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Digital Advocacy Strategies with Data Analytics Framework: A Case Study for Effective Campaigns

Nurellezia Suleiman[1], Jacey-Lynn Minoi[1,*], Rochmat Aldy Purnomo[2]

[1] Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia
[2] Faculty of Economy, Muhammadiyah University of Ponorogo, Kabupaten Ponorogo, Jawa Timur 63471, Indonesia

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ABSTRACT

This paper presents a case study of a digital campaign on social media to formulate an extensive novel framework using data analytics method to measure the effectiveness of a social media campaign. The Social Media Impact Discovery (SMID) framework is built from the concept of digital advocacy strategies and data analytics techniques, which will provide a systematic approach in both domains to carry-out an effective advocacy campaign. Since the advent of social media such as Twitter in providing platforms for freedom of speech, digital advocacy has become the new approach for delivering campaigns to a wider range of targeted audiences. The use of digital advocacy has generated interest among politicians and advocators to spread their messages across. Despite the numerous and widespread use of digital advocacy, there is still no formal framework that study the success of the technique as end outcomes in terms of the technological aspect of knowledge and the data analytic. The impact of the campaign is evaluated in terms of its effectiveness using deep machine learning methods on the acquired data on social media of a digital campaign. The results have shown that continuous loops using Support Vector Machine (SVM) and the Naïve Bayes classifier support the dynamic approach in the SMID framework to increase campaign effect and is in line with the iterative structure. The loop's cyclical structure is in tune with the shifting user trends and social media user behaviours. The framework's ability to include fresh data and modify models as advocacy campaigns change over time provides a tactical advantage responsive to shifting conditions. Thus, the overall processes of the campaign should be supported with accurate and reliable data to build trust among its audiences. A case study of sexual harassment on Twitter is used to assess the SMID framework's practicality. It centred on a young Malaysian advocate named Ain Husniza, whose notable catchphrase is #MakeSchoolASaferPlace. For the first time, digital advocacy for sexual harassment campaigns has been used and analysed in this study. It has demonstrated its contribution by amplifying survivors' voices and fostering online solidarity, with the aim of raining public awareness of the issue and promoting informed policy.

[*] *Corresponding author.*
E-mail address: jlminoi.unimas@gmail.com

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1. Introduction

The term digital advocacy refers to tools, tactics and strategies that are based on conventional activism whilst incorporating various social media technologies [1]. The conventional way to start a movement is usually by mass campaigns directed at the general public using media, such as newspapers, radios and televisions which has lower response rate these days and that leads to high waste [2]. Therefore, with the emerging technologies, digital transformation in advocacy is applied through online campaigns using Twitter hashtags to spark an issue and possibly start a social movement [8,13,14]. To measure the effectiveness of a campaign, public opinion matters to gain the trust and loyalty population and thus, the spiral of silence theory states that people influence each other's willingness to express opinions through social interaction [2,26]. Through digital advocacy, social interaction is made easily accessible, and their sentiments can be gathered in a more systematic way through data analysis processes, specifically sentiment analysis, which will transform the large amount of data into meaningful insights that can help in decision-making for the campaign preparation and evaluation [8,11,12].

Although the theoretical foundations of digital advocacy have received considerable amount of attention, there is still a significant technical gap, especially when it comes to utilising data analytics throughout the campaign lifecycle [21]. For the development of viable, credible, and genuine influence on online movements, it is crucial to bridge this gap between the theory and practice of digital advocacy. The goal of this research is to create a ground-breaking platform that combines data analytics and digital advocacy in a fluid manner. The resulting framework provides practitioners with tools to inject creativity and strategy into their campaigns in addition to illuminating the predictive possibilities hidden in public opinion data.

Hence, the focal point of this study integrates a practical case study on sexual harassment with the hashtag #MakeSchoolASaferPlace, being first time used by a female teenager in a social movement in Malaysia advocating against sexual harassment, to illustrate the effectiveness of the proposed framework. The present case demonstrates clearly how effective the suggested structure is in practise.

The order of the paper are as follows: Section 2 provides a literature overview of data advocacy, data analytics while also elaborates the classification algorithms used for public opinion. In addition, section 3 describes the framework of digital advocacy using data analytics. In section 4, a case study is presented on sexual harassment in Malaysia, through the movement of #MakeSchoolASaferPlace and lastly, sections 5 provide the experimental results and finally, conclusion and results are presented in section 6 and 7.

Therefore, this research essentially sets out on a revolutionary journey, connecting the theoretical and technical spheres of digital advocacy. By laying out a strong framework, not only it advances the understanding of this crucial intersection, but it also lays the foundation for a more effective, data-driven, and impactful social movements in the digital age.

