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Comparative Study of Composite Stock Price Index (JCI) Prediction Using *the Autoregressive Integrated Moving Average* (ARIMA) and *Facebook Prophet Methods*

By

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Abstract

The current development of information and communication technology has brought significant changes in various sectors, including the financial sector. One of the technologies that is getting more attention is Artificial Intelligence (AI), By using machine learning algorithms and AI data analysis techniques can predict stock prices. This study aims to determine which analysis model is better in predicting the Composite Stock Price Index (JCI) in the last 20 years, the analysis models used are the Autoregressive Integrated Moving Average (ARIMA) and Facebook Prophet. In a comparative analysis of predictive models, ARIMA (0,1,1) was proven to show better performance compared to Facebook Prophet. This can be seen from the lower MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), MASE (Mean Absolute Scaled Error), SMAPE (Symmetric Mean Absolute Percentage Error) and MSE (Mean Squared Error) values in the ARIMA model. These values indicate that ARIMA produces more accurate predictions with a smaller error rate than Facebook Prophet.

Keywords*: Composite Stock Price Index, Artificial Intelligence (AI), Autoregressive Integrated Moving Average (ARIMA), and Facebook Prophet*

INTRODUCTION

The development of information and communication technology, especially Artificial Intelligence (AI), has brought significant changes in various sectors, including finance. In the Indonesian capital market, AI has great potential to help predict stock prices through big data analysis and decision-making automation. The Indonesian stock market, represented by the Jakarta Composite Stock Price Index (JCI), has shown an average annual growth of 4.39% in the last 10 years (2014-2023). However, market volatility and uncertainty make stock price predictions a major challenge for investors.

AI, specifically through Machine Learning (ML), can analyze data from various sources such as financial reports, economic news, and technical analysis to predict stock movements. Some of the ML models that have been tested in previous studies include Long Short-Term Memory (LSTM), ARIMA, and Facebook Prophet. For example, research by Julian and Pribadi (2021) shows that LSTM is able to predict the price of mining stocks on the IDX with an error (RMSE) of 31.71. Meanwhile, another study conducted by Karto (2020) compared LSTM and ARIMA, where LSTM proved to be more accurate in predicting PT Telkom Indonesia's share price. Facebook Prophet also showed good performance in predicting retail sales in Bosnia and Herzegovina with an error (MAPE) of 6.06% of research conducted by Zunic, Korjenic, Hodzic Donko (2020).

Although various ML models have been tested in different contexts, there is no definitive conclusion regarding which model is the most effective for predicting JCI. Therefore, this study aims to analyze the application of AI more specifically by comparing the ARIMA and Facebook Prophet models in predicting JCI movements. Thus, AI is expected to help investors make more precise and accurate investment decisions amid market uncertainty.

LITERATURE REVIEW

1. **Stock**

Stocks are investment instruments that are proof of ownership of a company (equitas). Shareholders have the right to vote in the company's decisions in accordance with the proportion of shares they own, and are entitled to the profits (dividends) distributed by the company. However, investors also bear the risk of the ups and downs of the company's performance. Shares are defined as securities that show ownership of a company, where the holder has a claim for dividends or other

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profit distributions (Asri et al., 2023; Hanifatusa'idah et al., 2019).

In choosing stocks, investors usually consider various factors, such as the company's financial condition, public confidence in the products/services offered, and stock price comparison with similar companies. Like the analogy of buying eggs in the store, investors will choose stocks that are considered "cheaper" or have a good value than their competitors if they are of similar quality (Mladjenovic, 2023). In addition, investors also consider appropriate investment strategies before deciding to buy stocks.

2. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA (Autoregressive Integrated Moving Average) model was introduced by Box and Jenkins in 1970 as a methodology for analyzing and predicting time series data. This model is particularly effective for short-term forecasting and often outperforms more complex structural models. ARIMA combines three main components: Autoregressive (AR), Integrated (I), and Moving Average (MA), which are represented by three parameters: *p*, *d*, and *q*.

