these time series with traditional methods are often inadequate and time-consuming. Artificial neural networks, on the other hand, have great success rates in modeling these complex data thanks to their capacity to learn the relationships between non-linear data. As a result, they are particularly useful in forecasting short-term price changes.

B. Studies on BIST 100 Index in Turkey

As mentioned earlier, global and local factors significantly affect the stock market at high rates in developing countries such as Turkey and these countries are sensitive to these factors. These factors cause short and long-term fluctuations on the BIST 100 Index, making it difficult to analyze the markets and creating uncertainty and confusion for investors. In order to avoid this complexity, artificial intelligence-supported studies have been carried out before and some of these studies have been able to make realistic predictions. Through the date range of the dataset used in the project, it will be possible to observe how important events in a period of approximately 4 years and 3 months affect this index and make inferences about it.

C. Deep Learning Based Structures and Strategies

Recently important deep learning models such as LSTM and GRU outperform traditional models by capturing time dependencies more effectively while reducing vanishing gradient problems and are now widely used in stock market and economic analysis [7]. Sudden price changes and uncertain cycles and trends, which are frequently encountered in financial series, can be analyzed in more detail with these structures and can guide investors, financial companies and banks at critical times.

LSTM and GRU models have demonstrated significant success in capturing long-term dependencies in sequential data, effectively addressing the vanishing gradient problem and improving the performance of time series prediction tasks [8]. Therefore, we used classical LSTM and GRU structures. These models provided satisfactory accuracies in terms of learning patterns over time, while at the same time providing a more controlled process in terms of training and hyperparameter optimization. In addition, we also used Polynomial Regression to

compare the performances. In this way, a detailed comparison between classical approaches working with linear structures and deep learning-based methods can be made in terms of performance and the impact of model selection on prediction success can be objectively demonstrated.

D. Gaps in the Literature and the Position of this Study

A review of the existing literature and studies shows that most of the studies on “BIST 100 Index Prediction” focus on limited time periods, limited number of features, and a single model or traditional models. This situation has caused the developed projects to be insufficient in terms of flexibility and consistency in real world conditions. The limited time horizons of these models limit their predictive capabilities and lead to a disconnection from reality.

One of the important differences of this study is that it covers a wide time period of approximately 4 years and 3 months (February 19, 2021 - May 6, 2025) and helps me to examine how financial modeling performs for major events that occur during this time period. In addition to the major deep learning models used, the inclusion of polynomial regression in the analysis allows for the comparison of models.

Several comparative studies have examined the relative performance of classical statistical models and deep learning approaches in stock market prediction, emphasizing the advantages of neural architectures in capturing non-linear relationships and temporal dependencies across diverse economic indicators [9].

In these aspects, the project aims to contribute to the literature in both academic and practical aspects and aims to develop a more grounded and more realistic decision support system for individuals.

III. DATASET

A. About the Dataset

The dataset used in this project was daily between February 19, 2021 and May 6, 2025, as mentioned before. The data set includes indicators of the BIST 100 index of Borsa Istanbul together with the main macroeconomic parameters of the Turkish economy and international financial indices. Various data from sites such as *investing.com*, *tradingeconomics.com* combined, and preprocessed in MATLAB and transferred to the Python. This dataset consists of 59 features, which can be grouped into daily price movements, technical indicators, and macroeconomic features, time features, and inter-market relationships. From date, day, week, quarter, and year features were constructed to describe correlations and seasonality. Daily open, high, low, volume features are used to represent the daily price movements. Exponential Moving Average (EMA) of periods 20, 50, 200 days, Relative Strength Index (RSI) with 14 days period, Moving Average Convergence /Divergence (MACD), bollinger bands, Average True Range (ATR) with 14 days period were used. Inter-market relationships were described by the Turkey 10 and 2 year bond yields, 10 year and 2 year CDS, USD/TRY exchange rate, gold price (XAU/USD), the dollar index, the volatility

