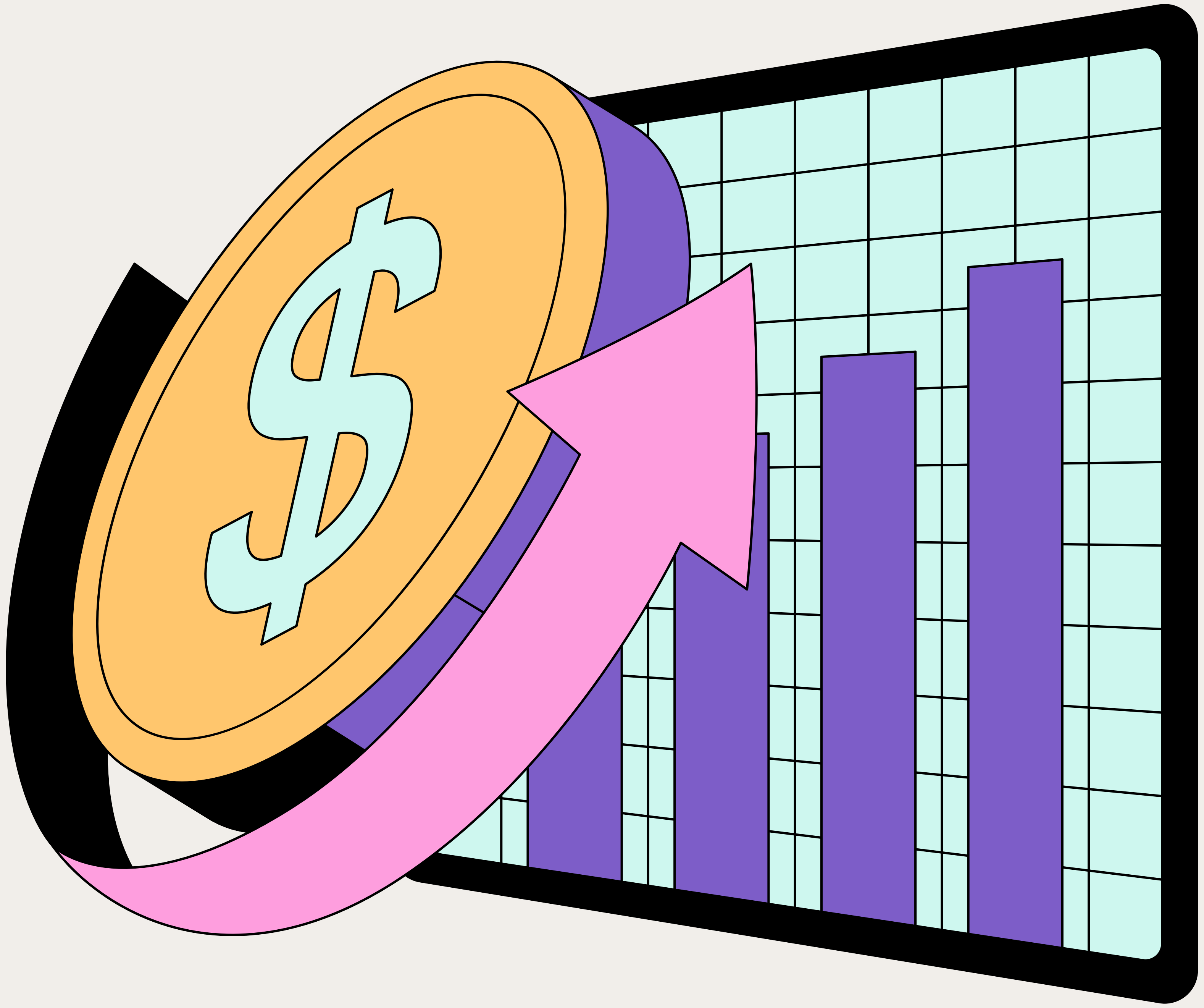
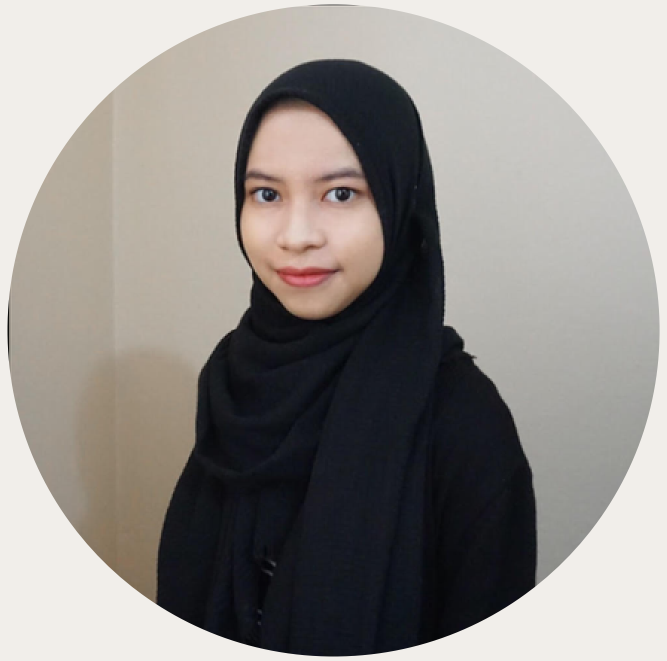
Indofood
LAMBANG MAKANAN BERMUTU

