BIST 100 INDEX PREDICTION

Using LSTM, GRU, and polynomial regression,
1-day and 15-day BIST 100 Index predictions are made.

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CONTENTS

0.985
20,000
3.030
112,968
1.950
176,745
1.260
1,349,237
0.250
100,000
0.396
43,409
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I. INTRODUCTION

Importance of Financial Forecasting

- Complexity of Financial Markets

Financial systems are affected by political, economic, and even psychological factors.

- Volatility in Emerging Markets

In developing countries like Turkey, sudden market shifts are more frequent and harder to predict.

- BIST 100 as an Economic Indicator of Turkey

The BIST 100 shows the performance of Turkey’s top companies and indicates economic stability.

Challenges of Forecasting and the Role of ANN

- Time Series are Nonlinear, Noisy

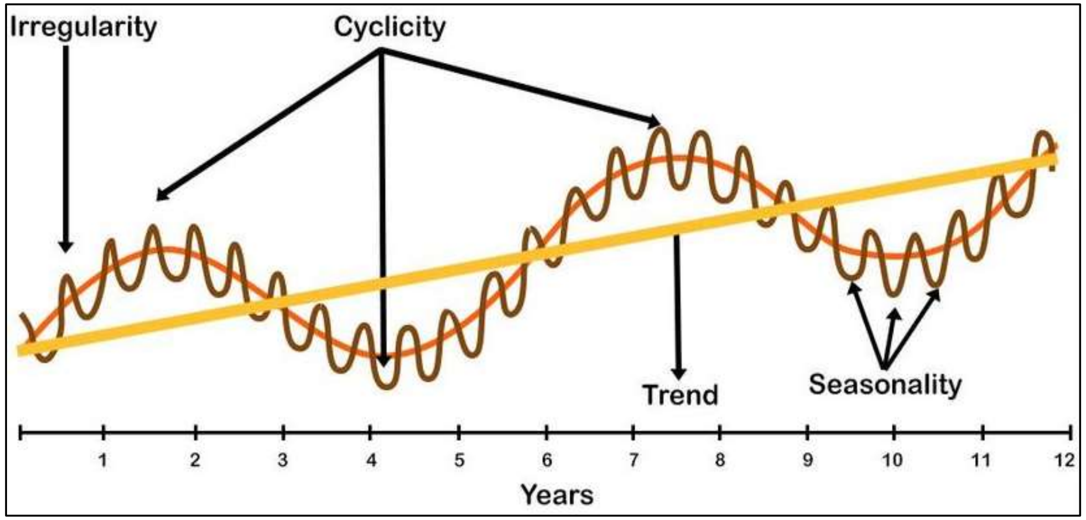
Financial time series often show irregular, unpredictable patterns over time.

- Traditional Models are Limited

Models like ARIMA cannot adapt well to sudden changes or hidden patterns in the data.

- ANN Offers Flexibility and Adaptability

Artificial Neural Networks can learn complex behaviors from data without strict assumptions.



Why LSTM and GRU?

- RNN Limitations (vanishing gradient)

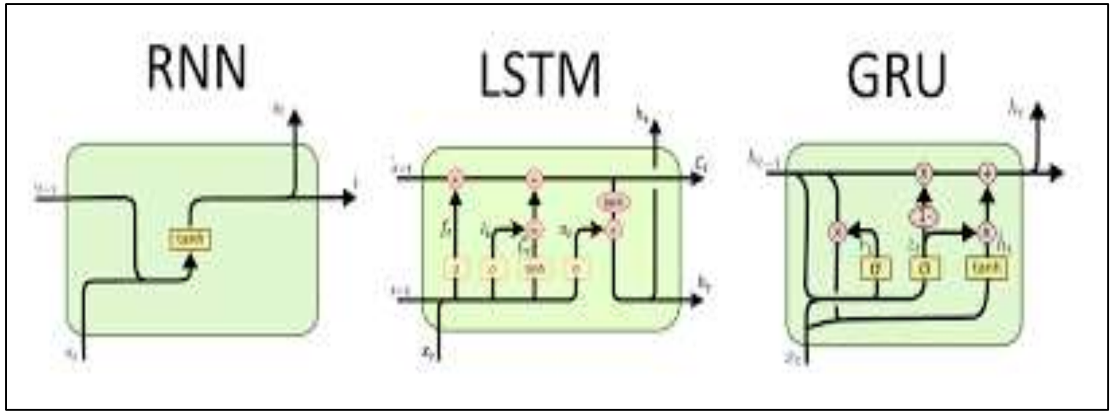
Traditional RNNs have a problem with remembering long-term information during training.

- LSTM and GRU as Advanced RNN Types

These models use gating mechanisms to manage information flow and memory.

- Strength in Handling Long-Term Dependencies

Powerful in handling long-term dependencies and sudden changes.



Turkish Economic Context & Dataset Overview

- Turkey's Sensitivity to Internal/External Factors

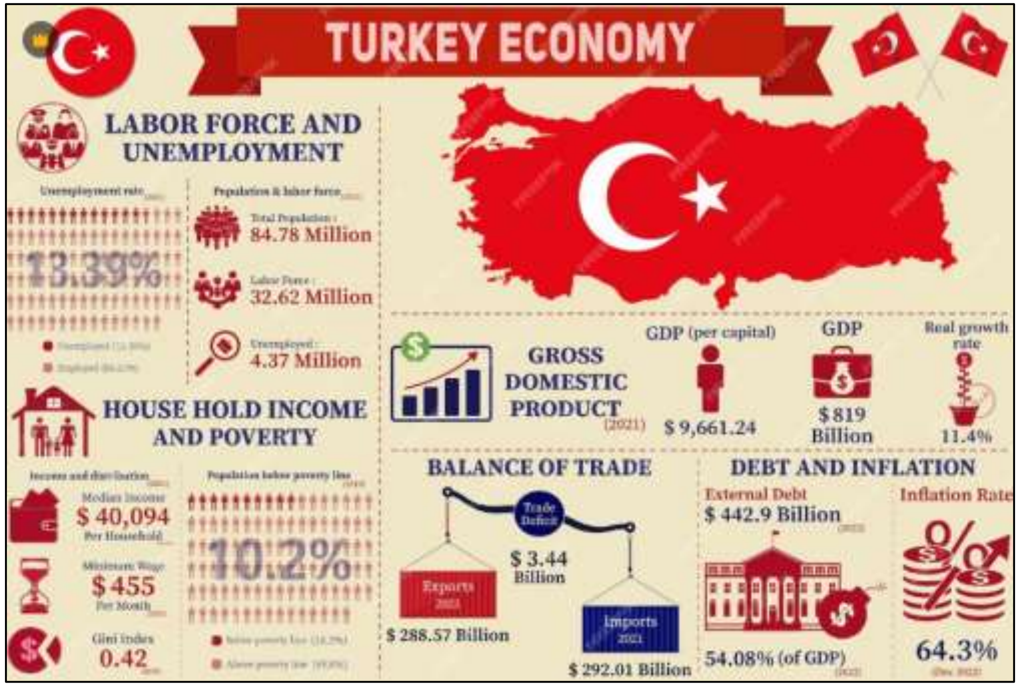
Exchange rates, inflation, and global crises heavily impact the Turkish market.

- Dataset Range: 2021–2025

The study uses 4+ years of daily data, capturing both local and global indices.

- Wide Range of Features: Macroeconomic, Global, technical

The dataset includes over 50 features from various economic and financial sources.



II. LITERATURE REVIEW

ANN in Financial Forecasting

- ANN is Increasingly Used in Finance

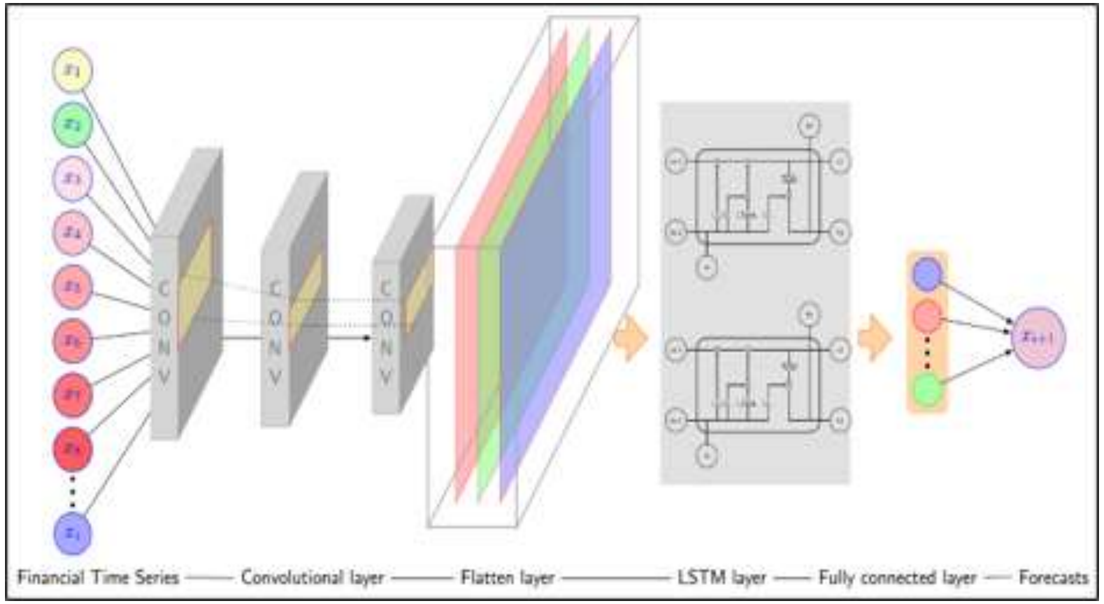
Neural networks are now common in financial forecasting due to their accuracy.

- Strong at Modeling Non-linear, Multivariate Relationships

ANNs can handle multiple interacting features better than traditional models.

- More Successful in Short-term Forecasting

Especially for short-term behaviours, neural networks perform better than classic methods.



Past Studies on BIST 100

- Most Studies are Limited in Time and Features

Earlier research often used short datasets and lacked diverse inputs.

- Use Only One Model

Many studies tested just one prediction model, missing comparison chance.

- Lack Flexibility for Real-World Use

Models not tested on real-world-like conditions often fail in practice.

