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SENTIMENT ANALYSIS OF THE STATE GLOBAL ISLAMIC ECONOMY ON TWITTER WITH SUPPORT VECTOR MACHINE RAPID MINER

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ABSTRACT

This study uses the Support Vector Machine (SVM) algorithm on the RapidMiner platform to collect sentiment towards the State of the Global Islamic Economy (SGIE) in Twitter data related to the 2024 Vice Presidential candidate debate. Initial data obtained through Twitter crawling reached 22,673 entries. The data used for analysis was 12,135 entries after duplicate data was removed, then about a quarter of the data, or 2,925 entries were labeled as training data. The dataset was taken from Twitter with the search keyword SGIE in December 2023. SVM analysis predicts the negative sentiment class with an accuracy level above 90%. The dominance of negative sentiment and evaluation shows quite good accuracy of 76.30%, precision of 67.92%, and recall of 99.69%. These results provide important insights into public responses to global Islamic economic issues, highlighting the relevance of sentiment analysis methods in understanding the dynamics of public opinion and their contribution to developing future policies and strategies.

Keywords: *State of the Global Islamic Economy (SGIE), 2024 Vice Presidential Candidate Debate, Sentiment Analysis, SVM, Twitter, RapidMiner.*

1. INTRODUCTION

In today's interconnected world, marked by the rapid dissemination of information, understanding public sentiment is paramount, particularly regarding intricate topics such as the global Islamic economy. The rise of social media platforms, notably Twitter, has revolutionized the landscape of public discourse, offering a vast arena for individuals to engage in discussions, express opinions, and respond to ongoing events. Amidst significant events like the 2024 Vice Presidential candidates' debate, where economic issues like the State of the Global Islamic Economy (SGIE) take center stage, Twitter serves as a crucial barometer of societal sentiment, reflecting public perceptions and reactions in real-time. Leveraging advanced analytical tools like the Support Vector Machine (SVM) algorithm and RapidMiner, researchers aim to delve deep into Twitter data, unraveling nuanced sentiment patterns surrounding SGIE to inform policymakers and stakeholders [1]. Sentiment analysis serves as the cornerstone of this research endeavor, aiming to extract meaningful insights from the extensive reservoir of Twitter data associated with the State of the Global Islamic Economy (SGIE). Central to this analytical process is the utilization of Support Vector Machine (SVM), a sophisticated algorithm recognized for its adeptness in handling intricate data configurations. Through the application of SVM, researchers embark on the task of unraveling the complex tapestry of sentiments prevalent within Twitter's digital domain. However, the analytical pursuit transcends mere identification of sentiment polarity; it entails a deeper exploration of the subtle nuances and evolving trends, offering a nuanced comprehension of how societal perceptions regarding SGIE manifest and evolve within the online discourse [2]. The research's core focus lies in sentiment analysis, aiming to extract valuable insights from Twitter data concerning the State of the Global Islamic Economy (SGIE). Leveraging Support Vector Machine (SVM), a robust algorithm renowned for its adeptness in handling complex

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data structures, the study seeks to unravel the intricate tapestry of sentiments expressed across Twitter's digital landscape [3]. This analytical endeavor delves beyond mere sentiment polarity, diving into nuanced trends to offer a comprehensive understanding of how societal viewpoints toward SGIE evolve and resonate in the online sphere. The methodology underscores a commitment to precision, from meticulously curating Twitter data to fine-tuning SVM parameters and rigorously applying cross-validation techniques, all aimed at ensuring the reliability and robustness of sentiment analysis outcomes. Ultimately, the research aims to furnish policymakers and stakeholders with actionable insights, facilitating informed decision-making and policy formulation in the global Islamic economic domain, while fostering greater awareness, dialogue, and collaboration amidst the complexities of globalization and technological advancement [4].