index (VIX), emerging markets ETF EEM, and other exchange indices S&P500, DAX and NIKKEI. Lastly, macroeconomic features, which are Turkey PMI, M2 money supply, yearly inflation, interest rates, unemployment, Gross Domestic Product (GDP) growth, Federal Reserve rates are used. The daily price differences and close prices are also included at the end of the feature matrix. Date, open, high, close, volume, Turkey 2 year and 10 year bond yields and Turkey 2 year and 10 year CDS, USD/TRY, XAU/USD, VIX, EEM, S&P500, DAX and NIKKEI were obtained from *investing.com*, and PMI, M2, inflation, interest rates, unemployment, GDP growth, Fed rates were obtained from *tradingeconomics.com*. The remaining features were constructed by feature engineering.

B. Data Preprocessing and Feature Engineering

In the data preprocessing part, missing or inconsistent data were identified and appropriate fixing procedures were applied, with manual checks performed multiple times to apply data integrity. Inconsistent data were resampled and all features were normalized to be suitable for training the model. In addition, future information is not included in this dataset, so that the model remains close to real-world applications.

Using dates, day (2-6), week (1-53), month (1-12), quarter (1-4), and year features were extracted to examine correlation and seasonality. However, even if there is a 1 month difference between the first and last months, this representation can falsely be interpreted by the neural network as there are 11 month difference between the month 1, and month 12. This is also applies to day, week, and quarter, which the features should be improved. To resolve the problem, day, week, month and quarter features are represented by sine and cosine waves with the formula

$$ysin = \sin(2\pi \cdot x / max(x)) \quad (1)$$

$$ycos = \cos(2\pi \cdot x / max(x)) \quad (2)$$

Technical indicators are derived from price. Using MATLAB’s Financial Toolbox, and our custom functions, EMA, RSI, ATR, MACD, Bollinger band features were constructed.

Furthermore, since our macroeconomic features are released in a month, this required us to add additional features describing at which samples those values are updated and how many days past since the last update for each macroeconomic feature. The order feature, feature update, and days since update was preserved. Feature update is a binary feature represents the day whose value changed by 1, and others by 0, and days since update feature counts the number of days from the last update.

Normalization is done per window using MinMaxScaler and StandardScaler, and is fitted only on the training set to avoid data leakage, in which future data leak into past values. Instead of global normalization, feature matrix is normalized per feature. Binary features and time features which consists of sine and cosine are not normalized.

Methods such as PCA (Principal Component Analysis) could be used to simplify the data, but not included in this study.

Fig. 1: A Section From Dataset

IV. SYSTEM MODEL

Having prepared our features, we explain the models that are used in our proposed approach. Using LSTM and GRU models, 1-day and 15-day index price is predicted. Polynomial regression model is also used to compare the performance of models. Furthermore, upon predicting, we evaluate our models with evaluation metrics RMSE, R², MAE, MAPE, and accuracy. Since, those quantitative metrics alone may be misleading, we further analyze the performance of our models with qualitative metrics which are actual vs. predicted plots and residual plots. Special attention is paid to prevent overfitting, underfitting, and data leakage. We first define and provide the formulae we used to calculate our quantitative evaluation metrics.

A. Evaluation Metrics

1) RMSE (Root Mean Squared Error): RMSE is the square root of the mean square of the squares of the differences between the model predicted values and the actual values. This metric penalizes large errors more and the unit of errors is the same as the predicted variable. It is therefore often preferred in the interpretation of models.

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

2) **R^2 (R-squared / Determination Coefficient):** The R^2 score measures how well the predictions fit the true values. An R^2 value close to 1 indicates that the model explains the data very well; a value close to 0 means a poor relationship.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

3) **MAE (Mean Absolute Error)**: MAE is the average of the absolute values of the differences between predictions and actual values. It measures only the magnitude of the errors. Its unit is the same as the predicted variable, so this situation makes it easy to interpret.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (5)$$

4) **MAPE (Mean Absolute Percentage Error)**: MAPE expresses the ratio of prediction error to actual values in percent. It is often used to compare data sets of different sizes. Smaller values show that the model is more successful.