Deep Learning Strategies in the Literature

- LSTM and GRU Outperform Classical Models

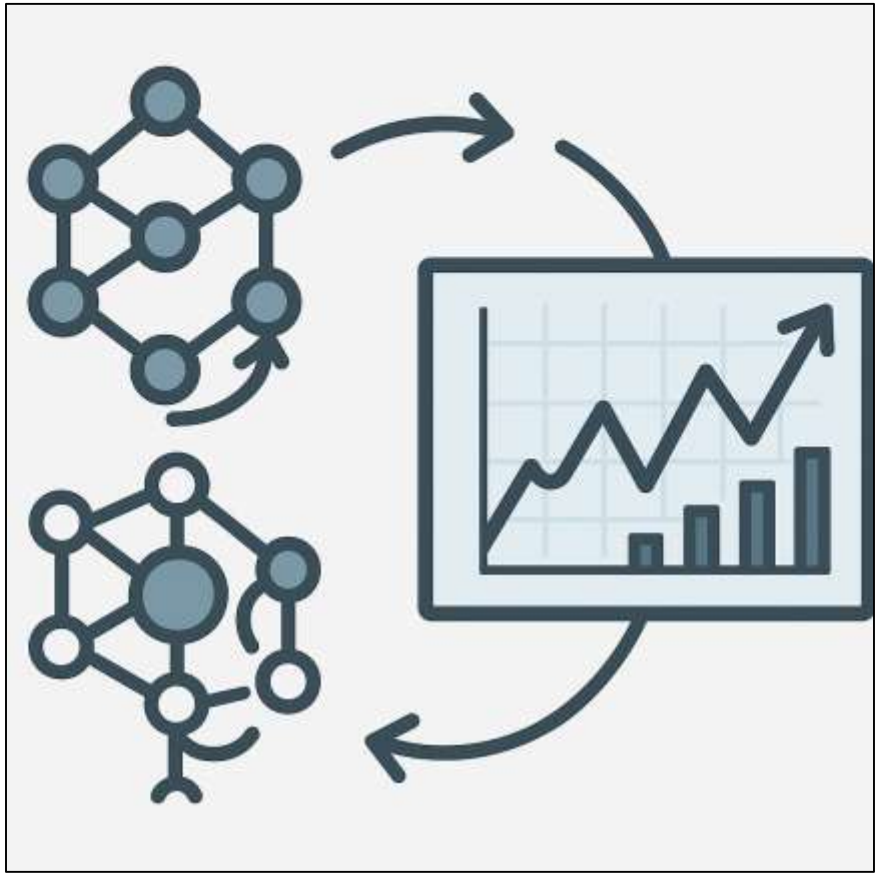
These deep learning models handle complex temporal patterns better.

- Better at Learning Time Dependencies

They remember past information more effectively than traditional approaches.

- Success in Volatile Series Like Stock Prices

They are robust to noise and sudden changes in financial data.



Contribution of This Study

- Covers ~4 Years of Data

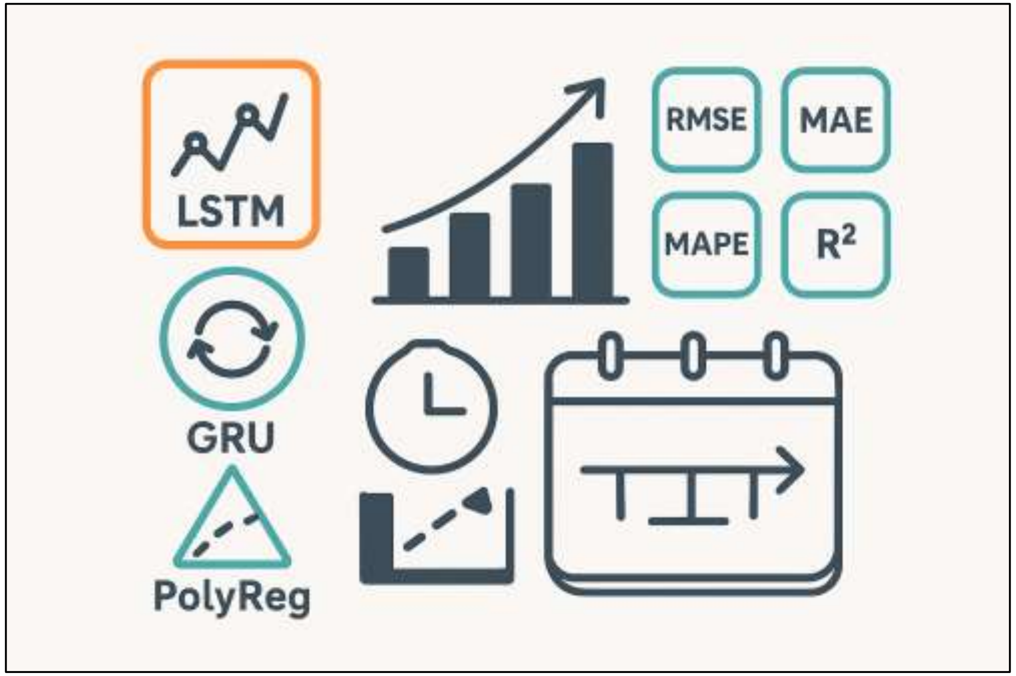
The study includes a long and rich dataset for more realistic results.

- Compares ANN with Classical Models

LSTM, GRU, and polynomial regression are tested.

Uses Multiple Evaluation Metrics for Better Analysis

Metrics like RMSE, MAE, MAPE, and R^2 give a better overall view of the results.



Future Works

- Try Transformer-Based Models

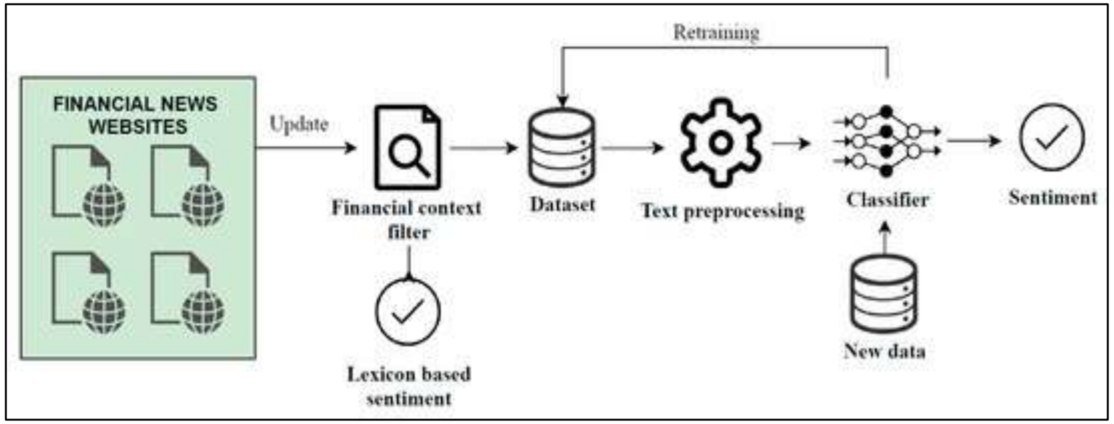
Advanced models like Transformers may improve long-term forecasting..

- Sentiment Analysis

Adding real-time text data could catch market sentiment more effectively.

- Use Feature Selection or Ensemble Models

Selecting the best features or combining models may improve performance.



III. DATASET

Dataset Overview

- **Period:** February 19 2021 – May 6 2025
- **Target:** BIST 100 closing price
- **Total features:** 59
    - Price action, technical indicators, macro variables, temporal features, inter-market links
- **Primary sources:** Investing.com (prices, yields, CDS, global indices) & TradingEconomics.com (macroeconomic releases)
- **Extractions & preprocessing:** Data merged in MATLAB, engineered and exported to Python for modeling

FEATURE GROUPS

- **Daily Price Action**
  - Open, high, low, close, volume
- **Technical Indicators**
  - EMA 20/50/200
  - RSI (14-day)
  - MACD (line, signal, histogram)
  - Bollinger Bands
  - ATR (14-day)
- **Cross-Market Metrics**
  - Turkey 2- & 10-year bond yields & CDS
  - USD/TRY, XAU/USD
  - VIX, EEM, S&P 500, DAX, Nikkei
- **Macroeconomic Data**
  - PMI, M2, inflation, policy & market rates, unemployment
  - GDP growth, Fed funds rate
- **Temporal Features**
  - Day, week, month, quarter, year encoded as sine & cosine waves

DATA CLEANING & ENGINEERING

- **Missing / inconsistent records: Manual inspection → resampling & correction**
- **No look-ahead bias: Future information removed**
- **Cyclic time variables:**
- **Converted with sin(2πx/max) & cos(2πx/max) to respect periodicity**
- **Technical indicators: Generated via MATLAB Financial Toolbox + custom code**
- **Macroeconomic release tracking:**
- ***feature_update* (binary flag on release day)**
- ***days_since_update* (elapsed days since last release)**

SCALING & MODEL READINESS

- **Window-based normalization**
- MinMaxScaler & StandardScaler fitted **only on training windows** to avoid leakage
- Binary flags and sine/cosine time features kept unscaled
- **Dimensionality reduction:** Not applied (PCA optional)
- **Outcome:** Clean, leakage-free 59-dimensional feature matrix ready for daily BIST 100 closing-price prediction.

IV. SYSTEM MODEL

System Overview

- **Goal:** Predict BIST 100 closing price **1 day** and **15 days** ahead
- **Models compared:**
  - Long Short-Term Memory (**LSTM**)
  - Gated Recurrent Unit (**GRU**)
  - **Polynomial Regression** (baseline for non-linear trends)
- **Validation focus:** Avoid over-/under-fitting & data-leakage
- **Assessment:** Combine **five quantitative metrics** with **visual diagnostics** (actual vs predicted, residual plots)

QUANTITATIVE EVALUATION METRICS

Metric	What it measures	Key point
RMSE	√(mean squared error)	Penalises large errors; same unit as price
R^2	Goodness-of-fit (0–1)	1 ≈ perfect explanation
MAE	Mean absolute error	Intuitive size of typical error
MAPE	% error of each point	Size-independent comparison
Accuracy	1 – (MAE / mean price)	Closer to 100 % → better

$$\mathrm{RMSE} = \sqrt{\left[(1 / n) \cdot \Sigma (y_i - \hat{y}_i)^2 \right]}$$

$$R^2 = 1 - \Sigma (y_i - \hat{y}_i)^2 \; / \; \Sigma (y_i - \bar{y})^2$$

$$\mathrm{MAE} = (1 / n) \cdot \Sigma \mid y_i - \hat{y}_i \mid$$

$$\mathrm{MAPE}\ (\%) = (100 / n) \cdot \Sigma \mid (y_i - \hat{y}_i) / y_i \mid$$

$$\mathrm{Accuracy} = (1 - \mathrm{MAE} / \bar{y}) \times 100$$

LSTM ARCHITECTURE

Why LSTM?

• Captures long-range dependencies and handles the volatility typical of stock indices.