2. LITERATURE REVIEW

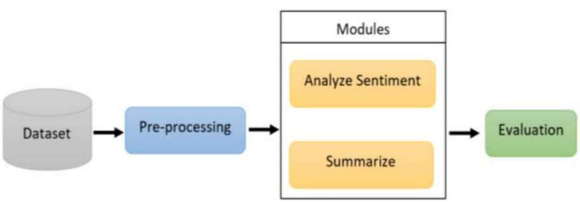

FIGURE 1. The concept of sentiment analysis

The Architecture Model for Multi-Document Summarization and Sentiment Analysis operates through a structured process, as depicted in Figure 1. Initially, the system retrieves from Twitter, serving as the primary source of data. These files are then subjected to pre-processing to transform unstructured data into a structured format. This pre-processing step involves several tasks, such as converting upper-case characters to lower case and extracting the root words using an English dictionary. By standardizing the format of the data, the system prepares it for further analysis [5]. Subsequently, the models for sentiment analysis and summarization are applied concurrently. In the sentiment analysis phase, the system assesses the opinion conveyed in each review extracted from the data. Simultaneously, the summarization phase condenses the content of each review into a succinct form, typically comprising a limited number of sentences. This simultaneous application of both models allows for a comprehensive analysis of the data, capturing both its sentiment and key points [6]. Once the sentiment analysis and summarization processes are completed, the resulting outputs undergo evaluation using an extrinsic evaluation approach. This evaluation method assesses the effectiveness and accuracy of the sentiment analysis and summarization outputs in real-world contexts. By examining how well the system's outputs align with external criteria or objectives, stakeholders can gauge the system's performance and suitability for practical applications [7]. Further insights into the simulation results obtained from executing the models are provided in Section result and Discussion. These insights offer a detailed analysis of the system's performance, providing valuable information on its strengths, weaknesses, and overall effectiveness. By delving into the simulation results, readers can gain a comprehensive understanding of how well the system performs in analyzing sentiment and summarizing multi-document data [8].

3. METHODOLOGY

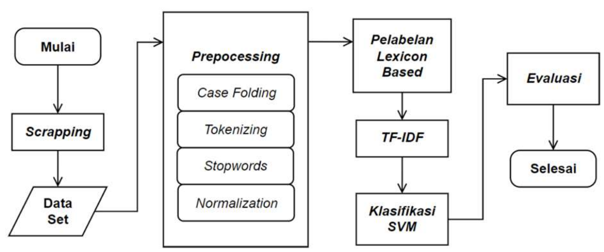

Figure 2. Research Process

The theoretical flow of the research is described as follows:

a. Twitter crawling process is the initial stage in the data collection process, using Google Colabs with Python language to explore the Twitter platform with the aim of collecting relevant data. This stage involves searching for tweets based on certain keywords or predefined user profiles. The obtained data includes tweets that meet the specified search criteria, enabling the acquisition of a representative dataset according to the needs of the analysis to be conducted. This crawling process is an important initial step in obtaining the necessary data for various analyses, including sentiment analysis, prediction modeling, or other research utilizing data from the Twitter platform. The data collection process will yield a dataset of tweets [9].
b. The preprocessing stage involves filtering tweet comments to generate cleaner and more relevant

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data. It includes tokenization, where text is segmented into tokens like words or phrases, followed by letter transformation to ensure uniformity. Irrelevant words, or stopwords, are then removed to focus on informative content. Additionally, data is cleaned of noise like URLs and punctuation marks. These steps prepare the data for further analysis, enhancing its suitability for sentiment analysis [10].

c. The weighting stage assigns a score to each word based on its importance in the document's context, often using TF-IDF. This method considers how often a word appears in a document (Term Frequency) and its uniqueness across all documents (Inverse Document Frequency). Words appearing frequently in one document but rarely in others are given higher weights, indicating their significance. This process highlights key words with substantial influence in the dataset, facilitating further analysis and modelling [11].

d. The Support Vector Machine (SVM) model is used as a tool to classify the labels obtained from the weighting and labeling process in the previous stage. SVM is a machine learning method commonly used for classification or regression. Its main goal is to separate two different classes by finding the best hyperplane that can separate these classes. This hyperplane is used as the decision boundary that allows SVM to classify new data into one of the two existing classes based on its relative position to the hyperplane. SVM enables the efficient formation of models to classify data based on patterns identified in the weighting stage, aiding in further analysis and understanding of the relevant dataset [12].

e. The accuracy testing stage is crucial for evaluating the model's performance. It utilizes predefined test data to gauge the model's ability to predict correct labels. By assessing how well the model captures patterns and predicts labels accurately, researchers can determine its effectiveness. Evaluation metrics like accuracy, precision, recall, and F1-score are calculated using the test data to gauge overall performance. This step ensures the model can reliably provide accurate results beyond its training data, enhancing its applicability to new datasets [13].

f. The sentiment analysis results stage is the final phase of the analysis process, where the sentiment predictions from the SVM model are assessed and presented. This evaluation helps understand the sentiment patterns within Twitter data concerning the State of the Global Islamic Economy (SGIE). Researchers gain insights into public responses, identifying trends and crucial patterns. Analyzing sentiments enables a deeper understanding of how the public perceives the issue, aiding in policy development and communication strategies for addressing global Islamic economy concerns more effectively [14].