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (6)$$

5) Accuracy: Accuracy shows how small the MAE value is compared to the average of the true values. Values close to 100% mean high accuracy.

$$\text{Accuracy} = \left(1 - \frac{\text{MAE}}{\bar{A}}\right) \times 100 \quad (7)$$

Here, \bar{A} represents the mean of the actual values.

In the following, each model is described in detail under its own heading, along with the basic formulas related to the model and graphs with the obtained prediction results and train losses.

B. LSTM (Long Short-Term Memory)

The LSTM model is particularly successful in time series with volatile structures such as financial data and stock market data due to its ability to recall past information for a long time. Therefore, it has become necessary to use LSTM for a highly volatile index such as BIST 100.

LSTM cells use gates to remember information or add new information. Thus, it decides which information to keep or delete.

The basic formulas of the LSTM structure used are as follows:

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) && \text{(Forget Gate)} \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) && \text{(Input Gate)} \\
\tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) && \text{(Candidate Cell State)} \\
C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t && \text{(Cell State Update)} \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) && \text{(Output Gate)} \\
h_t &= o_t * \tanh(C_t) && \text{(Hidden State / Output)}
\end{aligned}$$

The formulas above show how the LSTM model processes information. The LSTM contains three separate gates (forget, input and output) that decide when to forget past information, when to add new information and when to give output. This structure allows the model to provide accurate results, especially when long-term forecasts and variables are important.

C. GRU (Gated Recurrent Unit

GRU is simpler than the LSTM model, but both models fulfill similar functions. Having fewer parameters allows the training time to be shorter than the LSTM model. In this study, GRU is used in the forecasting and testing phase as an alternative to LSTM for both short and medium term forecasts.

Basic formulas used for GRU:

$$\begin{aligned} z_t &= \sigma(W_z \cdot [h_{t-1}, x_t]) && \text{(Update Gate)} \\ r_t &= \sigma(W_r \cdot [h_{t-1}, x_t]) && \text{(Reset Gate)} \\ \tilde{h}_t &= \tanh(W \cdot [r_t * h_{t-1}, x_t]) && \text{(Candidate Activation)} \\ h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t && \text{(Final Hidden State)} \end{aligned}$$

The formulas given above describe how the GRU model manages information flow. GRU has a simpler structure than LSTM and uses only two gates: Update and Reset. These gates decide which information the model should carry and which it should refresh.

D. Polynomial Regression

Polynomial Regression is a simple but effective machine learning model for capturing non-linear trends in data. Especially in short-term market movements, it was able to work in harmony with the features used in the project where it tried to explain the index trend with graph curves.

In this model, the data is transformed into polynomial functions and then the classical linear regression method is applied.

General Polynamial Regression formula:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \varepsilon \quad (8)$$

The formula above shows how polynomial regression works. It is similar to linear regression but can also fit curved relationships between input x and output y . The terms $\beta_0, \beta_1, \dots, \beta_n$ are the values the model learns during training. These values help the model draw the best curve through the data. The symbol ε shows the possible error between the real and predicted values. The degree of the polynomial, n , controls how flexible the model is — higher degrees can fit more detailed curves, but they might also lead to overfitting.

V. PROPOSED APPROACH

To forecast 1-day and 15-day index price, we propose two different approaches, one for 1-day ahead prediction, and the other for 15-day prediction. Unlike similar studies in which training and test set are chosen chronologically, this study adopts a walk-forward analysis, which is much similar to real-time experience. From historical prices, one can observe that the index is highly volatile from time to time, which then may lead to distribution differences between test and training set, resulting in poor performance. Walk-forward analysis enables us to test our model with a better distribution. In walk-forward analysis, we train and test for each walk and repeat.