Gate equations (per time step t)

Forget gate: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$

Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$

Candidate cell state:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Cell-state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Output gate: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$

Hidden output: $h_t = o_t \odot \tanh(C_t)$

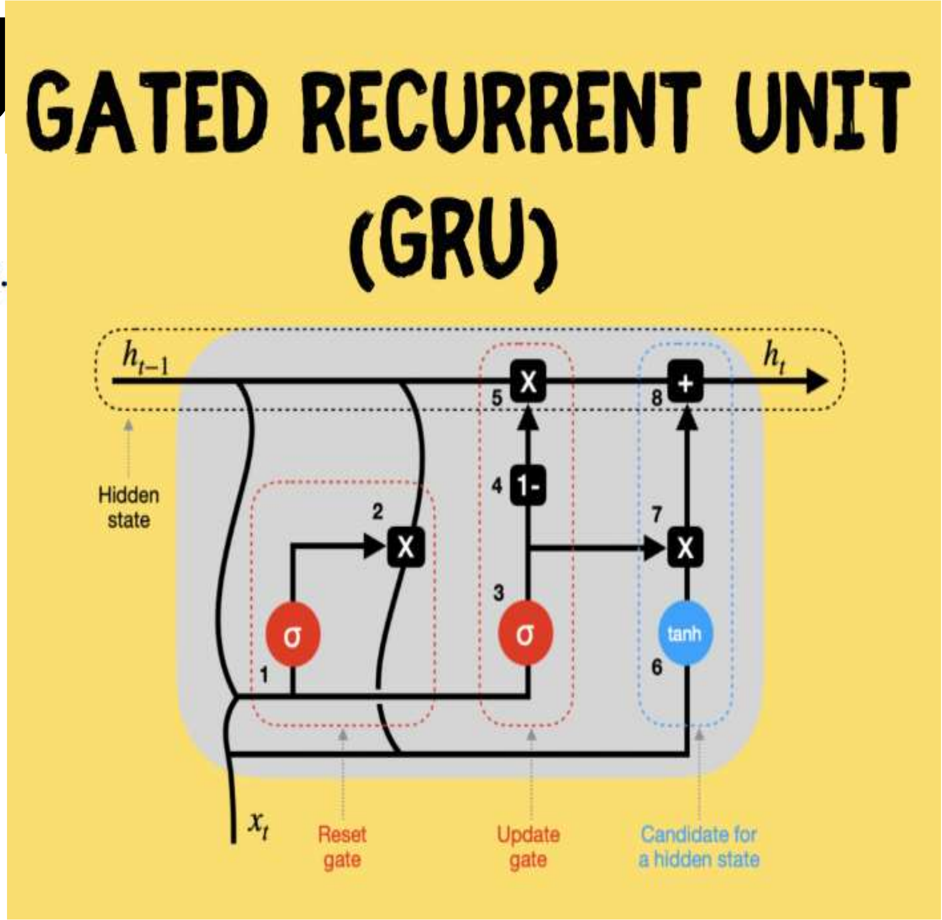
Strengths

• Excels at multi-step forecasts

• Retains relevant past information

• More parameters → heavier to train than GRU

GRU ARCHITECTU



Motivation

- Similar accuracy to LSTM, but with fewer parameters → faster training.

Gate equations (per time step t)

Update gate: $z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$

Reset gate: $r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$

Candidate hidden state:

$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t])$$

Final hidden state:

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t$$

Typical use

- Short- and medium-term forecasts where training speed is crucial.

POLYNOMIAL REGRESSION BASELINE

- **Purpose:** Simple benchmark for capturing near-term non-linear trends
- **Model equation:**

  $y = \beta_0 + \beta_1 x + \beta_2 x^2 + \ldots + \beta_n x^n + \varepsilon$
- **Key considerations:**
- Degree nnn tunes flexibility (higher ⇒ risk of overfit)
- Linear least-squares after feature expansion
- Serves as sanity-check against deep models

TRAINING PROTOCOL

- **Rolling-window training** to mimic live trading
- **Hyper-parameter tuning** (units, layers, dropout, polynomial degree) via grid search
- **Regularisation:**
- Dropout & early stopping for LSTM/GRU
- Ridge penalty for high-degree polynomials
- **Data leakage safeguards:**
- Train/validation split strictly chronological
- Scalers fit on training windows only

QUALITATIVE DIAGNOSTICS

- **Actual vs Predicted plots** highlight trend-tracking ability
- **Residual plots** (errors over time & histogram) expose bias, heteroscedasticity, outliers
- **Interpretation strategy:**
- Random scatter ≈ well-calibrated model
- Patterns ⇒ systematic error → revisit features or model complexity
- **Result summary:** LSTM excelled in 15-day horizon; GRU offered fastest convergence; polynomial fit competitive for single-day moves but degraded on longer windows.

V. PROPOSED APPROACH

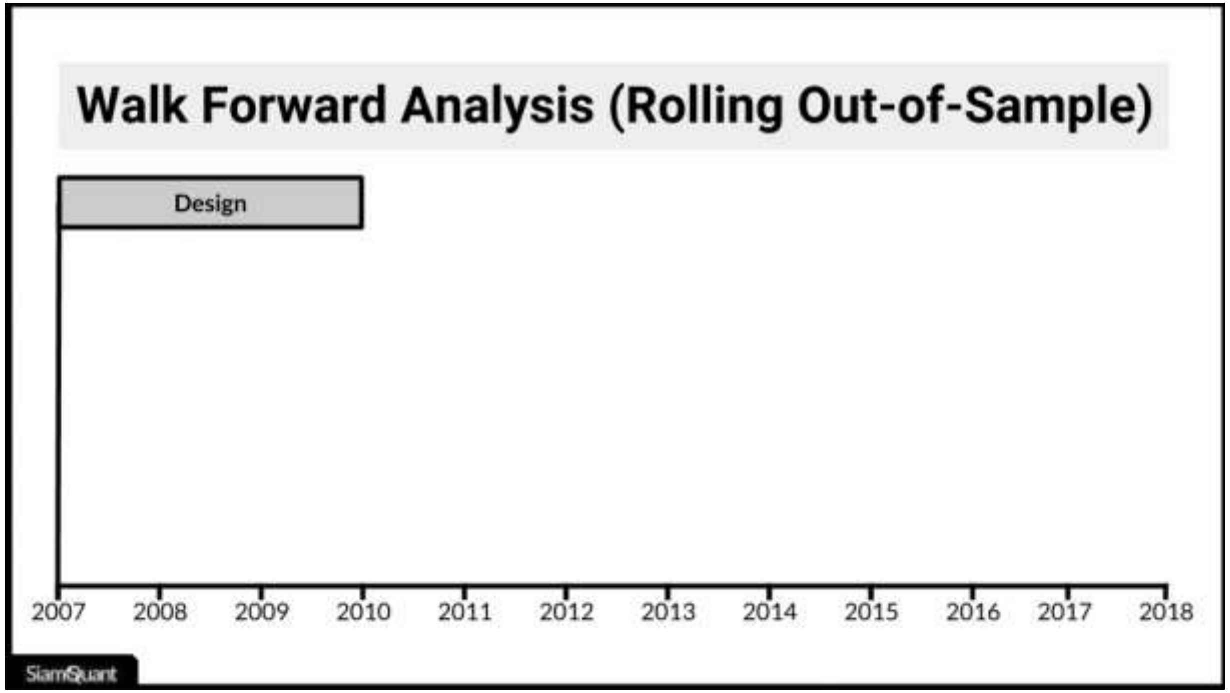
We propose two different approaches, one for 1-day predictions and the other for 15-day predictions

WALK-FORWARD ANALYSIS

- In walk-forward analysis, we divide our samples into multiple "walks" in which we train and immediately test.
- After each walk, we slide our samples and move through new samples in each walk.
- This is continued as we reach the last samples whose number is enough to "walk" through.

WALK-FORWARD ANALYSIS

- We determine how many training and test samples there will be at the beginning, and also how many sample we will shift for the next walk.
- The case where we shift the same number of testing samples is illustrated in the figure beside.



Adapted from https://www.siamquant.com/walk-forward/

PROPOSED APPROACH FOR 1-DAY PREDICTIONS

- For 1-day predictions, we use the walk-forward analysis in which our model trains for 10 models and tests for 1 day for each walk. Upon a walk, we shift our indices by 11, for our next walk.
- In this case, our training and test samples are not overlapping.

PROPOSED APPROACH FOR 15-DAY PREDICTIONS

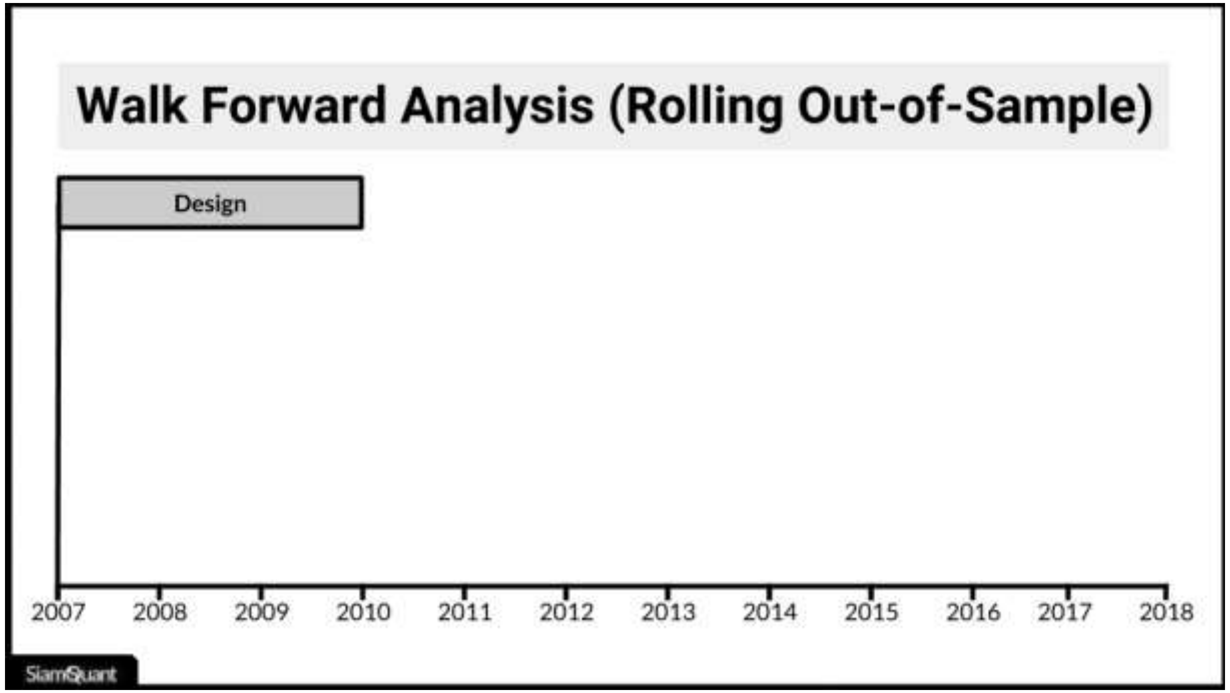
- For 15-day predictions the same logic is used, but in this case, we make sure that our samples are spaced by 15 days. Otherwise, we will end up with overlapping training and test prediction that will make harder us to evaluate and plot them.

PROPOSED APPROACH FOR 15-DAY PREDICTIONS

- Furthermore, unlike the set-up we used for our 1-day predictions, we set the shift equal to the number of test samples, which in our case is 1. We train for 10 samples, and test for 1 sample in each walk, then shift our indices by 1 for the next walk. For this case, we have overlapping training samples and predictions, but our test predictions don’t overlap.

PROPOSED APPROACH FOR 15-DAY PREDICTIONS

- Since our test predictions don’t overlap unlike the training predictions, we depict all our test predictions in a single plot.