4. RESULT AND DISCUSSION

4.1 Data Crawling

Crawling data refers to the automated process of collecting data or information from various sources on the internet. Data collection is done using specialized software, such as computer programs or bots, which systematically explore web pages, follow links, and extract relevant information. The principle of data crawling is similar to how humans browse the internet, but this process is automated by software without human intervention. This crawling process is the initial step in gathering data by utilizing the twitterscraper facility [15].

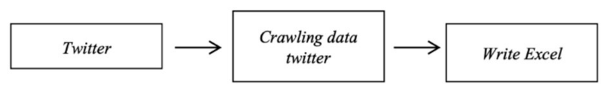

Figure 3. Data Crawling General Step

The data retrieval process begins by utilizing Google Colabs, a web-based cloud platform that facilitates the development and execution of Python code directly. Some keywords used as data search criteria include 'SGIE,' 'SGIE Gibran,' and 'SGIE Vice Presidential Debate,' which are relevant to the research object. The obtained data is in CSV format and is collected into one file for subsequent merging. The final result of this data retrieval process is a dataset consisting of 22,673 entries, which will be used in further analysis [16].

```
# Crawl Data

filename = 'SGIE.csv'
search_keyword = 'SGIE gibran lang:id'
limit = 5000

!npx --yes tweet-harvest@2.2.8 -o "{filename}" -s "{search_keyword}" -l {limit} --token {twitter_auth_token}
```

Figure 4. Keywords For Data Crawling

4.2 Data Cleaning

Data cleaning is a vital process in data analysis aimed at ensuring the accuracy, completeness, and consistency of the data used in the analysis. The first step in this process is to identify data that may be incomplete, inaccurate, or unstructured, which could interfere with the analysis results. Missing data can be caused by various factors, such as input errors or imperfect data collection processes. The first step in data cleaning is to remove incomplete data or fill in missing values with valid and contextually appropriate values. Data duplication

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also needs to be addressed as it can cause bias in the analysis by giving disproportionate weight to the same data [17].

Invalid or out-of-format data, which can be a significant hindrance to the analysis process, must be thoroughly corrected or removed to guarantee consistency throughout the analysis. Following the cleaning steps, it is crucial to conduct further evaluation to address any anomalies or outliers that may still be present in the data. Techniques such as outlier detection are particularly useful in identifying and handling unusual or unrepresentative values within the dataset. By ensuring comprehensive data cleaning, the data becomes more consistent, relevant, and reliable, ultimately paving the way for more accurate and meaningful analysis.

The importance of data cleaning cannot be overstated. It is a critical step in ensuring that the data used in analysis is accurate, reliable, and free from errors. Without proper data cleaning, the analysis results may be skewed or even meaningless. Therefore, it is essential to invest time and resources in thoroughly cleaning the data to ensure that the analysis is based on high-quality data. This not only enhances the credibility of the analysis but also helps in making more informed decisions based on the insights gained from the analysis [18].