In 1-day predictions, we train for 10 samples, and immediately test for 1 sample in each walk. And we skip those windows by shifting 11 windows. In each walk, there is a separate normalization for each walk using train set to prevent data leakage. We use a single layer with 256 units, and "tanh" activation. Also 0.2 Dropout layer is added at the end of the single layer. Number of epoch was 15. The shuffle was disabled, since we work with a time series in which chronological order matters, and a callback to reduce

the learning rate ,which was initially set to 0.001, when the loss is not improving is added. In addition, quantile loss of 0.5 was used.

In 15-day predictions, walk-forward approach is altered to shift the samples by the number of test sample. Each sample is separated by 15 days, so that our models predict the next 15 day, and the next prediction is made after 15 days. Otherwise test predictions cannot be depicted with a single plot, over complicating the evaluation. We use two layers each with 150 units, and "tanh" activation for both GRU, and LSTM. Attention is paid to keep shuffle is disabled again, and we used Huber loss with delta that is equal to 1 Also in this setup, window size is chosen as 50.

To compare with LSTM and GRU models, a polynomial regression model is also constructed with the same walk-forward approach for 1-day and 15-day predictions.

VI. COMPARISON OF MODELS AND NUMERICAL VALUES

A. 1 Day Predictions

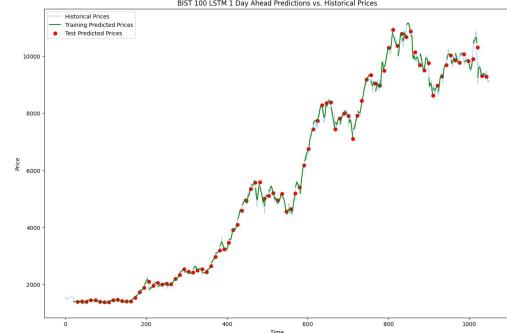


Fig. 2: 1 Day Predictions of BIST 100 Index Using LSTM and Actual Values

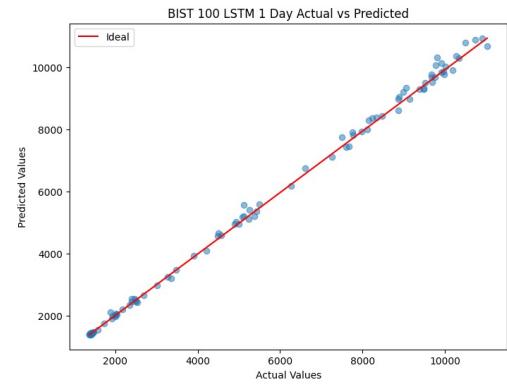


Fig. 3: BIST 100 1 Day Actual vs Prediction Plot for LSTM

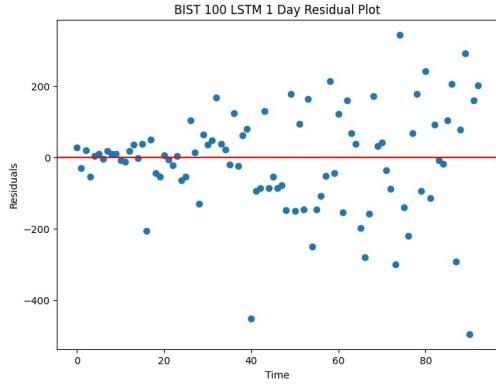


Fig. 4: BIST 100 1 Day Residual Plot for LSTM

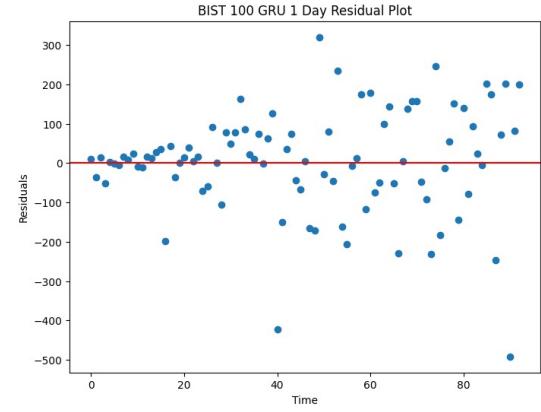


Fig. 7: BIST 100 1 Day Residual Plot for GRU

TABLE I: Evaluation Metrics for 1 Day LSTM Predictions

TRAIN RMSE:	67.98093019703079
TRAIN R2:	0.9995861581057603
TRAIN MAE:	42.666530934979846
TRAIN MAPE:	0.0076621312103121045
TRAIN ACC:	99.24763563542427
TEST RMSE:	142.62194018247172
TEST R2:	0.9981778667470572
TEST MAE:	104.15193810903894
TEST MAPE:	0.018654977463676885
TEST ACC:	98.1753958883439

TABLE II: Evaluation Metrics for 1 Day GRU Predictions

TRAIN RMSE:	63.56609435698632
TRAIN R2:	0.999636779475637
TRAIN MAE:	40.16513318002354
TRAIN MAPE:	0.0070451942409244794
TRAIN ACC:	99.29174427259768
TEST RMSE:	131.39237524840178
TEST R2:	0.9984478472397017
TEST MAE:	93.40873645413303
TEST MAPE:	0.017172593941735946
TEST ACC:	98.36360256282143

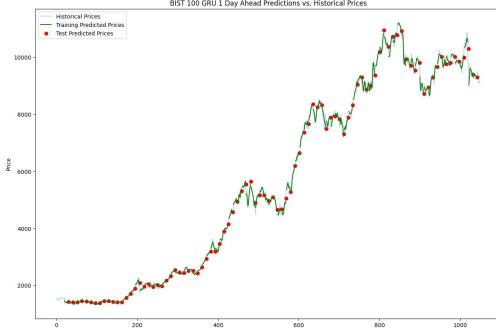


Fig. 5: 1 Day Predictions of BIST 100 Index Using GRU and Actual Values

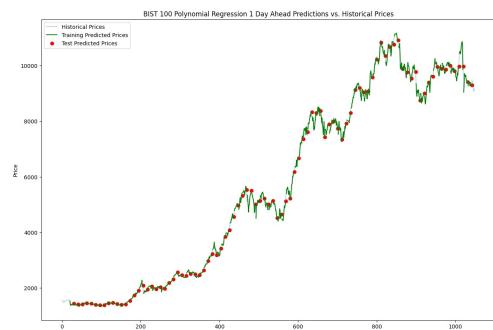


Fig. 8: 1 Day Predictions of BIST 100 Index Using Polynomial Regression and Actual Values