Time Series Forecasting:

Predicting Stock Price of INDF



Our Team



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Background

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Indofood: A Consumer Goods Company

PT Indofood Sukses Makmur Tbk. (ticker: **INDF.JK**) is a prominent consumer goods company listed on the Indonesia Stock Exchange (IDX).

Predicting the future price of its stock is essential for investors who are aiming to optimize their portfolios and institutional investors seeking to manage risk and allocate assets effectively.

Problem Statement

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Developing a robust method for forecasting future stock prices

For investor managers, an inaccurate forecast can translate into suboptimal decisions, potential financial losses, and missed opportunities.

Consequently, establishing a reliable approach to time series forecasting is critical to mitigate risks and improve overall decision-making quality.

Analytical Approach

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Data Collection and Exploration

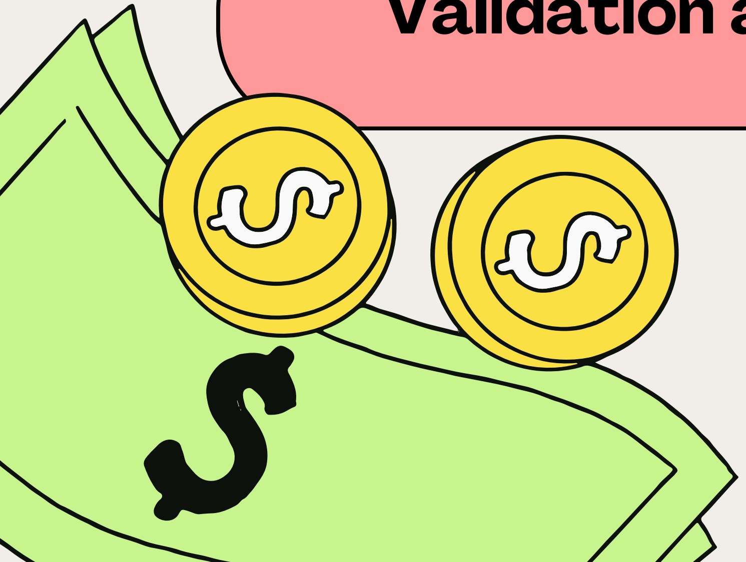
Gather historical stock price data (closing price) for INDF.JK for the 3-year period 2021-2023 using yahoofinance module in python.

Model Development

Utilize time series forecasting technique, Prophet, to predict future price.
Perform hyperparameter tuning and model selection to identify the best-performing approach.

Validation and Testing

Split the dataset into training and validation sets.
Evaluate the forecast performance using the MAE and MAPE.



Model & Evaluation

EDA: Multiplicative seasonality

The line chart indicates **multiplicative seasonality**, which is indicated by the larger price increases each year, so we have adjusted the seasonality mode parameter in the model to be *multiplicative* instead of the default *additive*.