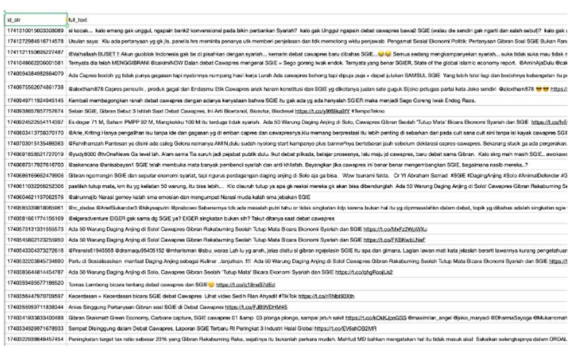

Figure 5. Example Of Csv Format Raw Data Taken From Twitter

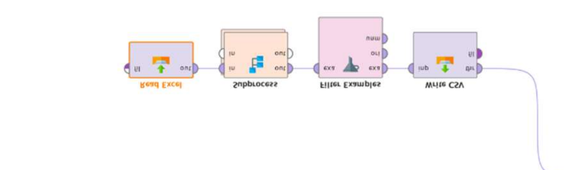

Figure 6. The Sequence Of Operators Used For The Data Cleaning Process

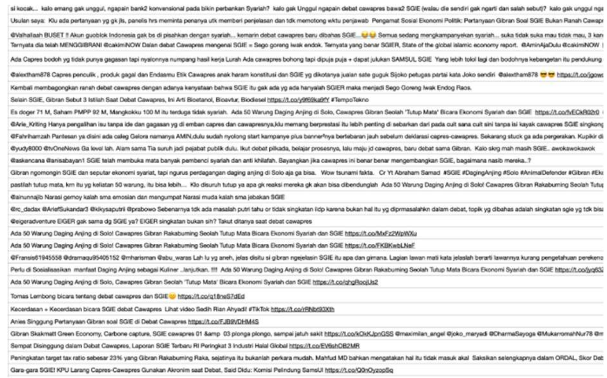

Figure 7. Dataset Before Cleaning

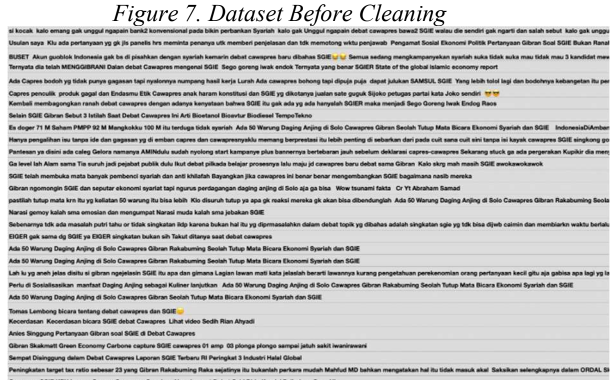

Figure 8. Dataset After Cleaning

4.3 Data Preprocessing

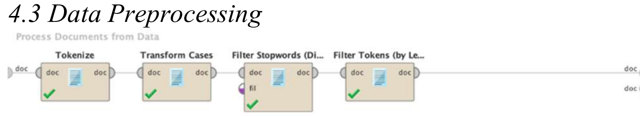

Figure 9. Sequence Of Operators Used For Data Preprocessing

a. Tokenize

Tokenization is a crucial step, breaking down text into smaller units known as tokens. This process simplifies further analysis by treating words or phrases as separate entities. For instance, in the sentence "SGIE is an abbreviation," tokenization would separate the text into individual tokens like ["SGIE", "is", "abbreviation"]. Each token represents a distinct word or phrase, facilitating detailed analysis at the word or phrase level. This stage is vital for preparing text data before conducting subsequent analyses such as sentiment analysis or language modelling.

b. Transform Cases

Transform Cases is a stage in text processing that changes the format of letters in the text into a certain format, such as lowercase or uppercase, according to analysis needs. For example, if we have the sentence "State of Global Islamic Economy", in the Transform Cases stage, we can

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change that sentence to "state of global Islamic economy" to treat all words in lower case, or "STATE OF GLOBAL ISLAMIC ECONOMY" to treat all letters in uppercase. The purpose of this step is to ensure consistency in the processing and analysis of text data, as well as to simplify further processing. Further analyzes such as word frequency calculations or text classification become more consistent and effective with appropriate letter transformations [19].

c. Stopwords filter
Stopwords filtering is a process that involves removing commonly occurring and unimportant words, such as "and" and "in", from text data. The aim of removing stop words is to sharpen the focus of analysis on more informative content, thereby improving the overall quality of analysis. Analysis prioritizes retaining only words that are meaningful and relevant to understanding the underlying message or sentiment expressed in the text. This retention of light-reflecting words contributes to increased accuracy and effectiveness of analysis results.

d. Filter Tokens
Token Filtering is a step in text processing that aims to remove certain tokens based on certain rules or conditions. An example of using the Token Filter is to delete tokens that are less than three characters long. This helps eliminate less relevant elements or noise in the analysis. Short and possibly meaningless tokens can be eliminated using a token filtering step, improving the quality of the analysis by focusing on more informative and important tokens [20].