1) Autoregressive (AR): This model uses the past values of dependent variables to predict future values. The p-order indicates the amount of lag (past value) used. With the formula as below:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_1 Y_{t-q} + e_t$$

Y_t : stationary time series

θ_0 :Constant

$Y_{t-1}, \ldots, Y_{t-p}$: Related past values

$\theta_1, \ldots, \theta_p$:Coefficients or parameters of the *autoregressive model*

e_t : Residual at time t

2) Moving Average (MA): This model uses past residual (prediction errors) as an independent variable. The order *q* indicates the number of residuals used. MA notation (q) refers to the moving average order model

$$Y_t = a_t + \theta_1 a_t + \cdots + \theta_1 a_{t-q}$$

Y_t : The value of the Z time series on Time t

a_t : The value of the white process noise at t time

$a_{t-1} \ldots a_t$: The value of the white process noise on each T-1, T 2,..,T-Q. value A as variable free

θ_1 : Parameter moving average (MA)

3) ARMA: This model combines AR and MA components to predict future value. The general form of this model is.

$$Y_t = \gamma_0 + \partial_1 Y_{t-1} + \partial_2 Y_{t-2} + \ldots + \partial_n Y_{t-p} + \lambda_1 e_{t-1} + \lambda_2 e_{t-2} + \lambda_n e_{t-q}$$

Where Y_t and *et* are the same as before, γ_t is a constant, δ and λ is the coefficient of the model

4) ARIMA: This model is used when the data is not stationary (has a specific trend or pattern). The differencing process is carried out to create stationary data. The d parameter indicates how many times differencing is performed. Example: ARIMA (1,1,2) means that the model uses one dependent lag, one differencing, and two residuals.

The ARIMA model is highly flexible and can be adapted to different types of time series data, including economic and financial data. With the right parameters, ARIMA is able to generate accurate predictions, especially for short-term forecasting.

3. *Facebook Prophet*

The Prophet Facebook Model is a time-series data prediction algorithm developed by Taylor and Letham (2018). This model is based on an additive model that blends non-linear, seasonal (annual, weekly, daily) trends and holiday effects. Prophet is designed to handle data with strong seasonal patterns, missing data, trend shifts, and outliers. The main advantage of the Prophet is its ability to generate accurate predictions with short computing times, even with incomplete or "dirty" data.

The Prophet model adopts a Generalized Additive Model (GAM) that decomposes time-series data into three main components:

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

(g(t): Growth or trend function.
(s(t)): Seasonal patterns.
(h(t)): Holiday effect.
(ε(t)): Prediction error.

The prophet model considers the forecasting of time series data as a curve-fitting exercise and does not consider the temporal dependency structure in the underlying data (Malefors, et al., 2020)

RESEARCH METHODS

This study uses a quantitative research method, which is a research method that uses data in the form of numbers to then be processed and analyzed to obtain scientific information behind these numbers. The data used in this study is the Jakarta Composite Stock Price Index (JCI) for the period January 2004 to December 2024.

This research makes predictions through the ARIMA and *Facebook Prophet* models which consist of several stages which include: Data Management, Stationary Checking, ACF and PACF, *Modeling*, *Forecasting.* Comparison of MAE (*Mean Absolute Error*), MAPE (*Mean Absolute Percentage Error*), MASE (*Mean Absolute Scaled Error*), SMAPE (*Symmetric Mean Absolute Percentage* Error) and MSE (*Mean Squared Error*) values between the models to take the smallest error of the two models

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RESEARCH RESULTS

The Composite Stock Price Index (JCI) data used in this study amounted to 5,158 data. The data can be seen in the image below:

Figure 1

Composite Stock Price Index Chart

From the graph image above, it can be seen that the movement of the Composite Stock Price Index (JCI) has relatively increased significantly in the last 20 years, but we can also pay attention to the descriptive analysis test of objects as can be seen in the table below

Table 1
Descriptive Analysis

	JCI
Mean	4.313
Median	4.674
Maximum	7.905
Minimum	668
Std. Dev.	2.036
Observations	5.198