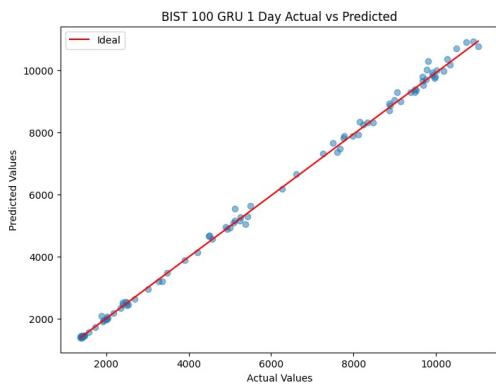


Fig. 6: BIST 100 1 Day Actual vs Prediction Plot for GRU

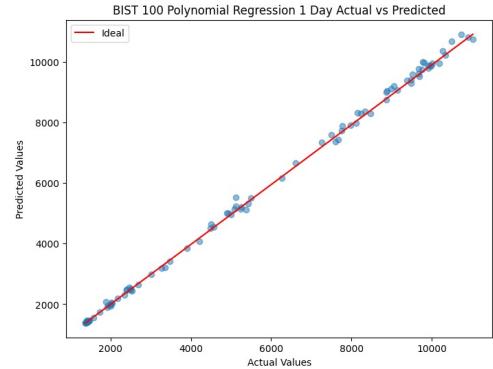


Fig. 9: BIST 100 1 Day Actual vs Prediction Plot for Polynomial Regression

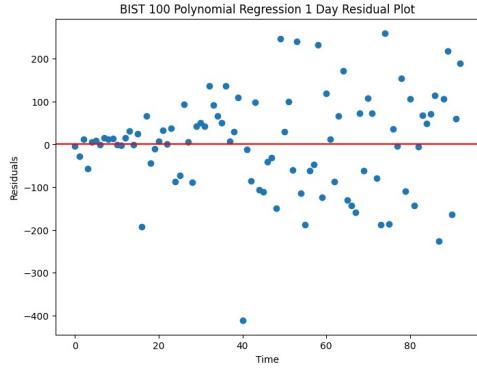


Fig. 10: BIST 100 1 Day Residual Plot for Polynomial Regression

TABLE III: Evaluation Metrics for 1 Day Polynomial Regression Predictions

TRAIN RMSE:	3.300857253231232e-13
TRAIN R2:	1.0
TRAIN MAE:	9.535025099232313e-14
TRAIN MAPE:	1.7851111716585175e-17
TRAIN ACC:	100.0
TEST RMSE:	113.78894587932699
TEST R2:	0.9988363168156089
TEST MAE:	85.64411075396366
TEST MAPE:	0.016186862970973416
TEST ACC:	98.49962852868649

B. 15 Day Predictions

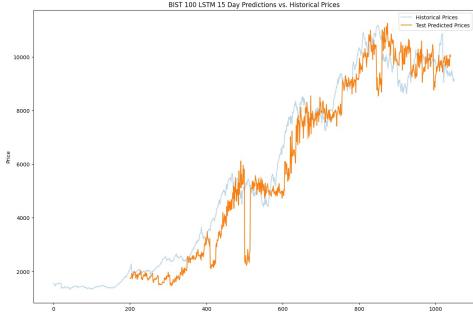


Fig. 11: 15 Day Predictions of BIST 100 Index Using LSTM and Actual Values

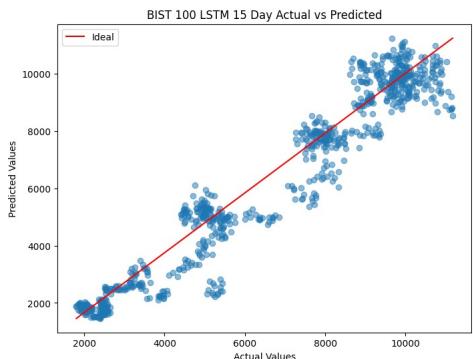


Fig. 12: BIST 100 15 Day Actual vs. Prediction Plot for LSTM

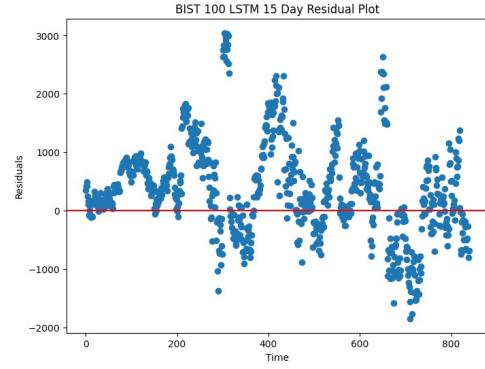


Fig. 13: BIST 100 15 Day Residual Plot for LSTM

TABLE IV: Evaluation Metrics for 15 Day LSTM

TRAIN RMSE:	153.1646239686778
TRAIN R2:	0.9975872877460942
TRAIN MAE:	104.8250685407366
TRAIN MAPE:	0.02242787056858104
TRAIN ACC:	98.17837149804429
TEST RMSE:	883.9749350218117
TEST R2:	0.9236964352383932
TEST MAE:	668.7183543178014
TEST MAPE:	0.16412837309394385
TEST ACC:	89.80812980089372