Prophet Model

Prophet uses a decomposable time series model with three main model components: trend, seasonality, and holidays.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

Trend

non-periodic changes in the value of the time series

Seasonality

periodic changes (e.g., weekly and yearly seasonality)

Holidays

effects of holidays which occur on potentially irregular schedules over one or more days

Error

represents any idiosyncratic changes which are not accommodated by the model

Holiday Component

Prophet package includes *make_holidays_df* function to account for national holidays/special dates (such as annual shareholders' meeting or cum dividend dates) that can be added into the model.

Adding special dates, gathering information from INDF corp action information from trading website Stockbit, to input as holidays (special dates)

	ds	holiday
0	2021-01-01	New Year's Day
13	2021-02-12	Lunar New Year
7	2021-03-11	Isra' and Mi'raj
11	2021-03-14	Day of Silence
10	2021-04-02	Good Friday

	ds	holiday
52	2023-07-06	corp_action
40	2023-07-19	Islamic New Year
33	2023-08-17	Independence Day
41	2023-09-28	Prophet's Birthday
34	2023-12-25	Christmas Day

Hyperparameter Tuning (1/2)

Using Itertools to iterate through the specified possible combinations to find the the best parameter combinations

changepoint_prior_scale	Determines the flexibility of the trend, and in particular how much the trend changes at the trend changepoints.
seasonality_prior_scale	Controls the flexibility of the seasonality. A large value allows the seasonality to fit large fluctuations, a small value shrinks the magnitude of the seasonality.
seasonality_mode	Can be changed from `additive` to `multiplicative` based on the observable magnitude of seasonal fluctuations which grows with the magnitude of the time series

Hyperparameter Tuning (2/2)

holiday_prior_scale	controls the regularization strength of holiday effects
yearly_seasonality	which automatically detects and includes yearly seasonality
weekly_seasonality	which automatically detects and includes weekly seasonality
daily_seasonality	which automatically detects and includes daily seasonality

Metric Evaluation

MAE (Mean Absolute Error)

Absolute deviation of the model's predictions from the actual prices (residuals), chosen to minimize the impact of outliers and interpretability.

MAPE (Mean Absolute Percentage Error)

Expresses prediction errors as a percentage of actual values, making it easier to compare forecasting performance across different scales.