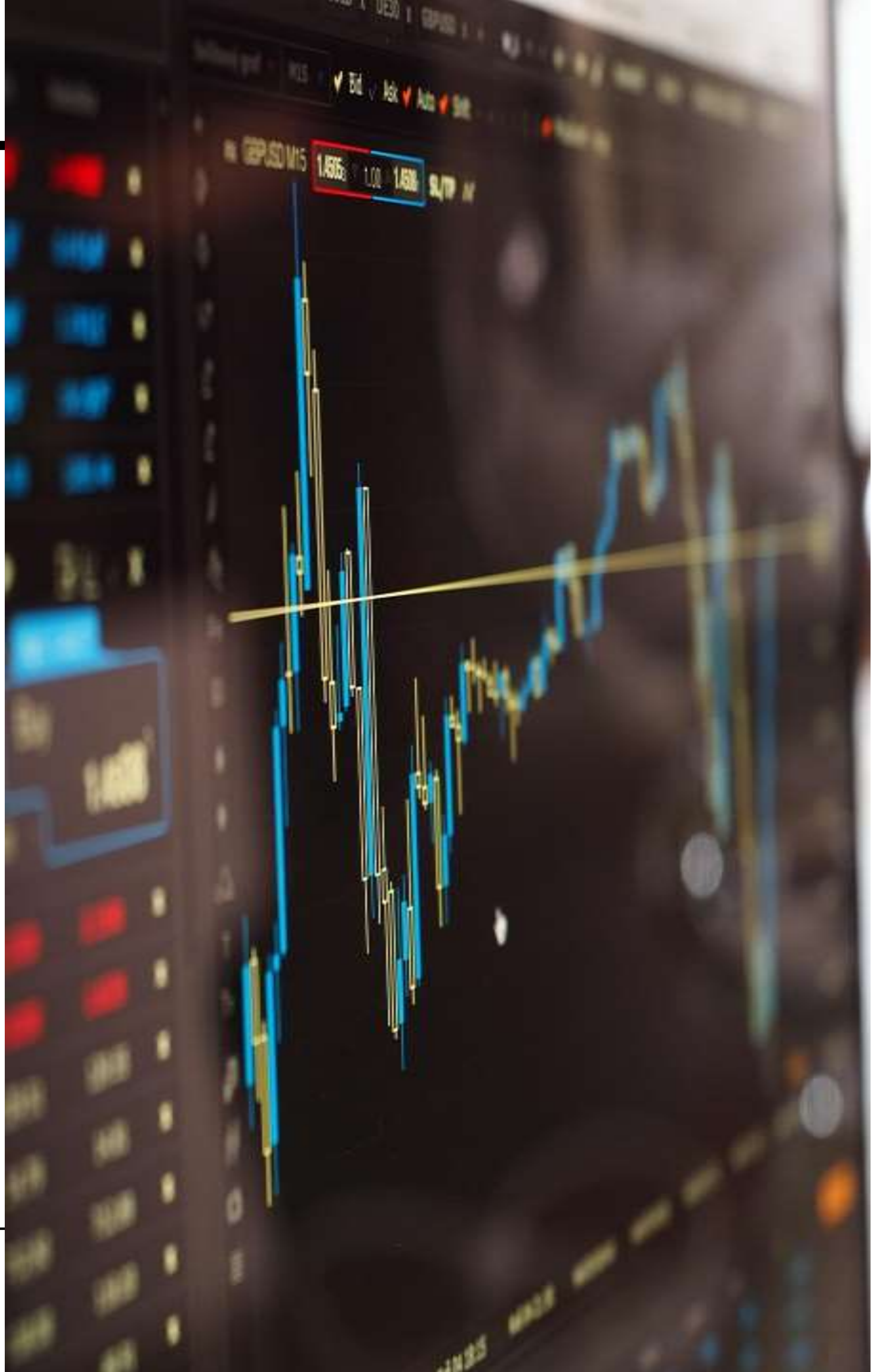
Adapted from https://www.siamquant.com/walk-forward/

PROPOSED APPROACH FOR 15-DAY PREDICTIONS

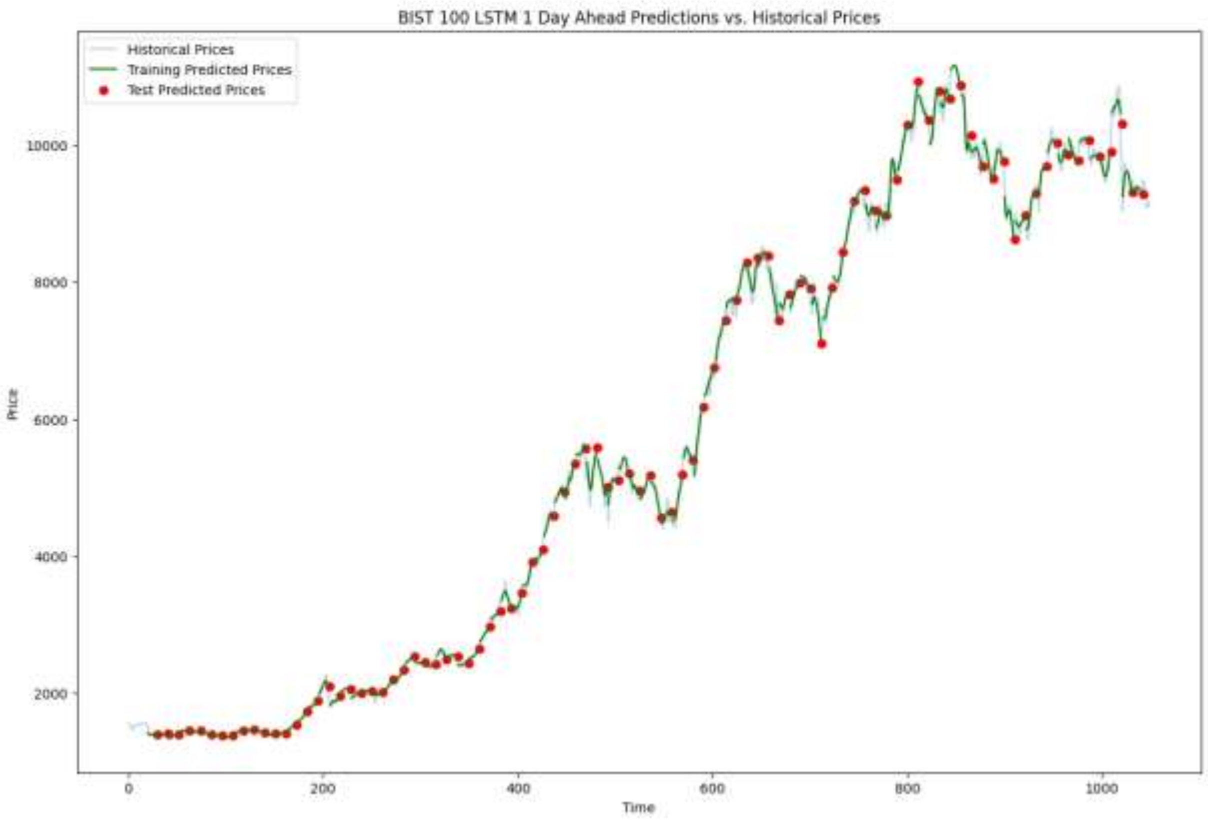
- Using LSTM, GRU, and polynomial regression, these explained set-ups for 1-day and 15-day predictions are implemented.
- In LSTM, and GRU we use "tanh" activation.

VI. COMPARASION OF MODELS AND NUMERICAL VALUES

A detailed comparison between LSTM, GRU, and polynomial regression from evaluation metrics and plots

