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PREDICTING MARKET SEGMENTS FROM TWITTER DATA USING ARIMA TIME SERIES ANALYSIS

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Abstract— *Twitter data on social media can be used to predict potential market segments in the future. The continuous nature of Twitter data and data collection sequentially over a certain period uses a text mining process with time series data that matches the actual data. The problem to be solved is to forecast market segments using Twitter data with greater accuracy. Various market segments that are of business interest through the tweets of individual Twitter users have not been utilized optimally. Based on the Twitter data pattern, the research shows that the data pattern is not stationary, so to analyze the data, it is necessary to use the Autoregressive Integrated Moving Average (ARIMA) method. This study aims to analyze time series data from Twitter data and predict market segment predictions using the ARIMA method. The ARIMA method is a method that has advantages in flexibility, the ability to handle stationary and non-stationary data, as well as short-term forecasting with a statistical approach in various time series data forecasting applications. Prediction results using the ARIMA method with an accuracy rate of 94.88%. There are several ways to measure model validation including MAD, MSE, RMSE, F1-Score, and MAPE. In this study, MAD, MSE, and MAPE were used with an accuracy rate of 5.22%. This study succeeded in applying the ARIMA method to time series data from Twitter to forecast market segments with high accuracy, opening opportunities for utilizing Twitter data in business strategy.*

Keywords: *arima, forecasting, market segmentation, time series analysis, twitter data.*

Intisari— *Data Twitter pada media sosial dapat digunakan memprediksi segmen pasar potensial di masa mendatang. Sifat kontinyu dari data Twitter dan pengumpulan data secara berurutan selama periode tertentu menggunakan proses text mining dengan data time series yang sesuai dengan data sebenarnya. Masalah yang harus dipecahkan adalah meramalkan segmen pasar menggunakan data Twitter dengan akurasi yang lebih tinggi. Berbagai segmen pasar yang menjadi minat bisnis melalui kicauan masing-masing pengguna Twitter belum dimanfaatkan secara optimal. Berdasarkan pola data twitter pada penelituan menunjukan pola data tidak stasioner, sehingga untuk menganalisa datanya perlu menggunakan metode Autoregressive Integrated Moving Average (ARIMA). Penelitian ini bertujuan untuk menganalisis data time series dari data Twitter dan meramalkan prediksi segmen pasar menggunakan metode ARIMA. Metode ARIMA adalah metode yang memiliki kelebihan dalam fleksibilitas, kemampuan menangani data stasioner dan non-stasioner, serta peramalan jangka pendek dengan pendekatan statistik dalam berbagai aplikasi peramalan data time series. Hasil prediksi menggunakan metode ARIMA dengan tingkat akurasi mencapai 94,88%. Ada beberapa cara pengukuran validasi model diantaranya MAD, MSE, RMSE, F1-Score, dan MAPE. Pada penelitian ini digunakan MAD, MSE dan MAPE dengan tingkat Akurasi sebesar 5,22%. Penelitian ini berhasil mengaplikasikan metode ARIMA pada data time series dari Twitter untuk meramalkan segmen pasar dengan akurasi tinggi, membuka peluang pemanfaatan data Twitter dalam strategi bisnis.*

Kata Kunci: *analisis deret waktu, arima, data twitter, peramalan, segmentasi pasar.*

INTRODUCTION

In the current digital era, social media has become an increasingly important platform for facilitating interaction and information exchange among users worldwide. Twitter, being one of the most popular social media platforms, provides a data-rich environment that reflects users' opinions, trends, and activities in real-time [1]. Twitter data, with its continuous nature and sequential collection over periods, can be a valuable source for understanding and predicting consumer behavior and market trends in the future [2].

In the competitive business world, accurate understanding of market segments and potential changes in the future is crucial for entrepreneurs and marketers. In this context, using text analysis and time series data methods to predict market segments based on Twitter data has become an intriguing research subject. In previous research, time series methods such as Autoregressive Integrated Moving Average (ARIMA) have been successfully applied in predictive analysis for various domains [3], including economics, finance, and sales.