4.4 Data Modeling

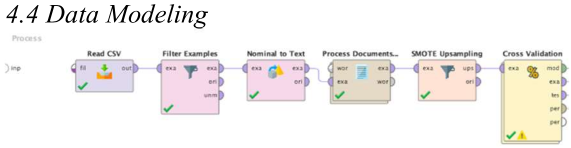

Figure 10. Operator Sequences For Data Modeling

Support Vector Machine (SVM) is a model rooted in statistical learning theory, renowned for its superior performance in categorizing labels acquired through weighting and labeling procedures. SVM streamlines sentiment analysis by segregating labels into two distinct classes: positive and negative. This binary classification simplifies the intricacies of sentiment analysis, aligning with the common binary nature of human expression—typically characterized as positive or negative. This inherent simplicity enhances the clarity and interpretability of sentiment analysis results, making SVM a preferred choice for discerning sentiments efficiently in data analysis tasks.

The sequence of operators in RapidMiner used in sentiment analysis on SGIE using the SVM model is as follows:

a. Read CSV: The Read CSV operator serves as a conduit for ingesting data stored in CSV (Comma-Separated Values) files, seamlessly importing datasets into the RapidMiner environment. Upon activation, this operator assimilates the dataset's structural blueprint, which is typically encoded in CSV format, and translates it into a format compatible with RapidMiner's analytical framework. This enables users to effortlessly access and explore the imported data, leveraging the myriad tools and functionalities embedded within the RapidMiner platform for in-depth analysis and insights extraction [21].

b. Filter Example: This operator is included in the first step. The Filter Examples operator operates by sifting through dataset rows and selectively discarding those that fail to meet predetermined conditions or criteria. Users wield the power to eliminate irrelevant rows or winnow datasets based on specified column values. With this tool, criteria can be established to weed out rows falling below or exceeding certain thresholds, or alternatively, to retain only those rows that align with specified criteria. Such functionality empowers users to refine and purify datasets in accordance with their unique analytical requisites, thereby enhancing the precision and relevance of subsequent analyses [22].

c. Nominal to Text: The Nominal to Text operator functions to convert nominal data types, which usually consist of categories or labels, into a more interpretable text format. Nominal data is categorical data, cannot be sorted, and has no numerical value. For example, nominal data include labels such as "red", "blue", or "green". By using the Nominal to Text operator, users can convert these categorical values into descriptive text, facilitating better understanding and analysis of the data. This conversion allows the representation of category or label data in a format that is easier to understand, thereby improving the

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interpretation of the results obtained from subsequent analysis [23].

d. Process Documents: The preprocessing phase is one of the important phases that must be carried out before the data analysis process. The data preprocessing stage in text data involves a series of systematic operations aimed at optimizing the handling of textual documents in the data set. Initially, tokenization breaks text into smaller units called tokens, which can include individual words or phrases, allowing for more in-depth analysis. After this, letter transformation ensures uniformity in text formatting by converting all letters to a specified format, usually lowercase or uppercase. Next, stopword filtering removes common but uninformative words, ensuring that the analytical focus remains on more meaningful content. Finally, token filtering selectively removes certain tokens based on predefined criteria, such as removing tokens that are less than three characters long, thereby further refining the data set. In essence, these successive steps lead down the text data processing path, making it more suitable for subsequent analysis and modeling efforts.

e. SMOTE Upsampling: Synthetic Minority Sampling Technique (SMOTE) is a method used to overcome the class imbalance that exists in a data set. SMOTE can balance unbalanced data. The main goal of this operator is to improve minority class representation by generating synthetic samples. By doing this, SMOTE effectively mitigates bias in model results, as algorithms trained on balanced datasets tend to exhibit superior performance. This technique works by creating synthetic samples that are very similar to existing samples but have slight variations, thereby enriching the pattern learning process in minority classes. As a result, SMOTE emerges as a valuable tool for improving prediction accuracy, especially on datasets characterized by class imbalance [24].

f. Cross Validation: Cross Validation stands as a pivotal technique in machine learning, pivotal for its methodology of partitioning datasets into multiple folds with overlapping segments. In this approach, each fold cyclically acts as the test set, while the remaining segments serve as training sets. This iterative process persists until every fold has undergone testing. The essence of Cross Validation lies in its holistic model evaluation strategy, averting dependency on particular data subsets and fostering resilience in model assessment. By embracing Cross Validation, researchers can offset biases potentially stemming from exclusive reliance on specific data segments, thus amplifying the model's reliability and its ability to generalize effectively.