2. Literature Review

2.1 Review of Digital Advocacy on Social Media

Rapid technological development has created new opportunities for advancing digital advocacy. Notably, recent research has illuminated the effectiveness of digital advocacy tactics at the interface of science and policy, such as the study carried out by researchers [21]. This study showed that using online petitions and social media platforms could successfully close the gap between scientific knowledge and its political application. The application of a focused-group strategy, which emphasised the significance of involving just relevant groups, was a major element of the many research's success. The study was able to identify the strategy in the case study through data analytic techniques on news stories, media campaigns, and online materials and information using data analytic techniques. However, other than this strategy, Twitter API also plays a vital role in determining how the public felt [17-20] and engaged with the incident of Klitih accident in Indonesia [22]. As a result, digital advocacy was crucial in closing the crucial gap in the science-policy interface, as well as, for the governing body of punitive justice. These results highlighted the significance and usefulness of digital advocacy in forming thoughtful decision-making processes [5,19,20].

2.2 Review on Data Analytics

In this section, data analytics is introduced in terms of its definition, its processes and how it is integrated with digital advocacy. Data analytics is the study of analysing unprocessed data to draw inferences about that information [3]. The inferences can help an organisation to optimise their performances effectively. For instance, opinion mining, also referred as sentiment analysis, is used to classify emotions from textual data [7]. Hence, the opinions gathered from the digital platforms can be extracted and transformed into meaningful visualisation. Data visualisation simplifies the analysis evaluations into a graphical manner that aids in a better understanding as it can visually reveal trends and metrics that would otherwise get buried in the sea of data. This allows digital advocacy campaign to improve its efficiency by tackling the right campaign strategies [17,18]. Not only that, by predictive analysis, the impact of the campaign is also analysed so that the resources for the next movement can be concentrated more on promising groups of followers. The processes of data analysis involved are as follows following the Knowledge Discovery in Databases (KDD), which is a process that seeks new knowledge about an application domain [4]. Figure 1 depicts the adapted KDD process and each of the stages' explanation is as described below.

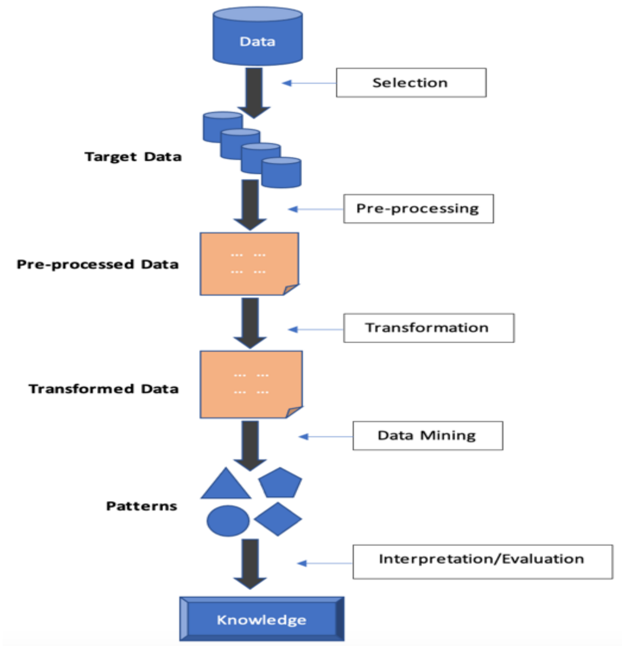

Fig. 1. Knowledge Discovery in Databases

The description of the KDD at each stage as shown below.

i. Data Selection: Data collection and gathering through a chosen digital platform for the campaign.
ii. Data Preprocessing: This stage prepares the data for the next stage which consists of:
iii. Data Preprocessing: Filtering and cleaning the raw data to remove noisy information such as unwanted characters, special characters and redundant information.
iv. Data Annotation: Labelling data with relevant tags to ease computer interpretation.
v. Data Transformation: Involves feature extraction to transform data into numerical data for data mining**.**
vi. Data Mining: Modelling cleaned dataset using the chosen mining techniques such as machine learning and the right type of mining such as opinion mining.
vii. Evaluation: Evaluating the meaningful patterns obtained from the analysis to help in strategizing. Visualisation is also involved in which graphics is illustrated to help users understand.
viii. Knowledge: The end desired results obtained from the discovery process in which new patterns and hypothesis is generated. In the case of digital advocacy, knowledge is the impact of the campaign.

Based on the KDD process, it can be derived that data analytics is useful for knowledge interpretation in various applications and domains. The discovery of new knowledge from raw data is useful for transformation and improvements in further applications. Hence, with the advancement of advocacy strategies, new strategy knowledge can help to mitigate better campaign acceptance results. Therefore, data analytics is going to be integrated in the discovery of new and fruitful strategies for an effective advocacy campaign.