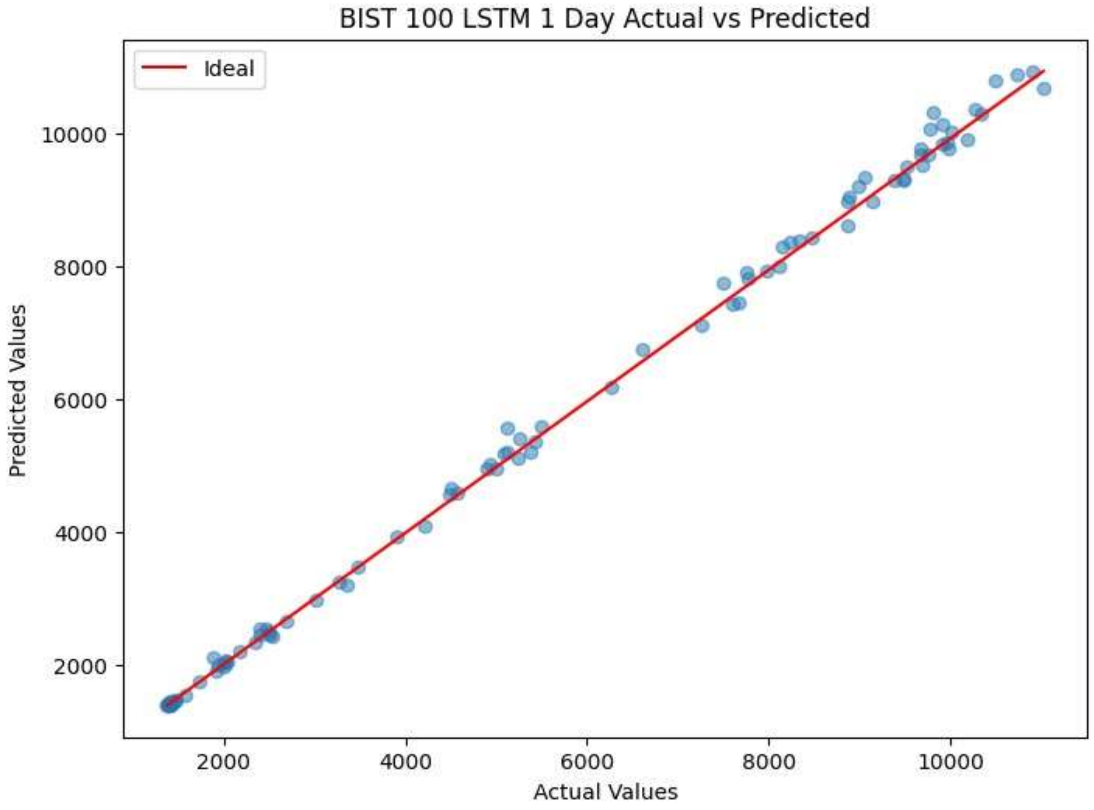


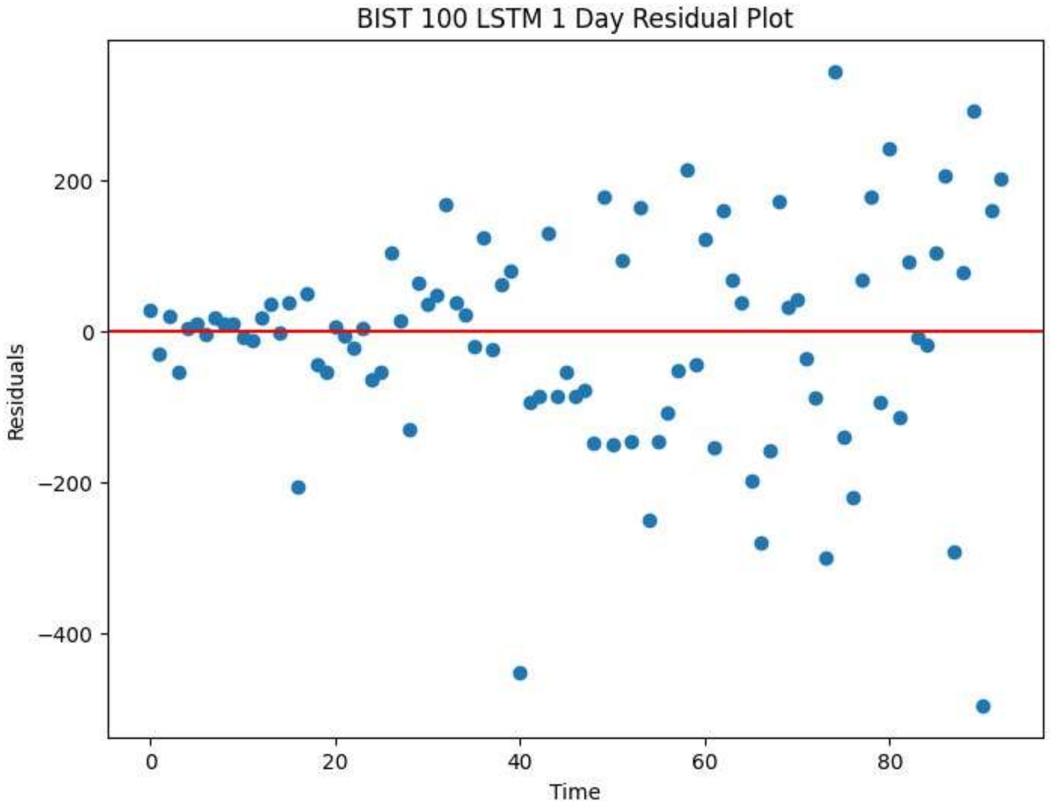
1 DAY PREDICTIONS, LSTM



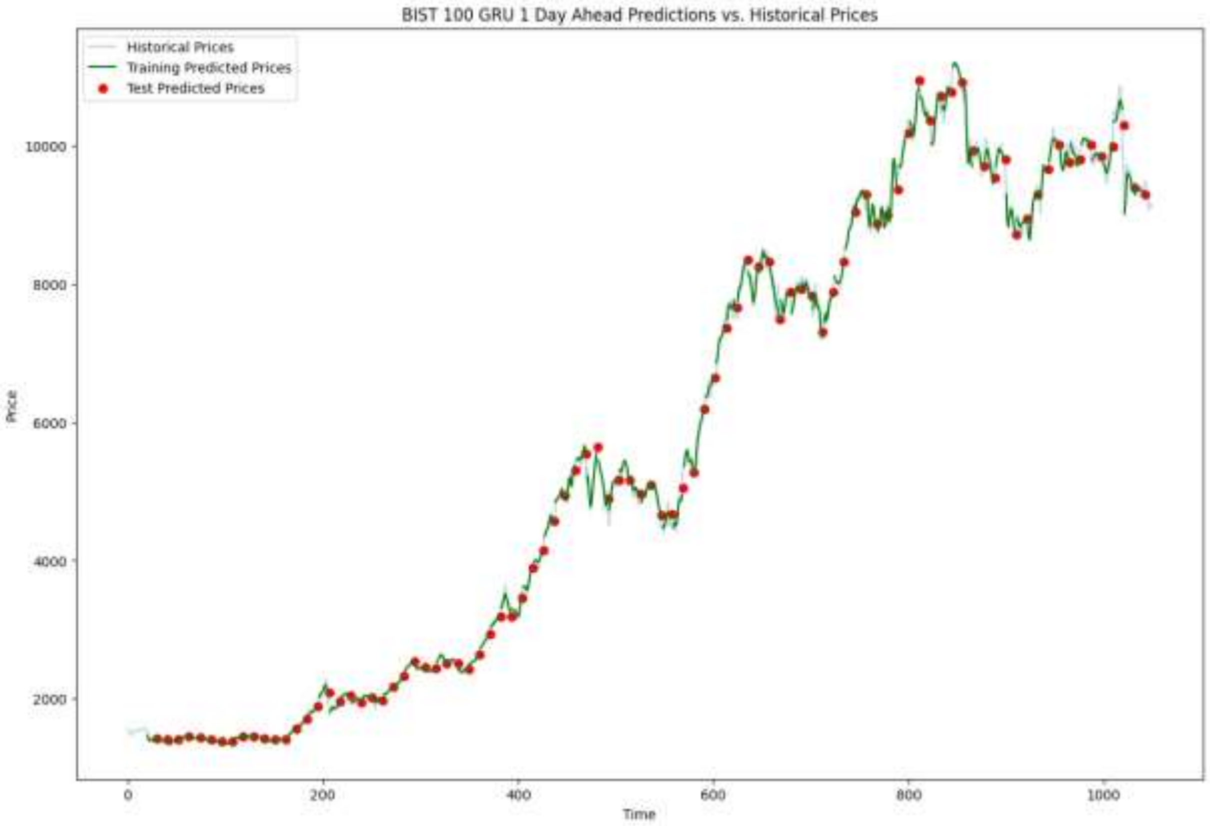
	TRAIN	TEST
RMSE	67.98	142.62
R^2	0.9995	0.9981
MAE	42.66	104.1519
MAPE	0.007	0.0186
Accuracy	99.24	98.175

1-DAY PREDICTIONS, LSTM





1-DAY PREDICTIONS, GRU



	TRAIN	TEST
RMSE	63.56	131.39
R^2	0.9996	0.9984
MAE	40.165	93.408
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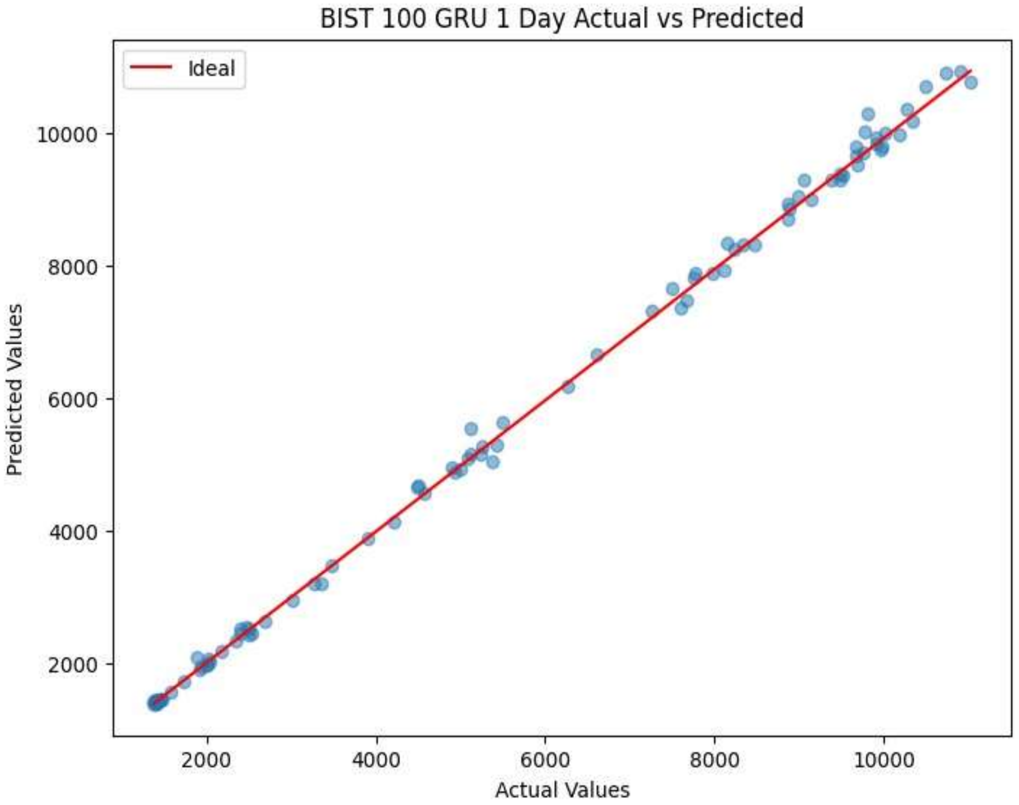
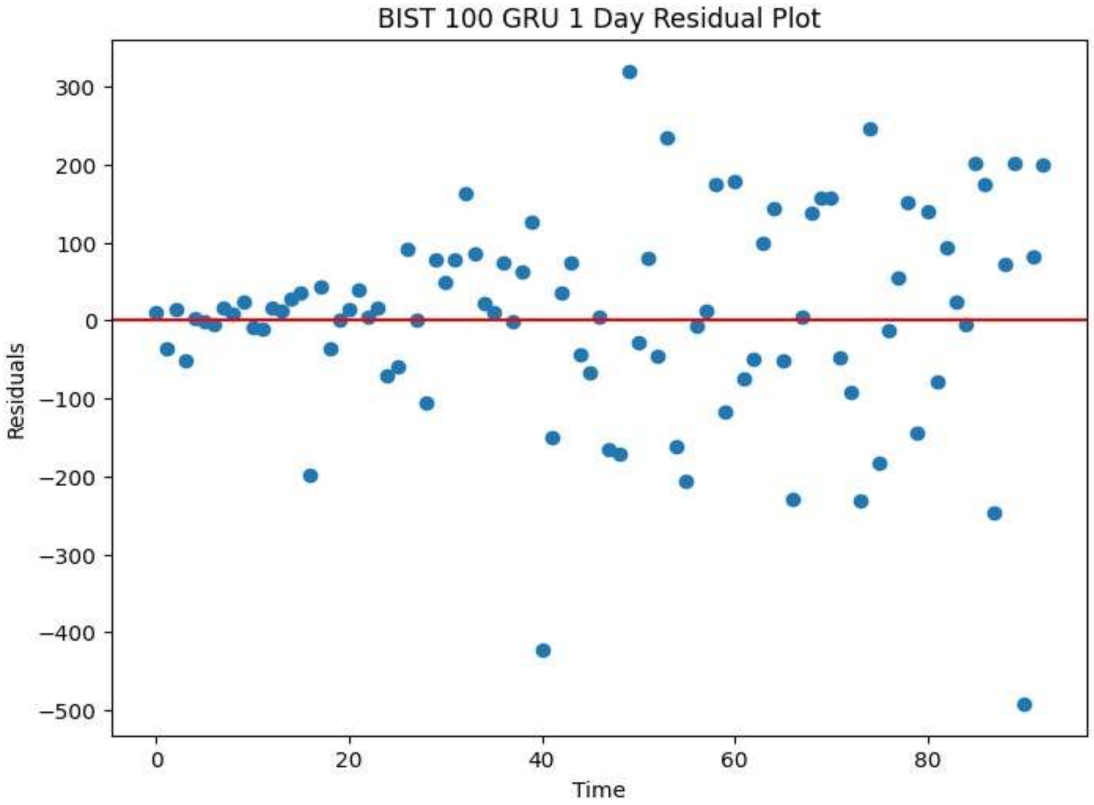
Accuracy	99.29	98.363