The Jakarta Composite Stock Price Index (JCI) has an average value of 4,313 with the highest value of 7,905 while the lowest value is 668 with a *standard deviation* value of 2,036 with a total of 5,198 observation data in the last 20 years. Then the data will be broken down into training data and testing data into 90% and 10% as shown in figure 2

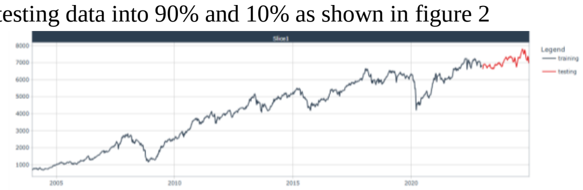

Figure 2

JCI Split Data Chart

The Stationary Test is a test that to find out whether the average, variation, and variation of data are constant all the time, this test is divided into two, namely *Autocorrelation Function* (ACF) and *Partial Autocorrelation Function* (PACF) where the function of the ACF test will show a correlation between observations at the tth time and observations at the previous time. ACF maps the correlation of the time series with itself at different intervals while the PACF test shows a partial correlation between observations at t-time and observations at previous times. PACF measures the same correlation as ACF, but after controlling for correlation between data points at time t and data points at time t-1. It can be seen from the ACF and PACF tests carried out in Figure 3

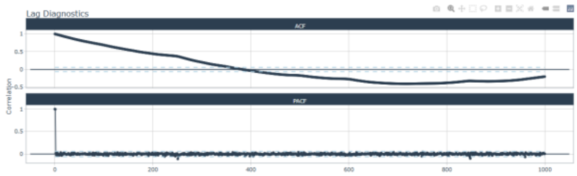

Figure 3

ACF and PACF tests

It can be seen from the results of the ACF and PACF tests that there is stationarity, it can be proven on the ACF graph that the line crosses the boundary line and forms a downward pattern which means there is a seasonal pattern or stationarity, while in the PACF graph in the first lag the graph crosses the boundary line which means there is stationarity in the data, with stanionarity means that the data is completely non-random which means that the researcher can predict the data or further research the data.

Forming the ARIMA model (p,d,q)

Based on the results of the data stationery analysis, the results of the data stationery test can be seen in the ACF and PACF graphs which show a significant lag of 1 in both graphs, so it is possible that the order notation in ARIMA (1,0,1) ARIMA(1,0,0) ARIMA(0,0,1) ARIMA(1,1,0) and ARIMA(0,1,1) but because it uses the ARIMA auto model, *machine learning* will only display the best model in the test, As the results of the table below:

Table 2
ARIMA Test Result (0,1,1)

```
parsnip model object

Series: outcome
ARIMA(0,1,1) with drift

Coefficients:
          ma1   drift
      -0.0682  6.1951
s.e.   0.0315  2.9366

sigma^2 = 9871:  log likelihood = -5968.47
AIC=11942.93   AICc=11942.96   BIC=11957.63
```

The results of the ARIMA model test show that the best ARIMA model is ARIMA (0,1,1) which means that the equation model does not have an *Autoregressive* (AR) component = 0, but the data *differencing* once is expressed in *Integrated* (I) = 1, and the Moving *Average* (MA) component = 1, if the ARIMA model equation is included it will be as follows:

$$y'_t = \epsilon_t + \theta_{1\epsilon_{t-1}}$$

Where is the θ_1*moving average* coefficient (MA). So if the results of the forecast of the Composite Stock Price Index (JCI) which are the results of the table, the MA(1) coefficient is -0.0682 with a Dift value (Constant) of 6.19151, then the equation of the ARIMA model (0,1,1) with drift becomes:

$$y'_t = Drift + \epsilon_t + \theta_{1\epsilon_{t-1}}$$

Substitution of coefficient values:

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$$y_t' = 6{,}1951 + \epsilon_t - 0{,}0682_{\epsilon_{t-1}}$$