Best Model

MAE: 207.18
MAPE: 3.23%

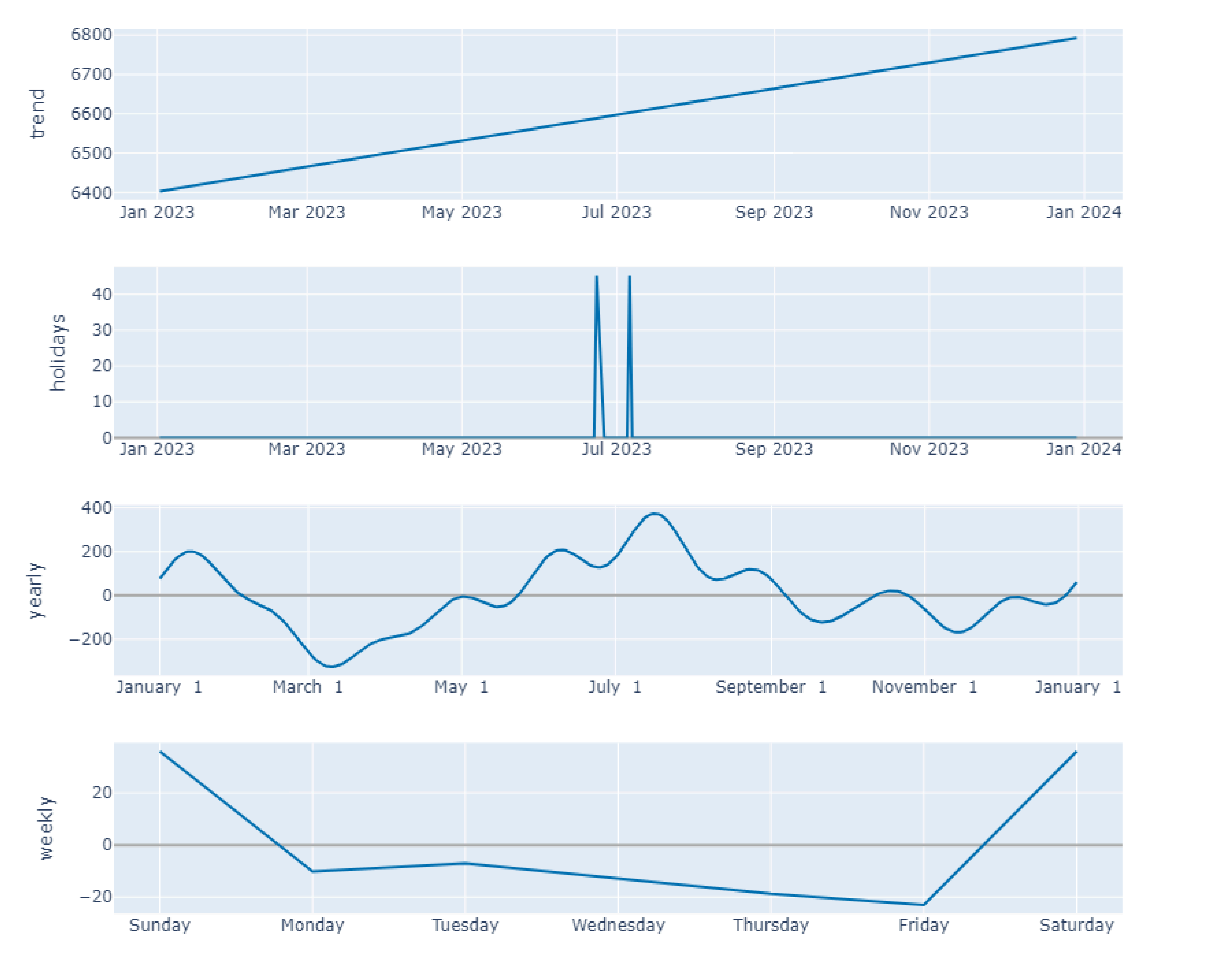
Changepoint Prior Scale	1.0
Seasonality Prior Scale	20
Holiday Prior Scale	10.0
Seasonality Mode	Multiplicative