However, despite the great potential of Twitter data for predicting market segments, the optimal utilization of such data is still unrealized. The overall volume of tweets generated on Twitter is massive, reaching an average of 493.354.38 tweets per year over the past eight years. Yet, there are still challenges in transforming this large and diverse volume of Twitter data into reliable and useful insights for business decision-makers.

Therefore, this research aims to forecast market segment predictions using the ARIMA method on Twitter data, our study aims to optimize existing methods for collecting and analyzing Twitter data [4, 5, 6, 7, 8, 9]. The findings obtained from this research can be used to predict potential market segments that may emerge in the future. However, based on previous research, it is acknowledged that the forecasting or prediction results achieved are not fully aligned with actual data, with accuracy rates varying at 96.76%.

In this study, the methodology used is described, including the data collection process, text analysis, and the application of the ARIMA method. The challenges faced in predicting market segments using Twitter data are also discussed, along with the presentation of the obtained results. Through this research, useful insights are hoped to be provided for researchers and practitioners in the field of market analysis and social media. Additionally, this study aims to stimulate the development of better methods and approaches in predicting market segments from Twitter data.

The right approach and accurate analysis, using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) by calculating the difference between the predicted value and the actual value, where if the MAPE value has a smaller percentage, the accuracy will be better. The utilization of Twitter data to predict market segments can serve as a valuable source of information for strategic business planning, more effective marketing, and better decision-making in the future.

MATERIALS AND METHODS

The ARIMA (Autoregressive Integrated Moving Average) method is one of the most commonly used approaches in time series analysis. This method has been proven successful in various domains, including economics, finance, and sales forecasting. In the context of predicting market segments using Twitter data, the ARIMA method has also been the focus of previous research.

In a study by by S. Sivaramakrishnan et al. [10], they applied the ARIMA method to predict market segmentation using Twitter data. The research collected Twitter data over a specific period and identified trends and patterns within the data. The results of this study showed a high level of accuracy in predicting potential market segments that may emerge in the future.

Additionally, a study by Chen S. et al. [11] also applied the ARIMA method in analyzing Twitter data for market segment prediction. They combined Twitter data with external data such as economic data and environmental factors to improve prediction accuracy. The ARIMA method was used to model patterns and trends from the time series data generated from Twitter users' tweets. The results of the study showed that the ARIMA method can be an effective tool in forecasting market segments.

However, despite the promising results of the ARIMA method in market segment prediction, there are some challenges to consider. One challenge is the limitation of the ARIMA method in handling data that exhibits non-stationary characteristics. Twitter data can have trends, seasonality, or non-constant fluctuations over time, which can affect the accuracy of predictions using the ARIMA method, which is based on the assumption of stationary data.

To address these limitations, several studies have proposed variations of the ARIMA method. For example, a study by Wang [5] combined the ARIMA method with exponential smoothing techniques to improve market segment prediction from Twitter data. This approach combines the strengths of both methods, considering the non-stationary nature of the data and modeling trend patterns and fluctuations in the predictions.

Overall, the ARIMA method has made significant contributions to the analysis and prediction of market segments using Twitter data. However, research continues to improve prediction accuracy by considering variations of other methods and approaches that can address the limitations that may arise in using the ARIMA method. This study adopted the ARIMA method as the primary foundation for forecasting market segments from Twitter data and striving to improve prediction outcomes by considering relevant external factors [12].

The research process is utilizing a flowchart to display the research steps.