1-DAY PREDICTIONS, GRU

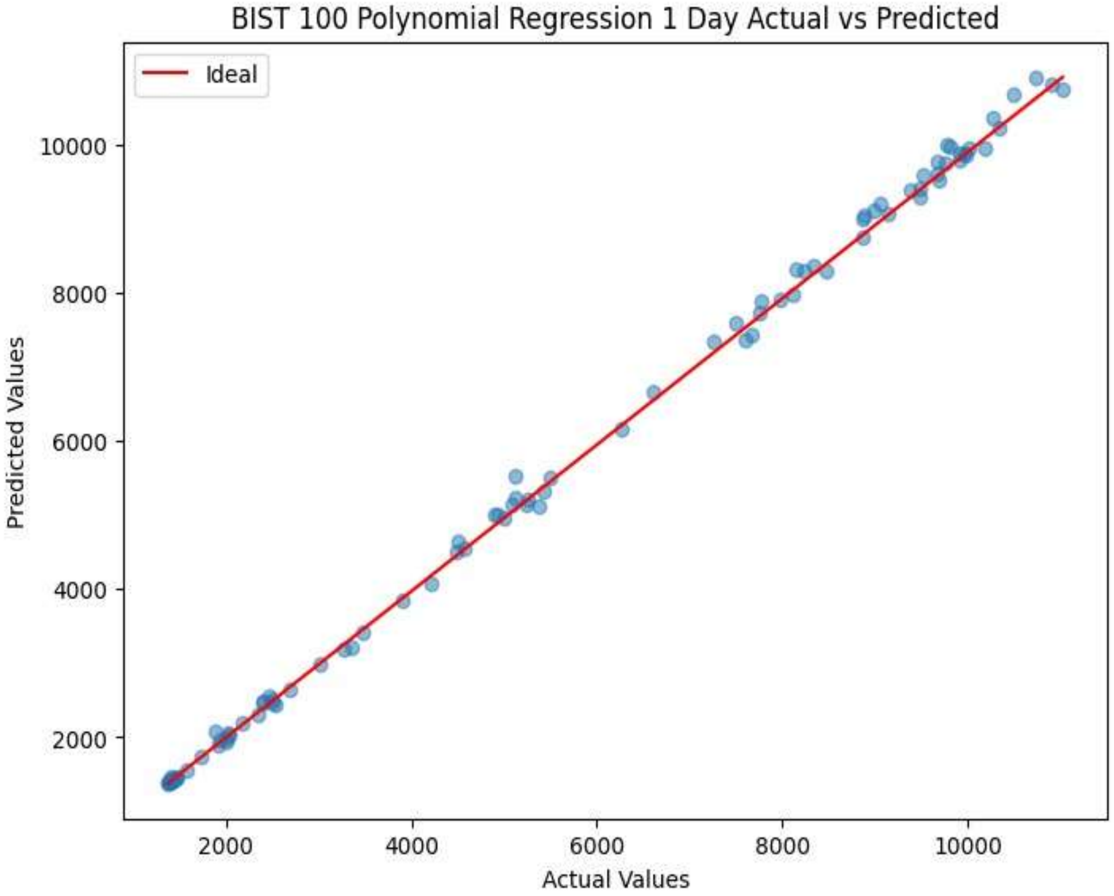


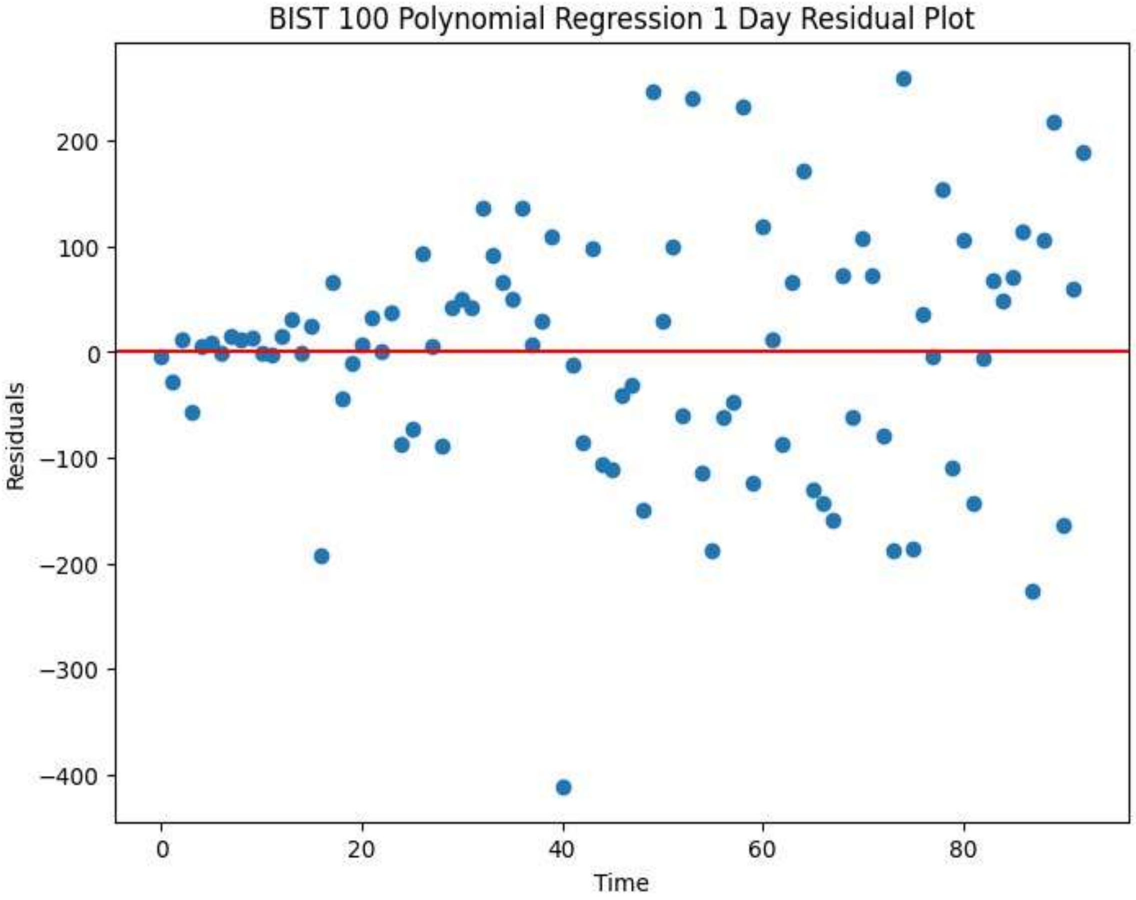


1-DAY PREDICTIONS, POLYNOMIAL REGRESSION

	TRAIN	TEST
RMSE	3.30e-13	113.78
R^2	1	0.9988
MAE	9.53e-14	85.644
MAPE	1.785e-17	0.016
Accuracy	100	98.499

1-DAY PREDICTIONS, POLYNOMIAL REGRESSION





COMPARISON, 1-DAY PREDICTIONS

LSTM

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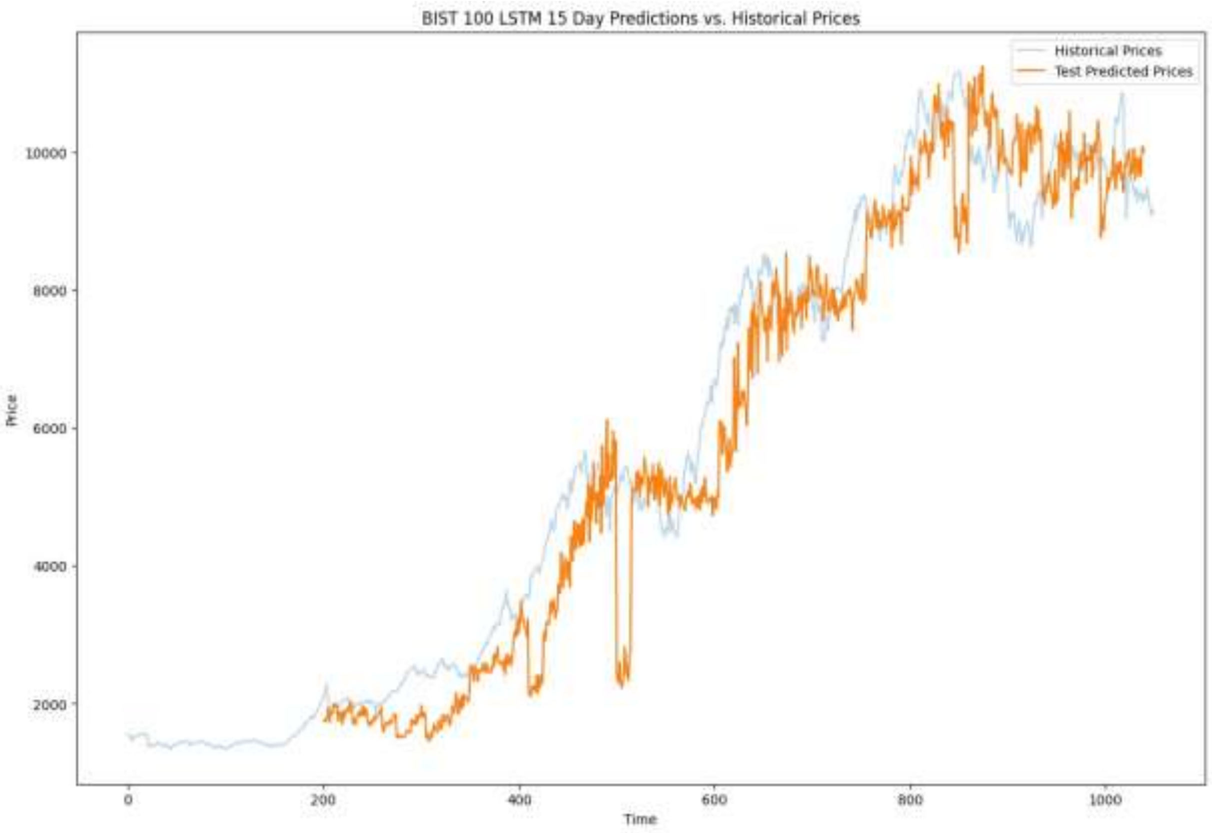
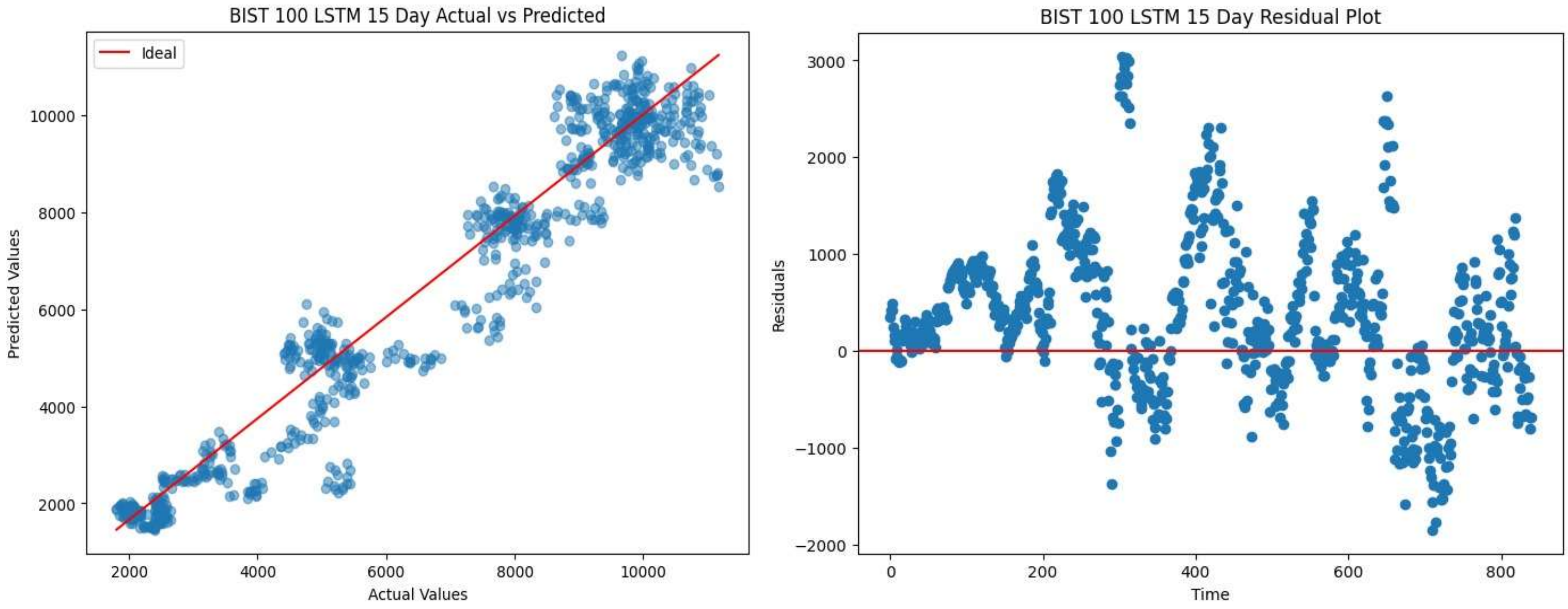
15 DAY PREDICTIONS, LSTM