Daily Seasonality	True
Weekly Seasonality	True
Yearly Seasonality	True

Decomposable Model

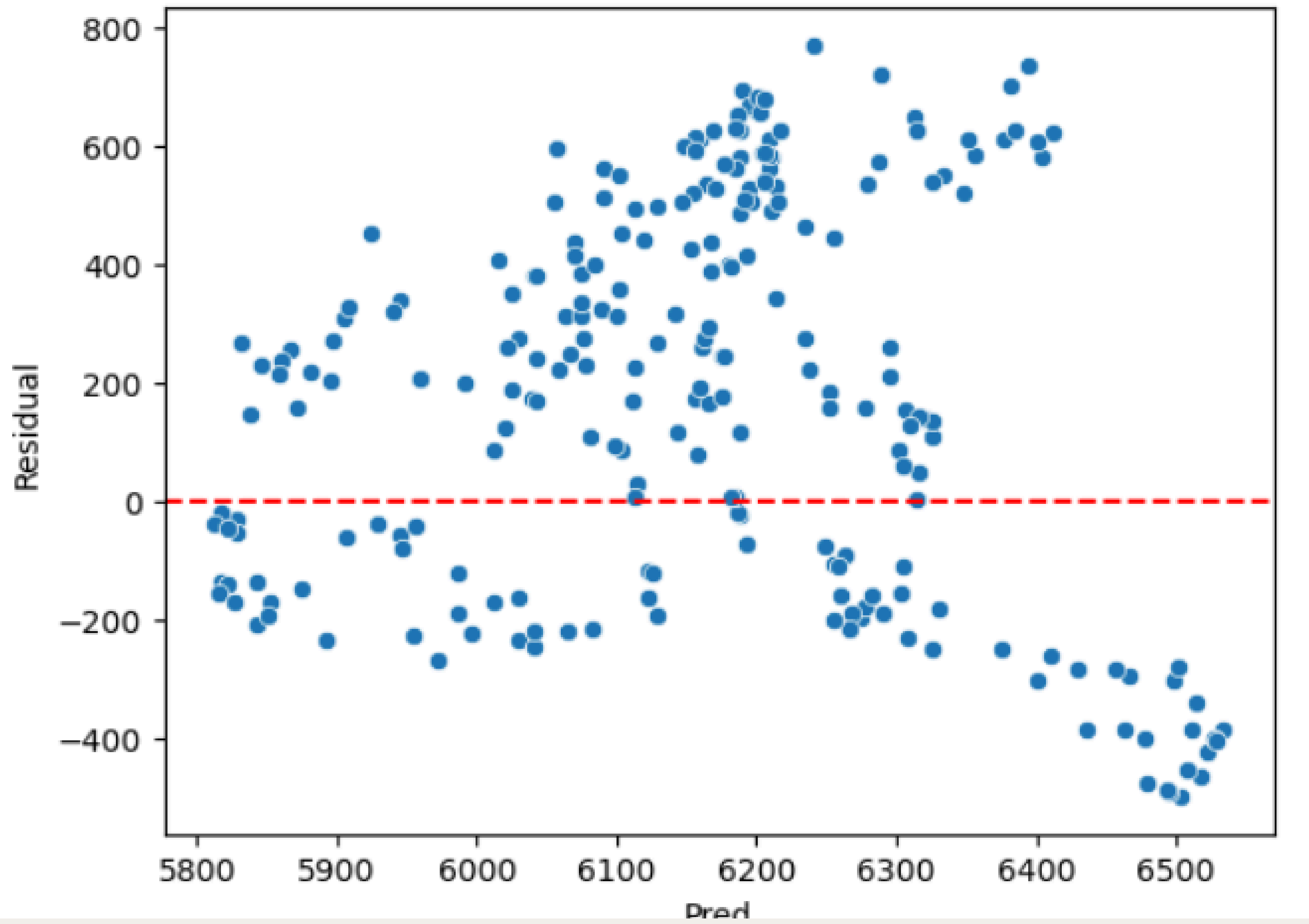
An important benefit of the decomposable model is that it allows us to look at each component of the forecast separately.This provides a useful tool to gain insight into our forecasting problem, besides just producing a prediction.