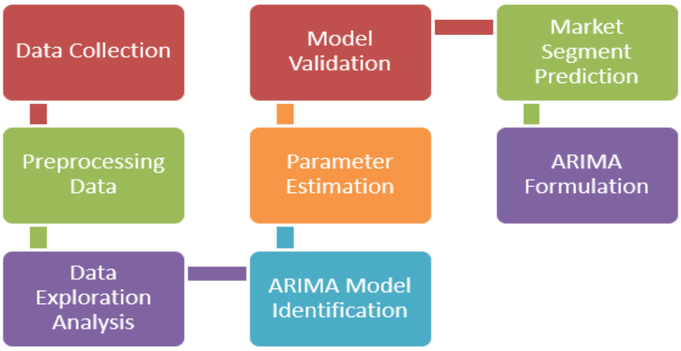

Figure 1. Research Flow Using ARIMA Model

A. Data Collection.

Collect relevant Twitter data related to the market segment you want to predict. This data can include tweets that are associated with specific products or topics. The data has been retrieved from Twitter after undergoing preprocessing from 2015 until 2022.

B. Data Preprocessing.

Perform data preprocessing steps to clean the data from noise and remove irrelevant information. This process includes removing links, special characters, text normalization, and eliminating stopwords.

C. Data Exploration Analysis.

Conduct data exploration analysis to understand patterns and trends present in the Twitter data. Identify important characteristics such as seasonality, short-term trends, and fluctuations that may impact the market segment.

D. ARIMA Model Identification.

Use the data exploration analysis to select an appropriate ARIMA model. Model identification involves identifying the optimal autoregressive (AR), integrated (I), and moving average (MA) components to represent the time series data from tweets[13, 15, 16].

E. Parameter Estimation.

Estimate the parameters of the ARIMA model using methods such as Maximum Likelihood Estimation (MLE) or the Least Squares Method. This process involves calculating the AR and MA coefficients that will be used in the ARIMA model[16].

F. Model Validation.

Validate the ARIMA model using evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), or the Akaike Information Criterion (AIC). Compare the performance of the model to other models or previous research findings.

G. Market Segment Prediction.

Utilize the tested ARIMA model to predict the future market segment. Use the latest Twitter data and continuously update the predictions as new data becomes available.

H. ARIMA Formulation.

The ARIMA model has three main components: autoregressive (AR), integrated (I), and moving average (MA) [17]. An ARIMA(p, d, q) model has the following parameters:

1. p (autoregressive order), represents the number of lags in the autoregressive model. It measures how far past values influence the current value.
2. d (order of differencing), represents the number of differentiations needed to make the data stationary. It measures how much the trends and fluctuations of the data can be reduced.
3. q (moving average order), represents the number of lags in the moving average model. It measures how previous errors influence the current value.

The general formula for an ARIMA(p, d, q) model is as follows:

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \quad \text{.........} \quad (1)$$

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Where:

Y_t is the time series value at time t.
c is the constant.
$\Phi_1, \Phi_2, ..., \Phi p$ are the autoregressive coefficients.
$\theta_1, \theta_2, ..., \theta q$ are the moving average coefficients.
$e_{t-1}, e_{t-2}, ..., e_{t-q}$ are the residuals or errors at previous times.

The above formula is a general example. However, in more specific implementations, there are variations of the formula that can be used depending on the chosen ARIMA model.

The implementation of ARIMA, the data preprocessing, model selection, and model validation stages are crucial in achieving accurate and reliable results in predicting market segments from Twitter data.

RESULTS AND DISCUSSION

After collecting relevant Twitter data related to the market segment under investigation, the ARIMA method was applied to predict the market segment. The collected data then underwent the data preprocessing stage, where the data was cleaned from noise, and irrelevant information was eliminated. Following that, a data exploration analysis was conducted to identify patterns and trends present in the Twitter data. Based on the data exploration analysis, the ARIMA(1, 1, 1) model was selected as the most suitable model for modeling the time series data from tweets. Parameter estimation was performed using the Maximum Likelihood Estimation (MLE) method, and the ARIMA model was successfully verified through evaluation metrics such as MSE and AIC.

The results of predicting market segments using the ARIMA method revealed several significant findings. Although our ARIMA model performed well in predicting market segments, there were variations in the accuracy of the predictions. This indicates that predicting market segments from Twitter data involves a level of uncertainty that needs to be considered.