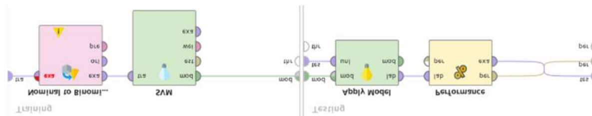

Figure 11. Operator Sequence In The Cross Validation Process

a. Nominal to Binominal
The "Nominal to Binominal" operator plays a crucial role in data preprocessing by transforming nominal variables into binary ones. It accomplishes this by converting categorical variables into binary representation, where each category is assigned two values: 0 or 1. A value of 1 signifies membership in a particular category, while 0 denotes its absence. This conversion process enhances the efficiency of analysis and modeling, particularly when utilizing algorithms or models that necessitate binary-formatted target variables. By converting qualitative variables into a more amenable format, this operation streamlines subsequent analysis and model construction processes [25].

b. Apply Model
The "Apply Model" operator serves as a pivotal component in machine learning workflows, facilitating the deployment of a trained model onto fresh or testing datasets. Its functionality empowers users to leverage the model for making predictions or classifying new data instances subsequent to the model's training phase using training data. By employing the "Apply Model" operation, users can gauge the model's performance on unseen data, thereby obtaining insights into its generalizability and predictive accuracy when confronted with new instances. This operational procedure underscores the importance of assessing a model's adaptability to novel data, enabling users to ascertain its robustness and effectiveness beyond the confines of the training dataset.

c. Performance
Performance evaluation in machine learning refers to the assessment of how effectively a model delivers accurate and relevant results in its designated task. This evaluation process entails the

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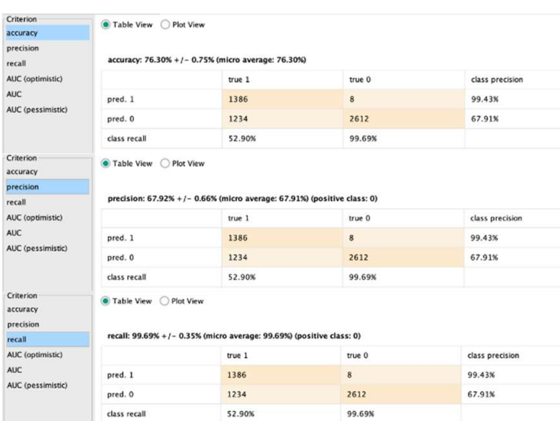
utilization of various metrics or indicators, including accuracy, precision, recall, and F1-score. Accuracy denotes the proportion of correct predictions relative to the total predictions generated by the model. Precision quantifies the percentage of true positive predictions among all positive predictions made by the model. Meanwhile, recall gauges the percentage of positive instances correctly identified by the model out of the total positive instances that should have been predicted. Additionally, the F1-score, a composite metric, combines precision and recall to offer a comprehensive evaluation of the model's performance. By conducting performance evaluation, users gain insights into the model's efficacy in handling specific classification or prediction tasks, while also identifying potential areas for enhancement within the model's framework.


Open in Turbo Prep Auto Model Interactive Analysis Filter (5,240 / 5,240 examples): all

Row No.	sentimen	prediction(...	confidence(...	confidence(...	aaron	abaikan	abcd	abirekso
1	1	1	0.756	0.244	0	0	0	0
2	1	1	0.634	0.366	0	0	0	0
3	1	1	0.618	0.382	0	0	0	0
4	1	0	0.429	0.571	0	0	0	0
5	1	0	0.391	0.609	0	0	0	0
6	1	1	0.597	0.403	0	0	0	0
7	1	1	0.670	0.330	0	0	0	0
8	1	1	0.634	0.366	0	0	0	0
9	1	1	0.640	0.360	0	0	0	0
10	1	0	0.347	0.653	0	0	0	0
11	1	0	0.462	0.538	0	0	0	0
12	1	1	0.588	0.412	0	0	0	0
13	1	1	0.647	0.353	0	0	0	0
14	1	1	0.668	0.332	0	0	0	0
15	1	0	0.391	0.609	0	0	0	0
16	1	1	0.669	0.331	0	0	0	0
17	1	1	0.714	0.286	0	0	0	0
18	1	1	0.594	0.406	0	0	0	0
19	1	1	0.501	0.499	0	0	0	0
20	1	1	0.635	0.365	0	0	0	0