Components Plot After Tuning

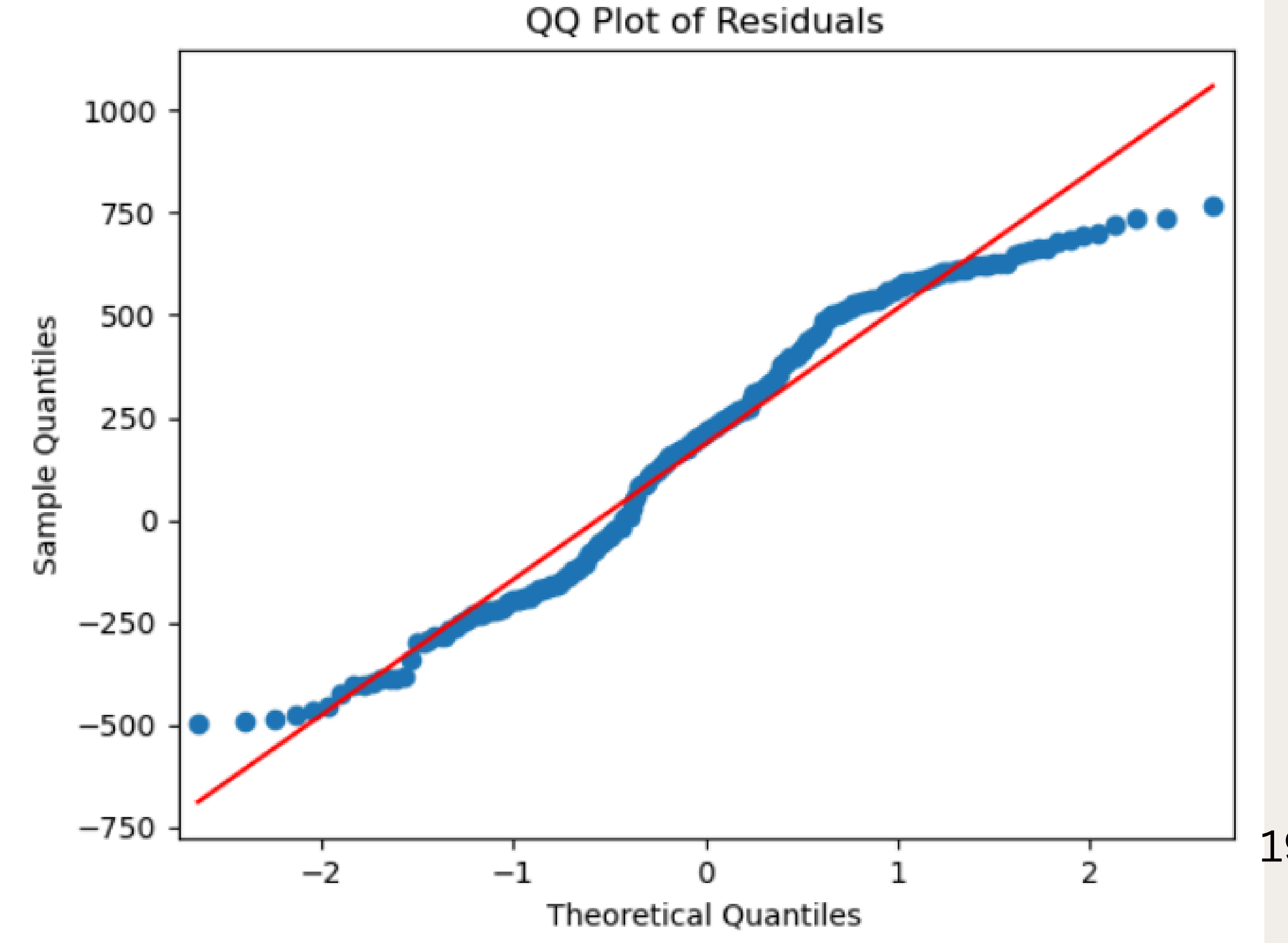


Residual Analysis

```
mean_squared_log_error:  0.0035
r2:  -0.1008
MAE:  325.8819
MAPE:  0.0501
MSE:  144192.8811
RMSE:  379.7274
Residual Mean 185.43679338498384
```

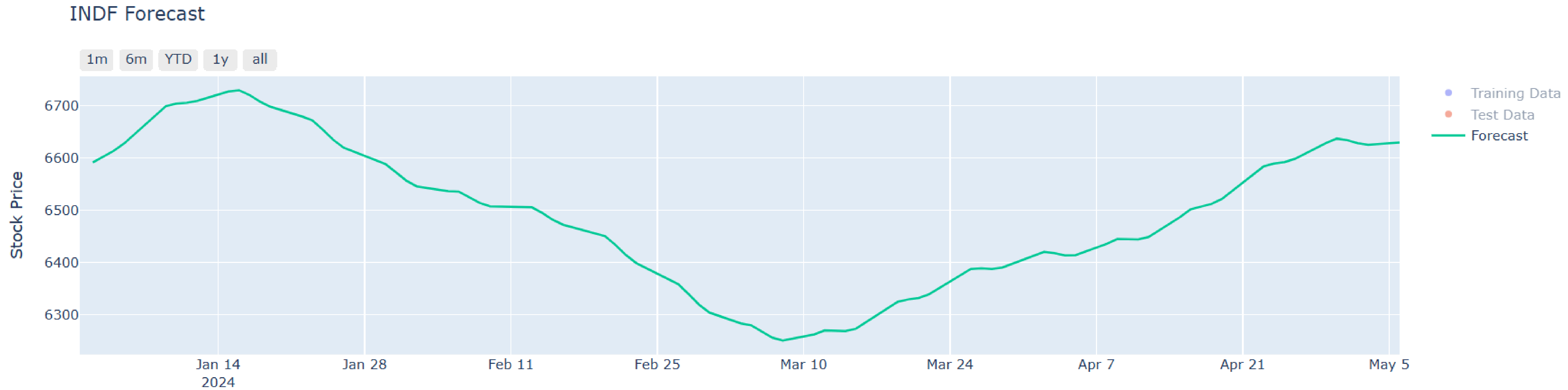


- T-test for mean=0 -> P-value: 0.00< 0.05 Residual mean is significantly different from 0 (model may be biased)
- Residuals are not normally distributed



Conclusions

Recommendations for Investors for the next 90 Days



Recommendation to buy (Good Entry Points) in Early March

- As the stock price bottoms out in the beginnning of march, it may present a good buying opportunity before the next uptrend.
- Investors looking for long-term growth may accumulate shares if the price stabilizes above 6000.