Fig. 14: 15 Day Predictions of BIST 100 Index Using GRU and Actual Values

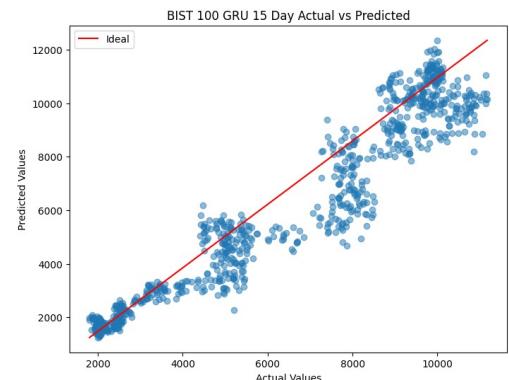


Fig. 15: BIST 100 15 Day Actual vs. Prediction Plot for GRU

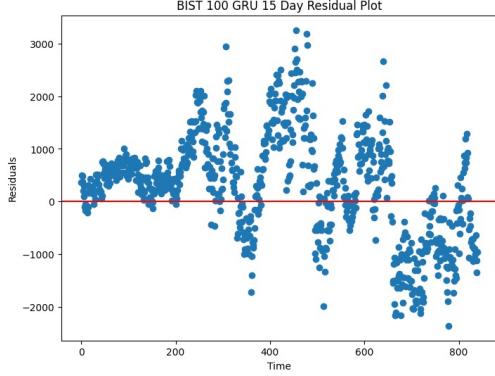


Fig. 16: BIST 100 15 Day Residual Plot for GRU

TABLE V: Evaluation Metrics for 15 Day GRU

TRAIN RMSE:	209.57130246953744
TRAIN R2:	0.9955001631155745
TRAIN MAE:	144.45010998128254
TRAIN MAPE:	0.030962503286941046
TRAIN ACC:	97.48977566992684
TEST RMSE:	1042.1123697213627
TEST R2:	0.9030076085272709
TEST MAE:	840.0230826590401
TEST MAPE:	0.17816088732563468
TEST ACC:	87.19729140461824

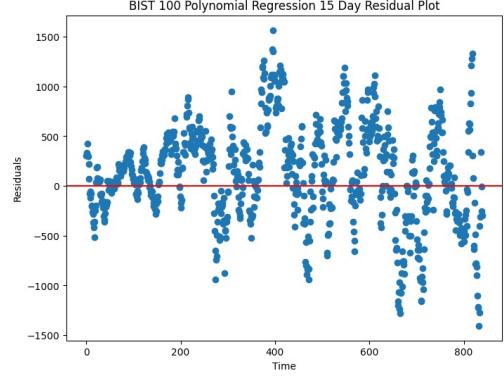


Fig. 19: BIST 100 15 Day Residual Plot for Polynomail Regression

TABLE VI: Evaluation Metrics for 15 Day Polynomial Regression

TRAIN RMSE:	1.3435584682486656e-12
TRAIN R2:	1.0
TRAIN MAE:	8.418781016232623e-13
TRAIN MAPE:	1.678757668829935e-16
TRAIN ACC:	99.99999999999999
TEST RMSE:	504.4491356266948
TEST R2:	0.9725891521040834
TEST MAE:	395.69739293579914
TEST MAPE:	0.07067451191575563
TEST ACC:	93.96921522957058