Because, the equation can be written in its original form():$y_t' = y_t - y_{t-1} y_t$

$$y_t' = y_{t-1} + 6{,}1951 + \epsilon_t - 0{,}0682_{\epsilon_{t-1}}$$

A drift value of 6.1951 indicates a positive linear trend in the data. Each period, the value tends to increase by 6.1951, outside of the influence of error, the MA(1) value of -0.0682 is the error value in the previous period has a small negative influence on the current value while the value is a random component value that cannot be predicted.$y_t'(\epsilon_{t-1}) y_t\ \epsilon_t$

Model Facebook Prophet

Facebook Prophet is a time series forecasting tool developed by Facebook that is designed to make it easy to forecast time series data in an intuitive and flexible way. In the use of *the Facebook Prophet* model, the researcher only uses *automatically* to find a better model in predicting JCI data, the results of forecasting using *Facebook Prophet* are obtained as follows:

Table 3

Prophet Facebook *Test Results*

```
PROPHET Model
- growth: 'linear'
- n.changepoints: 25
- changepoint.range: 0.8
- yearly.seasonality: 'auto'
- weekly.seasonality: 'auto'
- daily.seasonality: 'auto'
- seasonality.mode: 'additive'
- changepoint.prior.scale: 0.05
- seasonality.prior.scale: 10
- holidays.prior.scale: 10
- logistic_cap: NULL
- logistic_floor: NULL
- extra_regressors: 0
```

The parameters and configurations used in the Facebook Prophet model for data forecasting. This model uses a linear growth type, which assumes data trends will increase or decrease linearly over time. The n.changepoints parameter is set to 25, which means the model will try to detect 25 points where the trend of the data changes significantly. This change point is only considered in the first 80% of the data (changepoint.range), to avoid overfitting by not looking for trend changes in the last 20% of the data.

For seasonal components, the yearly.seasonality, weekly.seasonality, and daily.seasonality parameters are set to auto, so the model will automatically enable the seasonal component if it detects an annual, weekly, or daily seasonal pattern. The seasonal mode used is additive, where seasonal effects are added to the trend. It is suitable for data with relatively constant seasonal fluctuations. The changepoint.prior.scale parameter is set to 0.05, which makes the model more conservative in detecting trend changes, thereby reducing the risk of overfitting. Meanwhile, seasonality.prior.scale and holidays.prior.scale are set to 10, allowing the model to pay more attention to the impact of seasonal patterns and holidays on the data.

Because the model uses linear types, the upper and lower bound parameters (logistic_cap and logistic_floor) are irrelevant. In addition, no additional regressors are used in the model, as extra_regressors set to zero. Overall, this configuration is designed to balance the model's flexibility in detecting trend and seasonal changes, while reducing the risk of overfitting. The results of *the Facebook Prophet* model predict several *changepoints* that occur in the JCI, as depicted in the graph below:

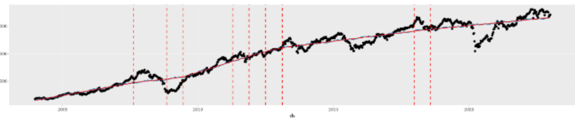

Figure 4

Changepoints on JCI

Changepoints in JCI occur several times in JCI, *changepoints* are significant change points that occur in trends that can be recognized by the *Facebook Prophet model,* it can be seen from the graph above that *changepoints* occurred before 2010 which experienced a significant decrease, then occurred after 2010 but there was no significant change, and the last one occurred before 2020 there was a considerable increase and continue to decline, but if observed further Facebook *Prophet* could not detect a significant decline in early 2020 which we know the occurrence of covid-19 which caused the economy to weaken, but it will not be discussed further in this study because outside of the discussion of the research, *the Facebook Prophet* modelBeing able to explain how the effects of seasonal, weekly, monthly, annual, and holiday patterns affect it is illustrated from the graph below:

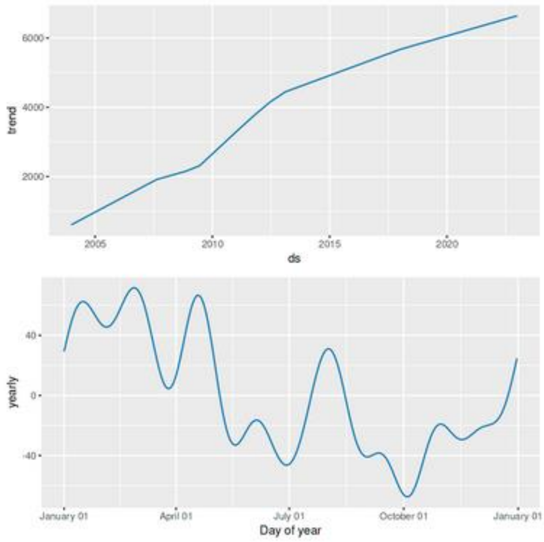

Figure 5

Plot Components Facebook Prophet

The Facebook Prophet Plot Components in the first graph is a trend graph showing the overall change in data over time. The viewable trend graph shows an increase in the value of the data over time. And the second graph is seasonality, showing a recurring pattern in the data. This can be a daily, weekly, or yearly pattern, the rise and fall on this chart shows how much influence the seasonal effect has on the data.

Model Comparison

Forecasting carried out using both the ARIMA and *Facebook Prophet* models produces predictions for the next 1 year which can be seen from the graph below:

Figure 6

ARIMA and FB Prophet Model Prediction Graph

The results of the prediction of the two models above show that the JCI will increase in the next 1 year with *the prediction of Facebook Prophet* higher than the prediction of ARIMA, it can also be seen that the value of *the increase in Facebook Prophet* in the graph above will beat the highest value of the JCI for the last 20 years but on the contrary ARIMA will only experience a stable increase without any significant changes. Furthermore, the two ARIMA and *Facebook Prophet* models will be compared from the error results of the two models which is better, it can be seen from the prediction results table below:

Table 4

Test Results of ARIMA and *Facebook Prophet Models*

.model_id	.model_desc	.type	mae	mape	mase	smape	rmse
<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	ARIMA(0,1,1) WITH DRIFT	Test	172.4764	2.455365	2.233186	2.424933	213.0901
2	PROPHET	Test	251.7172	3.447614	3.259179	3.547607	328.5300

In a comparative analysis of predictive models, ARIMA (0,1,1) was proven to show better performance compared to *Facebook Prophet*. This can be seen from the lower MAE (*Mean Absolute Error*), MAPE (*Mean Absolute Percentage Error*), MASE (*Mean Absolute Scaled Error*), SMAPE (*Symmetric Mean Absolute Percentage Error*) and MSE (*Mean Squared Error*) values in the ARIMA model. These values indicate that ARIMA produces more accurate predictions with a smaller error rate than *Facebook Prophet*. Overall, ARIMA (0,1,1) is considered more accurate and reliable for the dataset used in this analysis. Its ability to minimize prediction errors makes it a more recommended model than *Facebook Prophet* in the context of this dataset. Therefore, ARIMA can be considered as a top choice for future predictions, especially when the accuracy and reliability of the predictions are decisive factors.

CONCLUSION

Based on the results of the analysis, it can be concluded that the ARIMA and *Facebook Prophet* methods can be used to make good forecasts, especially in predicting the movement of the Composite Stock Price Index (JCI). The ARIMA method shows better performance than *Facebook Prophet*, this can be seen from the small difference between the actual value and the estimated value, as well as error values such as MAE (*Mean Absolute Error*), MAPE (*Mean Absolute Percentage Error*), MASE (*Mean Absolute Scaled Error*), SMAPE (*Symmetric Mean Absolute Percentage Error*), and MSE (*Mean Squared Error*) which is relatively small. The results of the parameter test also confirmed that ARIMA was superior in forecasting the JCI.

However, *the Facebook Prophet* method also shows a fairly good ability to predict JCI, with relatively small error values and is still reliable for prediction purposes. These two methods are able to predict the movement of the JCI in the next year in a positive direction, namely showing an upward trend. This is a positive signal for investors, especially in Indonesia, because it provides an optimistic picture of stock market growth in the short term.

Overall, even though ARIMA is superior in terms of accuracy, these two methods can still be used as effective tools for analyzing and predicting JCI movements, helping investors in making more informative and strategic decisions.

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