Recommendation to sell (Exit Strategy) for Early to Mid January

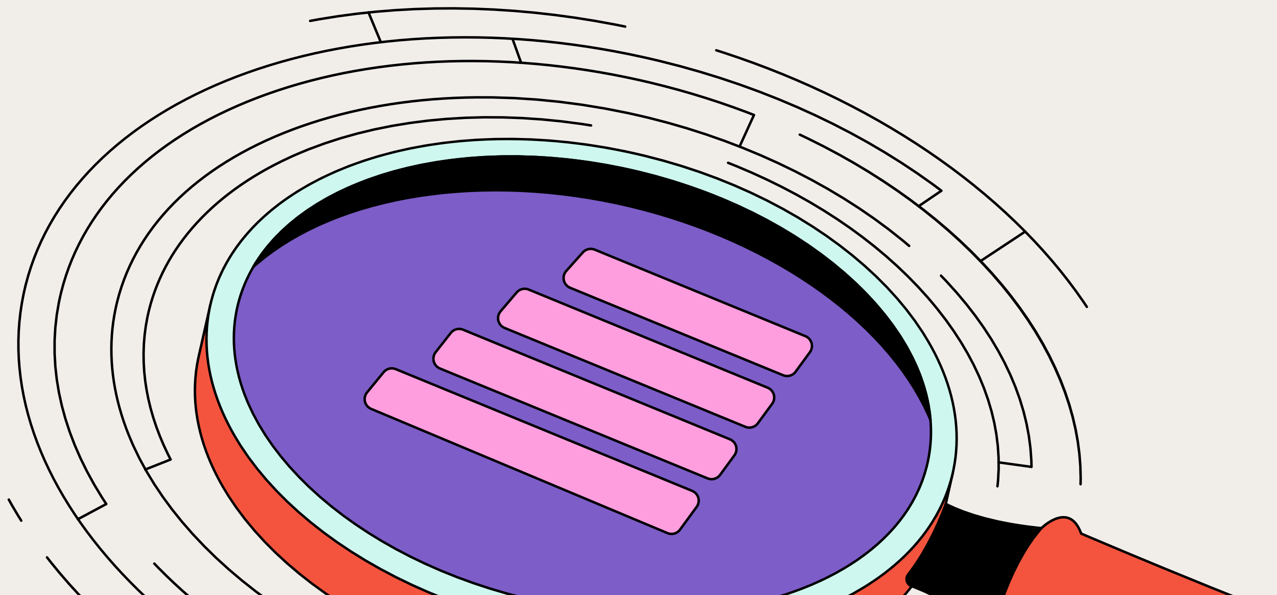
- If the price reaches 6500–6700 IDR, consider selling for short-term profits.

Model Limitations

Inability to Capture Market Efficiency & Random Walk Behavior
Stock prices follow a random walk (EMH), making past patterns unreliable for prediction. Prophet's deterministic approach struggles with volatility, sharp jumps, and unpredictable market shocks.

Weak Handling of Exogenous Factors & Market Sentiment
Prophet relies solely on historical prices and struggles to integrate crucial external drivers like macroeconomic data, news, and sentiment.

Lack of Adaptability to Regime Changes & Non-Stationarity
Structural breaks (e.g., bull/bear markets) disrupt Prophet’s trend assumptions, making it unsuitable for dynamic stock market conditions.



Model Improvement Ideas

Add External Regressors

Incorporate macroeconomic indicators, trading volume, interest rates, or sentiment data to provide additional predictive power beyond historical prices.

Use Shorter Time Horizons

Limit forecasting to short-term trends where seasonality and momentum effects may still hold some relevance, reducing long-term uncertainty.

Apply Post-Processing Adjustments

Use statistical corrections or smoothing techniques to adjust forecasts based on recent market conditions and volatility changes.

Thank You!