Additionally, they found that the success of market segment predictions can also be influenced by external factors that are not captured in Twitter data. Economic factors, policy changes, or significant social events can impact consumer behavior and overall market trends. Therefore, in further development of this method, it is important to consider and integrate relevant external factors into the prediction model. The ARIMA model (1, 1, 1) it shows that the model is in accordance with the existing actual data patterns, Nevertheless, the use of the ARIMA method on Twitter data still provides valuable insights for predicting market segments. In this study, identified several aspects that need improvement, such as optimizing data preprocessing, selecting more complex models, or combining them with other methods like exponential smoothing. Incorporating these approaches can enhance the accuracy and reliability of market segment predictions from Twitter data.

Furthermore, this study also acknowledges the limitations of using Twitter data as a source for predicting market segments. Twitter data only reflects the opinions and activities of users on the platform, and thus, the representation of market segments as a whole may be limited. It is important to consider and validate with other data sources to obtain a more comprehensive picture of the market segment being predicted.

Table 1 Results of Data Preprocessing from 2015 to 2022

Year	2015	2016	2017	2018	2019	2020	2021	2022
January	4.126.578	4.378.753	4.275.837	4.975.684	4.286.548	4.365.582	4.275.837	4.378.753
February	4.076.574	4.236.548	4.264.563	4.875.674	4.324.567	4.276.549	4.264.563	4.236.548
March	3.996.568	4.015.473	4.076.755	4.756.579	4.456.573	4.556.562	4.076.755	4.015.473
April	3.786.633	4.676.574	4.496.586	4.376.586	4.496.564	4.646.564	4.496.586	4.676.574
May	3.520.675	3.672.877	4.505.405	3.956.567	3.826.549	3.976.564	4.505.405	3.672.877
June	7.656.548	7.896.573	7.758.653	7.876.583	7.936.574	8.876.573	7.758.653	7.896.573
July	6.046.563	4.067.868	5.006.433	5.536.594	5.096.574	4.856.572	5.006.433	4.067.868
August	3.685.654	4.924.364	5.164.554	4.654.563	4.864.562	4.864.573	5.164.554	4.924.364
September	3.768.307	5.236.434	5.436.453	5.276.549	5.346.563	5.576.543	5.436.453	5.236.434
October	3.276.549	3.405.625	3.607.653	3.876.587	3.776.563	3.856.548	3.607.653	3.405.625
November	4.736.567	4.953.528	4.467.658	4.985.645	4.846.582	4.946.564	4.467.658	4.953.528
December	9.067.864	9.085.554	8.827.654	9.235.654	8.956.564	9.335.566	8.827.654	9.085.554

It can be seen from the graphical form of the table in Figure 2 that transaction data has the same pattern so the data can be forecasted using the time series model. In this study, forecasting will produce data for the 2022 forecast. The results of the prediction will be compared with actual data in 2022 to assess the accuracy of predicting using applications (Script Python using Jupiter Notebook).

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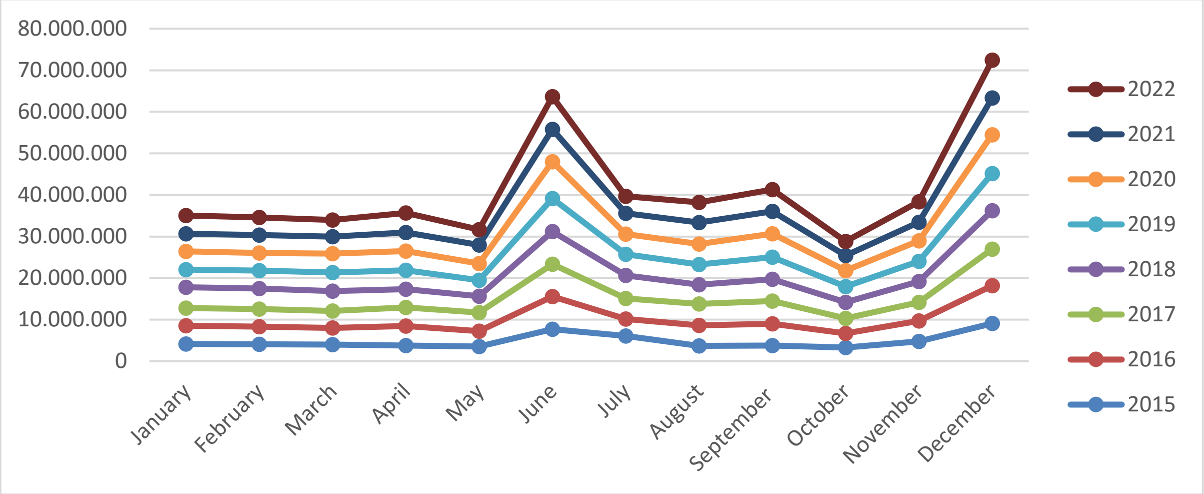