2.3 Review on Classification of Public Opinions

In this sub-section, the classification process and the rationale behind integrating two prominent algorithms, Naïve Bayes classifier and Support Vector Machine classifier [15,16], will be discussed. These decisions were influenced by an analysis of pertinent literature that supported its relevance to the suggested framework. The decision to employ Naïve Bayes and SVM stemmed from a comprehensive survey of existing research in the field of sentiment analysis and classification. In the field of sentiment analysis, Naïve Bayes is a well-known classification method. With the assumption that features are statistically independent of one another, this strategy makes use of Bayes statistics. Calculations are made simpler and learning is made more effective by this supposition. Additionally, Naïve Bayes has proven to be capable of handling high-dimensional data with little in the way of training requirements. Its scalability and lightweight characteristics, as highlighted by researchers like [23], make it especially ideal for processing continuously growing Twitter data over time. SVM was chosen because of its superior capacity for classifying data into discrete groups [24]. SVM can forecast data points' propensities towards distinct classes/ particular categories by locating a discriminant hyperplane that successfully distinguishes between classes. Finding support vectors—the locations closest to the hyperplane dividing the classes enables this [25].

In summary, the Naïve Bayes and Support Vector Machine (SVM) were chosen for this study because of their unique advantages. To handle huge datasets effectively and provide scalability, Naïve Bayes makes use of the statistical independence assumptions. On the other hand, SVM performs well in settings with non-linearly separable data points and excels at accurately classifying data into various groups. These characteristics make both algorithms ideal for classifying opinions in the suggested framework.

3. Methodology

The proposed framework for Digital Advocacy in Figure 2 is depicted using the resemblance of CRoss-Industry Standard Process for Data Mining as in [6,10], better known as CRISP-DM. This approach extends the steps of the KDD methodology (details in [4]) in a typical sequence of data mining applications, into six steps: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. Detailed information on CRISP-DM can be found in [9].

To corroborate the view of data analysis experts, CRISP-DM is a common model for data mining applications [6], and it have been adopted to different fields and domains. Since there is yet a standard framework for data mining in digital advocacy, an extension of CRISP-DM is formulated in our data mining and data analysis project on social media's hashtags and catchphrases to identify the impact pattern of the advocacy and its trends over time and spaces.

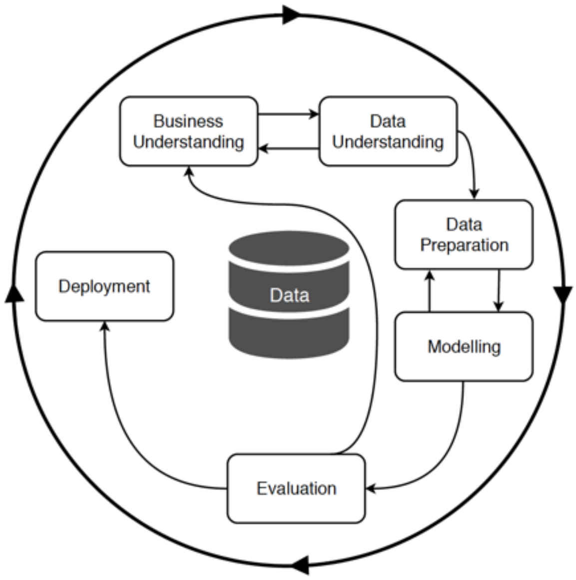

Fig. 2. The current CRISP-DM process model for data mining [Image is adapted from [6]]

The proposed data analytics framework, Social Media Impact Discovery (SMID) framework as shown in Figure 3 for digital advocacy is an approach to improve the effectiveness of the campaigns on social media. With data science methods, the likelihood of the consequences and impact can be predicted. In the following Figure 3, the framework's processes progress linearly, unlike the continuous loops in the original CRISP-DM process. To strategize the effectiveness of digital advocacy, a loop is created at the evaluation stage to the data modelling in which the measure of impact (from data and model perspective) is evaluated. This loop is continuous, but it is limited depending on the case study, the data type and size, the definition and outcome of impact for the end users. If the result is not desirable, then data modelling stage can take place again using different model to ensure that the most accurate model is used.