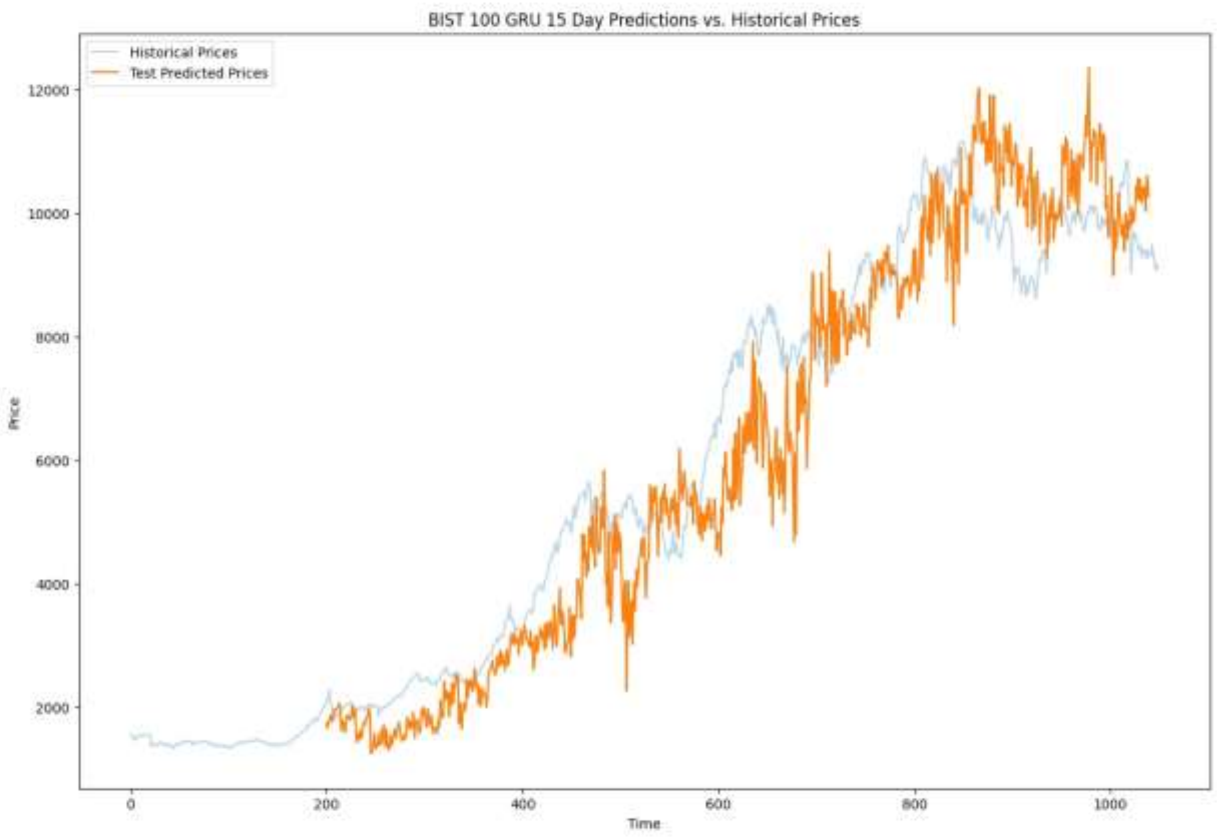


	TRAIN	TEST
RMSE	153.164	883.97
R^2	0.997	0.92369
MAE	104.82	668.718
MAPE	0.0224	0.1641
Accuracy	98.178	89.808