Figure 12. Example Of Sentiment Prediction Results


Criterion: accuracy, precision, recall, AUC (optimistic), AUC, AUC (pessimistic)
Table View Plot View

accuracy: 76.30% +/- 0.75% (micro average: 76.30%)

	true 1	true 0	class precision
pred. 1	1386	8	99.43%
pred. 0	1234	2612	67.91%
class recall	52.90%	99.69%	

precision: 67.92% +/- 0.66% (micro average: 67.91%) (positive class: 0)

	true 1	true 0	class precision
pred. 1	1386	8	99.43%
pred. 0	1234	2612	67.91%
class recall	52.90%	99.69%	

recall: 99.69% +/- 0.35% (micro average: 99.69%) (positive class: 0)

	true 1	true 0	class precision
pred. 1	1386	8	99.43%
pred. 0	1234	2612	67.91%
class recall	52.90%	99.69%	

Figure 13. Performance Results

4.5 Discussion

In the intersection of politics and business, the evaluation metrics of accuracy, precision, and recall serve as vital indicators of sentiment analysis model performance [26]. These metrics offer nuanced insights into the efficacy of political marketing strategies and business decisions by gauging the model's ability to accurately predict public sentiments. With an accuracy rate of 76.30%, the model demonstrates a commendable capability in making correct predictions, shedding light on the prevailing sentiments surrounding political and economic issues. This accuracy metric is particularly valuable for policymakers and businesses seeking to align their strategies with public opinion trends, thus enhancing their relevance and resonance [27].

Furthermore, precision, standing at 67.92%, serves as a crucial measure of the model's accuracy in identifying positive sentiments within the dataset. This metric provides insight into the effectiveness of political marketing strategies in eliciting favorable responses from the target audience. Despite a slightly lower precision rate, which implies some margin for error in positive predictions, the high recall rate of 99.69% highlights the model's robustness in capturing the majority of instances representing positive sentiments accurately. This aspect is pivotal for policymakers and businesses aiming to craft strategies that resonate positively with their constituents or customers, thereby fostering trust and engagement [28].

Overall, these evaluation metrics offer valuable guidance for refining political marketing strategies and business approaches to better align with public sentiments and preferences. By considering the nuanced insights provided by accuracy, precision, and recall, policymakers and businesses can fine-tune their strategies to enhance their effectiveness and relevance in addressing societal and economic challenges. This comprehensive evaluation underscores the importance of leveraging sentiment analysis models to inform data-driven decision-making processes, ultimately fostering greater resonance and impact in both political and business spheres [29].
This research is very important and needs to be developed further, such as how to implement and measure its success performance so that it can provide an optimal contribution to an organization or company.

5. Conclusion

The data obtained through crawling process on Twitter in this study resulted in a large initial dataset of 22,673. The number of data used for

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analysis decreased to 12,135 after removing duplicates. From these data, about a quarter or 2,925 data were labeled as training data. This data was selected from Twitter using search keywords related to the State of the Global Islamic Economy (SGIE) in December 2023. The analysis was conducted using the Support Vector Machine (SVM) method, which was able to predict negative sentiment classes with an accuracy rate above 90%.

The SVM prediction results showed domination of negative sentiment, and the evaluation concluded that Twitter users' sentiment regarding SGIE tends to be negative, yet still provides a fairly good accuracy rate of 76.30%. The model's precision reached 67.92%, while recall reached 99.69%, indicating the model's ability to classify sentiments well despite being predominantly negative. This research provides important insights into public responses to issues related to the global Islamic economy. The SVM classification model still provides predictions with good accuracy despite facing challenges in dealing with the dominance of negative sentiment. This demonstrates the relevance and usefulness of sentiment analysis methods in understanding and addressing public opinion dynamics and can significantly contribute to developing future policies and strategies related to the global Islamic economy [30].

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Authors Contribution

Wahyu Sardjono,
For all research processes and results to produce articles published in national and international reputable journals and coordinate research activities with research members including lecturers.

Aldo Lovely Arief Suyoso
Provide theoretical direction that is the basis of research, develop research instrument designs, determine research methods, and ensure the output of research results.

Erma Lusia,
Data collection, documentation, publication preparation, process execution, and monitoring

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