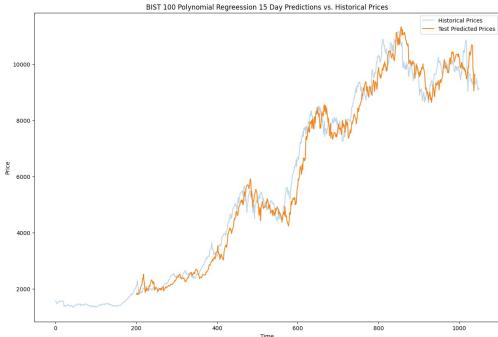


Fig. 17: 15 Day Predictions of BIST 100 Index Using Polynomial Regression and Actual Values

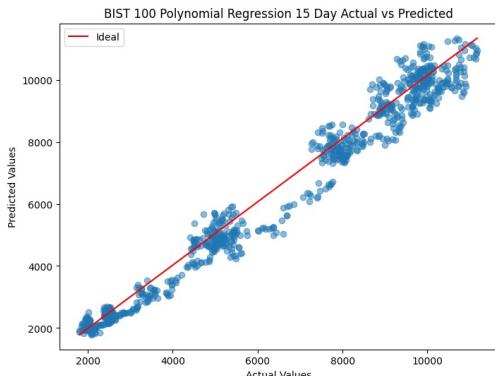


Fig. 18: BIST 100 15 Day Actual vs Prediction Plot for Polynomail Regression

C. Comparison of Models

For 1-day predictions, if we compare the evaluation metrics of LSTM, GRU and polynomial regression, we can see that GRU performs slightly better than LSTM, and polynomial regression gives the best performance. All of the models have approximately 99% R^2 , which means that all models are able to explain the variability of the index. Also, from test MAPE values, we can see that on average, LSTM predictions are off by 1.87%, GRU predictions by 1.7%, and polynomial regression predictions by 1.6% off from the actual values, and accuracies were 98.175%, 98.5% for LSTM, GRU, and polynomial regression, respectively. When we examine the actual vs. predicted plots, we can see that the predictions are very close to the ideal predictions, which indicates that our models were successful to make 1-day predictions. Residual plots, however, shows that residues are getting larger for following time steps caused by high volatility.

For the 15-day predictions, we see that our evaluation metrics indicate poorer performance than the 1-day predictions as expected. LSTM model is found to explain the 92.36% variability of the index, with 89.80% accuracy, making 668.7 points error on average, which corresponds to predictions being 16% off on average from true values. GRU performed worse than LSTM with R^2 of 90%, and 87% accuracy. On average it made 840 points of error, predictions are off by 17.81% from actual values. Lastly, polynomial regression had better performance than both LSTM, and GRU, with 93% accuracy, 97% R^2 , and much lower mean average error of

395.7 points with its predictions being off by 7% percent. All of actual and predicted plots showed similar patterns. All models had problems with predicting a certain range of values where the price moves sharply toward a direction. One can observe that actual vs. predicted plot of GRU is worse than LSTM, and although facing similar problem on the same range of values, polynomial regression had better plot than both. Examining the residual plots, those sharp movements of the index also caused residues increasing with time.

VII. CONCLUSION

In conclusion, this study compares the LSTM, GRU and Polynomial Regression models for forecasting the BIST 100 index. Using the dataset described in detail earlier, both 1-day and 15-day forecasts are made and the short and medium-term performance metrics of the models are demonstrated and compared. The dataset used in this study is not only limited to technical indicators and daily price data, but also macroeconomic and world market changes.

Our results indicates that our LSTM, GRU, and polynomial regression performed well to predict the 1-day ahead predictions and 15-day predictions. Our evaluation metrics and plots showed that our models are able to explain a great portion of variability of index with making reasonable errors, although predictions can be less accurate during times of significantly increased volatility.

In future studies, attention-based models that can learn much more complex structures (e.g. Transformer and Temporal Fusion Transformer) can be tested to make much longer-term predictions with higher accuracy. In addition, text-based external sources such as real-time news feeds and social media can be integrated into the model using Sentiment Analysis to get much more accurate results. Finally, the prediction accuracy of the model can be improved by using feature selection methods or ensemble models (using more than one model together).

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