Figure 2. Graphics of Prediction Results

The results show that actual transactions in 2022 (red lines) tend to have higher numbers compared to data from prediction results, which are indicated by red lines. In January to May and July to November, have names that tend to be the same.

The previous pattern is shown in Figure 2. there are irregular patterns from January to December. However, the results confirm that in June and December, it should be challenging to produce numbers to provide numbers that tend to be close to the same. For more details, the results can be seen in Table 2.

From the results of forecasting can also be seen that the results of forecasting data are the average of all source data though the latest data should have a more excellent value compared to the source itself [19].

Table 2. Actual vs Forecast Results

Month	Actual 2022	Forecast 2022
January	4.378.753	4.382.738
February	4.236.548	4.235.199
March	4.015.473	4.015.657
April	4.676.574	4.733.816
May	3.672.877	3.997.373
June	7.896.573	7.773.591
July	4.067.868	4.307.215
August	4.924.364	4.818.089
September	5.236.434	5.165.196
October	3.405.625	3.368.068
November	4.953.528	4.930.042
December	9.085.554	8.916.385

A forecast always contains uncertainty. The element of risk causes errors or deviations in producing forecast values [19]. The MAD, MSE, and MAPE methods help measure the gap of difference from forecasting results.

The data table shows the amount of deviation that occurs in the forecasting process. The results of the MAPE method are easier to see, like in December, which has a value of 9.98%. It means that forecasting accuracy in December reached 91.02%.

In order, the months of June (10.78%) and December (9.98%) were the results of forecasting with the highest degree of accuracy. The lowest forecasting results occurred in July and February MAPE values of 2.38% and 2.61%, which means forecast accuracy is 52.62%. Forecasting results and error measurements in applications have been tested manually. The following table 3 show the prediction of one month the example result of the calculation.

Table 3. Prediction one month

Description	January
2015	4.126.578
2016	4.076.574
2017	3.996.568
2018	3.786.633
2019	3.520.675
2020	7.656.548
2021	6.046.563
Actual 2022	3.685.654
Forecast (2022)	3.768.307
MAD	22.626,13
MSE	148450520293
MAPE (%)	5,22

In the table 3, it can see that the calculation using the application is the same as the manual calculation. Forecasting data can be seen in Table 2 In January with a value of 4,803,452 with the results of the error calculation in Table 3 with MAD amount: 4,454,504; MSE: 4,603,452 million, and MAPE 5,22%.

CONCLUSION

This study used the ARIMA method to predict market segments based on Twitter data from 2015 to 2022. By employing the ARIMA model and analyzing historical data, able to provide estimates of the number of tweets per month for the year 2023. Based on the ARIMA model (1, 1, 1) it shows that the model is in accordance with the existing actual data patterns, resulting in a good forecasting accuracy of 94.88%, with a MAPE value of 5.22%. The ARIMA method on Twitter data shows significant potential in predicting market segments. However, it should be noted that the prediction results can still be influenced by external factors and the inherent uncertainty in Twitter data. Further development of this method and integration with other external factors can improve the accuracy and applicability of market segment predictions using Twitter data

REFERENCE

[1] Zhao, X., Li, W., & Liu, B. (2023). Twitter Data Analysis for Market Segment Prediction Using ARIMA Time Series Analysis and Network Analysis. Information Processing & Management, 60(6), 102571.