15-DAY PREDICTIONS, LSTM

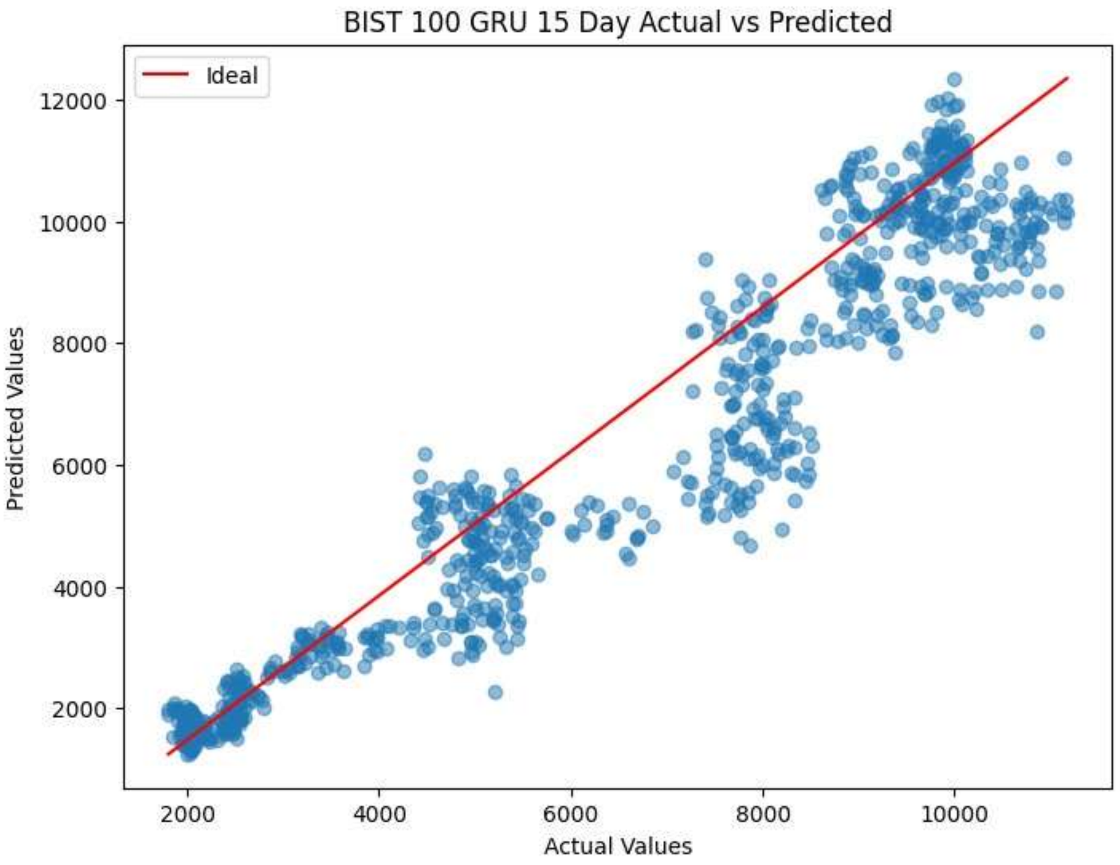


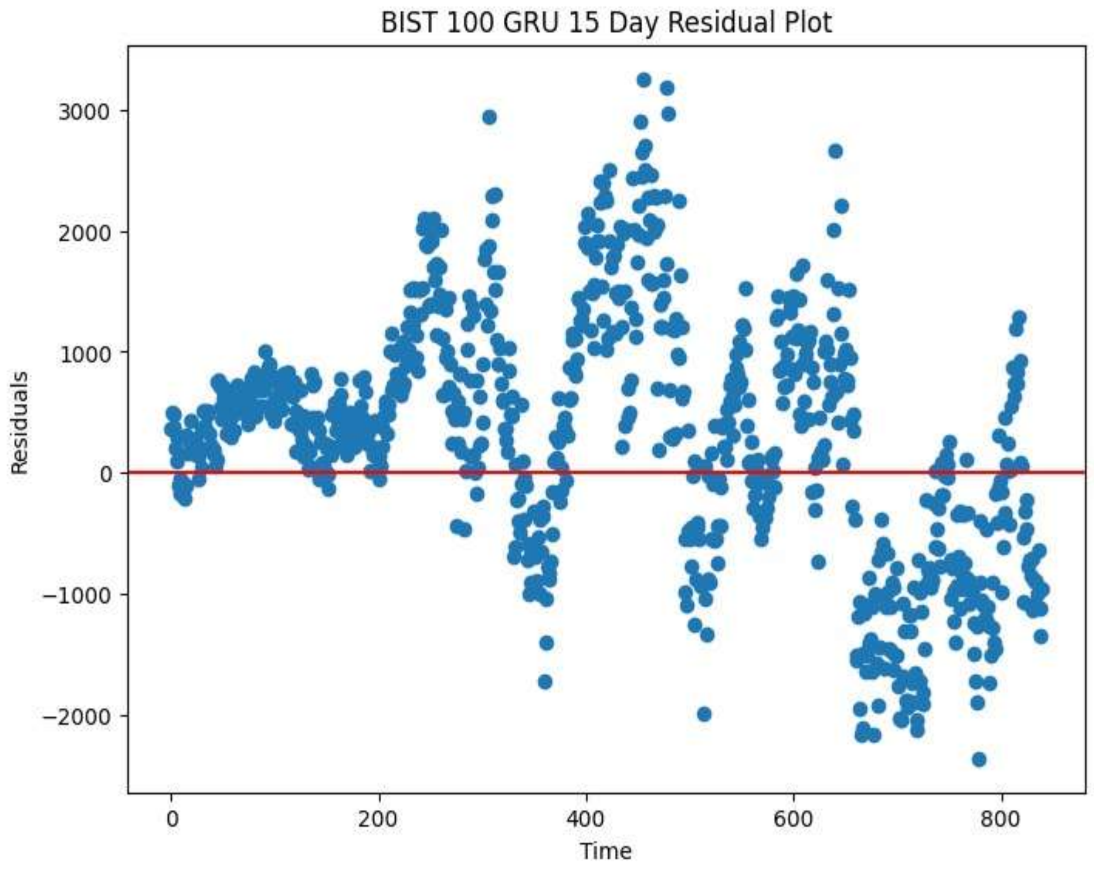
15-DAY PREDICTIONS, GRU



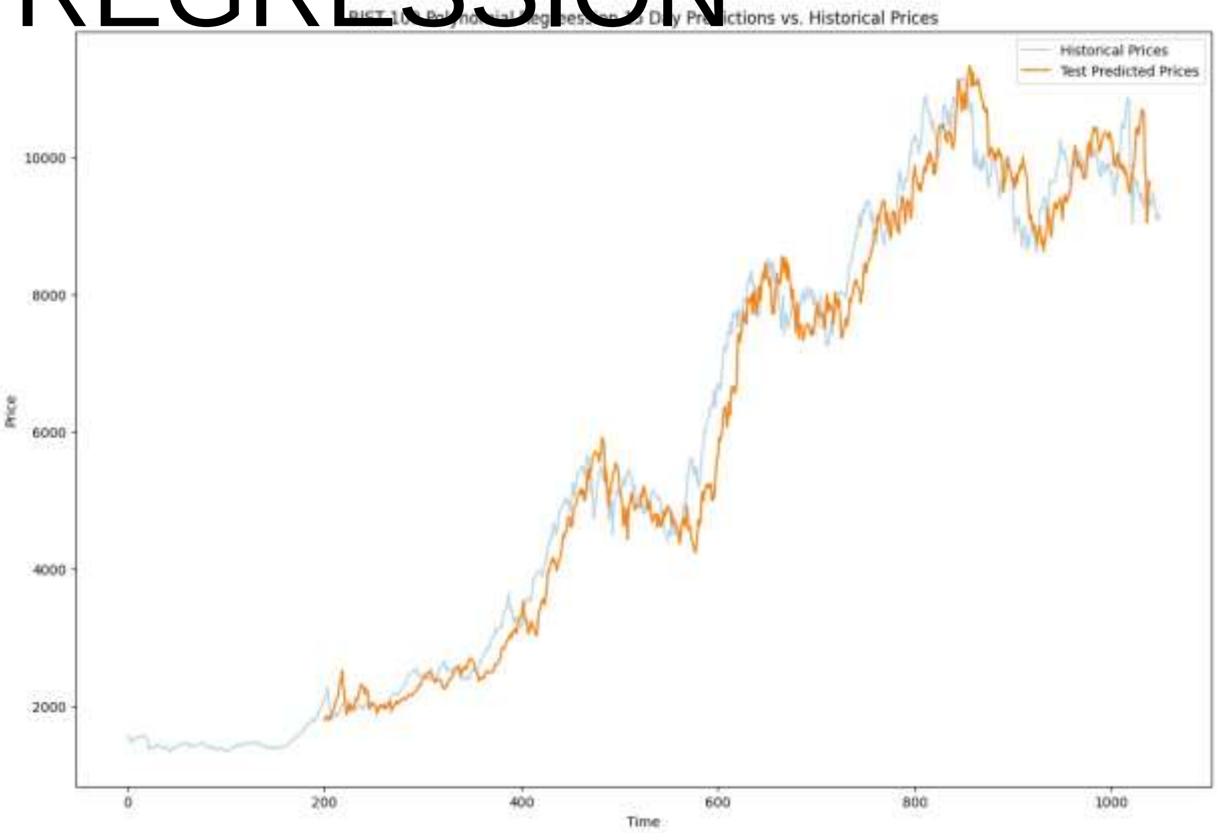
	TRAIN	TEST
RMSE	209.57	1042.112
R^2	0.9955	0.903
MAE	144.45	840.02
MAPE	0.0309	0.1781
Accuracy	97.489	87.19

15 DAY PREDICTIONS, GRU



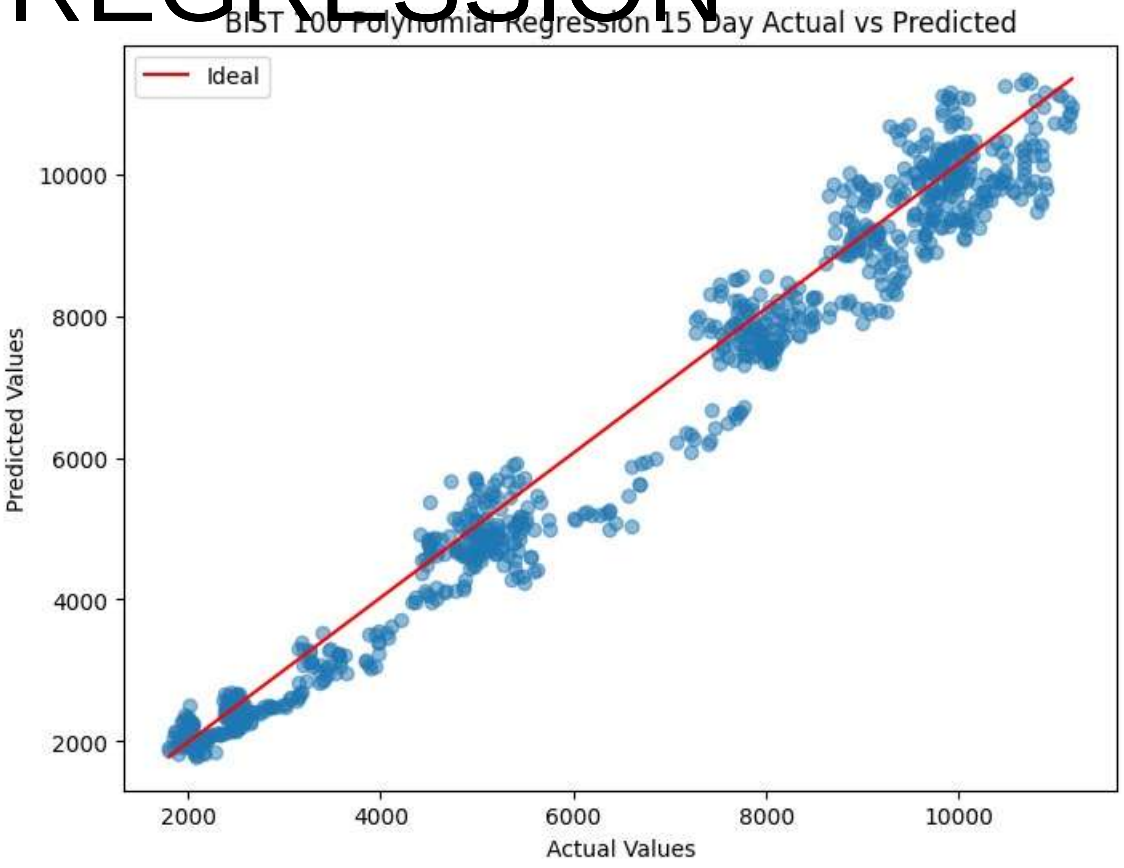


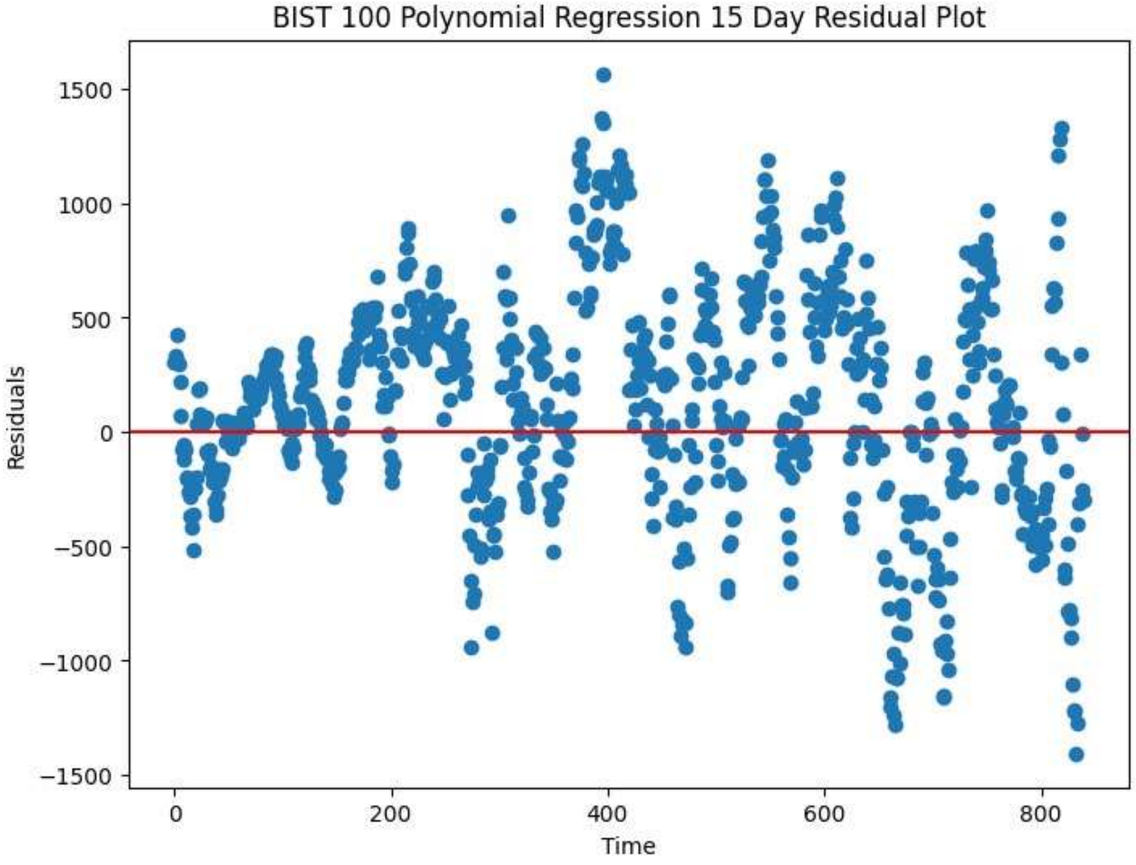
15-DAY PREDICTIONS, POLYNOMIAL REGRESSION



	TRAIN	TEST
RMSE	1.34e-12	504.449
R^2	1	0.972589
MAE	8.419e-13	395.69739
MAPE	1.67876e-16	0.07067
Accuracy	99.99	93.96921

15-DAY PREDICTIONS, POLYNOMIAL REGRESSION





COMPARISON, 15-DAY PREDICTIONS

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MAPE	1.679e-16	0.07067
Accuracy	99.99	93.96921

VII. CONCLUSION

CONCLUSION

- Using walk-forward approach, we implemented LSTM, GRU, and polynomial regression models to make 1-day and 15-day predictions of BIST 100 Index. From our evaluation metrics we conclude that our models are sufficient to predict the 1-day values of BIST 100 Index. Although the accuracy of predictions are lower in times of sharply increased volatility, evaluation metrics indicate that 15-day predictions are decent. Their response the increased volatility can be addressed in further studies.

THANK YOU FOR LISTENING TO OUR PRESENTATION AND FOR YOUR TIME TO JOIN US.