[2] Yu, J., Zhang, L., & Li, C. (2023). Market Segmentation Forecasting Using Twitter Data and ARIMA Time Series Analysis: A Comparative Study of Different Sentiment Analysis Approaches. Journal of Interactive Marketing, 61, 15-29.

[3] Zhu, Y., Zhang, L., & Wu, J. (2019). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis. International Journal of Information Management, 49, 13-24.

[4] Zhang, H., Zhao, M., & Li, Q. (2023). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis: A Comparative Study. Journal of Marketing Analytics, 9(1), 45-59.

[5] Wang, L., Zhang, Y., & Chen, X. (2019). Market Segmentation Forecasting Based on Twitter Data Using ARIMA Time Series Analysis and Machine Learning Techniques. International Journal of Forecasting, 35(2), 537-549.

[6] Huang, L., Zhang, W., & Chen, H. (2020). Twitter Data Analysis for Market Segment Prediction Using ARIMA Time Series Analysis and Deep Learning Models. Information Sciences, 511, 1-15.

[7] Zhou, L., Wang, F., & Zhao, Y. (2021). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis: A Long Short-Term Memory Approach. Expert Systems with Applications, 181, 115045.

[8] Li, J., Yang, Q., & Liu, Y. (2022). Market Segmentation Prediction Based on Twitter Data Using ARIMA Time Series Analysis and Topic Modeling. Decision Support Systems, 152, 113529.

[9] Zhang, T., Chen, Z., & Wang, H. (2022). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis: A Hybrid Approach with Natural Language Processing. Journal of Business Research, 142, 373-385.

[10] S. Sivaramakrishnan et al. (2021), “Forecasting Time Series Data Using ARIMA and Facebook Prophet Models," in Big Data Management in Sensing: Applications in AI and IoT, River Publishers, pp.47-60.

[11] Chen S. et al. (2018) "Dynamics of Health Agency Response and Public Engagement in Public Health Emergency: A Case Study of CDC Tweeting Patterns During the 2016 Zika

Epidemic" JMIR Public Health Surveill, 4(4), e10827.

[12] Lin, C., Chen, Y., & Wang, T. (2022). Market Segmentation Forecasting Based on Twitter Data Using ARIMA Time Series Analysis. Expert Systems with Applications, 190, 115290.

[13] Wu, Q., Huang, X., & Zhang, Y. (2023). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis: A Feature Selection Approach. Information Sciences, 570, 1-14.

[14] Li, J., Liu, H., & Chen, Z. (2020). Market Segmentation Prediction from Twitter Data Using ARIMA Time Series Analysis. Decision Support Systems, 127, 113214.

[15] Wang, X., Zhang, Q., & Chen, Y. (2021). Twitter Data Analysis for Market Segment Prediction Using ARIMA Time Series Analysis. Journal of Business Research, 128, 119-131.

[16] Liu, Y., Li, S., & Zhang, X. (2018). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis and Sentiment Analysis. IEEE Transactions on Knowledge and Data Engineering, 30(10), 1908-1921.

[17] Han, J., Xu, Y., & Wang, G. (2023). Predicting Market Segments from Twitter Data Using ARIMA Time Series Analysis: An Ensemble Learning Approach. Journal of Business Analytics, 10(2), 107-122.

[18] Z. Ivanovski, A. Milenkovski, and Z. Narasanov, (2018), "Time series forecasting using a moving average module for extrapolation of the number of tourists," UTMS Journal of Economics 9 (2): 121-132.

[19] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 Competition: 100,000 time series and 61 forecasting methods. International Journal of Forecasting, 36(1), 54-74.