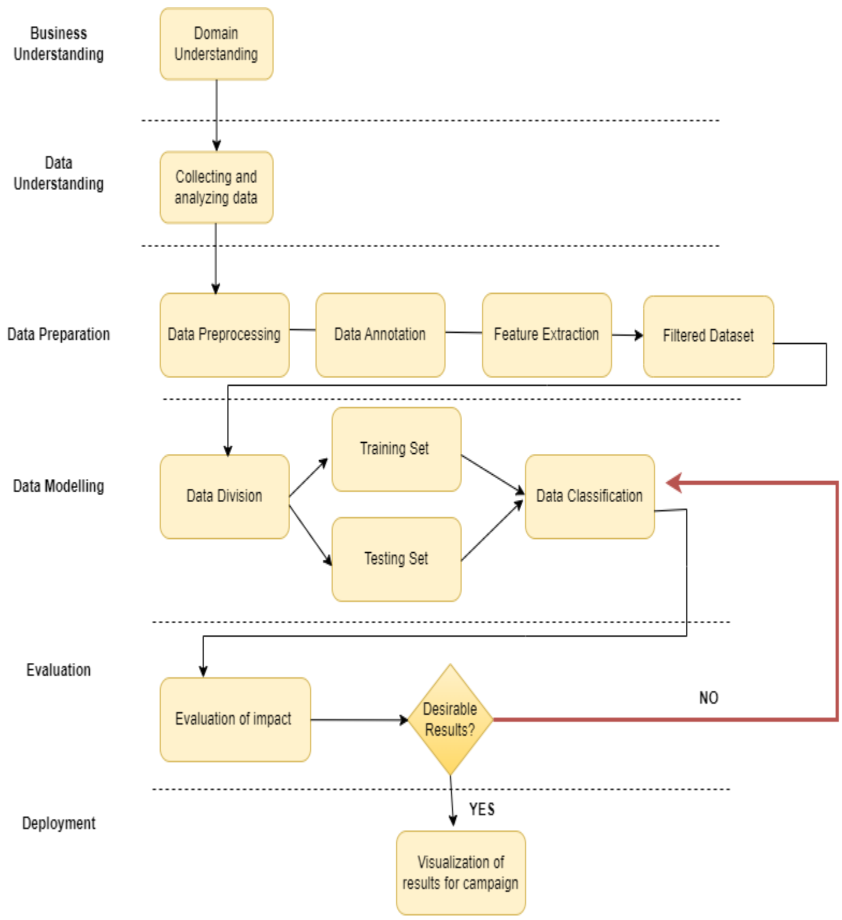

Fig. 3. The proposed Social Media Impact Discovery (SMID) Framework

The activities for each of the six stages are as follows:

i. <u>Campaign Understanding:</u> At this stage, the domain and ideas of the campaign are defined to achieve the right scope of the movement such as the digital platform used. During this stage, strategies of the campaign is standardized so that a clear vision of the movement is obtained. Not only that, the metrics for an effective campaign is also defined here.

ii. <u>Data Understanding:</u> Data collection takes place here in which the data is acquired from the chosen digital platform discussed from the first stage. The data acquired is further analysed to figure out the best categories of data classification as interesting hypotheses can be derived from the data.

iii. <u>Data Preparation:</u> This stage describes the processes of preparing the data for the next stage such as cleaning the data, labelling the data and transforming the data. The processes will be explained more extensively in the subcategories: Data Preprocessing, Data Annotation, Feature Extraction.

3.1 Data Preprocessing

The saved file from crawling during data acquisition stage is in a raw format such that it is filled with noisy information such as unwanted characters, special characters, and redundant information. Hence, the data is filtered and cleaned to ensure that the classifiers can correctly classify the given data. The pre-processing is done using Phyton libraries mainly Natural Language Toolkit (NLTK) in which it involves the following steps:

i. Converting all characters to lowercase
ii. Removing unwanted characters such as emoji, punctuation marks, special characters, numbers and stop words
iii. Removing duplicated data.

3.2 Data Annotation

The cleaned and filtered dataset is labelled into its respective classification categories. For instance, positive and negative categories against an issue.

3.2.1 Feature extraction

The annotated datasets dimensionality will be reduced effectively to enhance the accuracy of classification. Data dimensionality can be reduced with feature extraction as it can further filter out and choose the best features for data modelling. Hence, feature extraction is implemented using the following methods:

i. Term Frequency-Inverse Document Frequency (TF-IDF) Method
This is a statistical measure to determine the importance of words in the document. TF, Term Frequency, measures the frequency appearance of term in the document. Meanwhile, IDF, Inverse Document Frequency, measures the significance level.

The formula for calculating TF and IDF is Eq. (1) and Eq. (2) respectively.

$$\mathrm{tf}(\mathrm{t},\mathrm{d}) = \log(1 + \mathrm{f}_{\mathrm{t},\mathrm{d}}) \tag{1}$$

$$\mathrm{idf}(\mathrm{t}) = \log(\frac{1 + \mathrm{N}}{1 + \mathrm{n}_\mathrm{t}}) \tag{2}$$

Such that,
tf(t,d): count of term t in document d
N: total number of documents
n: number of documents that contains term t

3.2.2 N-gram method

N-grams are counts of n word sequences, where n can be one word (unigram), two words (bigram), or three words (trigram). In this study, unigram and bigram will be implemented.

i. <u>Data Modelling:</u> Classification of data using machine learning algorithm takes place here by using the right algorithms, such as Naïve Bayes classifier or the Support Vector Machine Classifier. Data division takes place first by splitting the data into training and testing data. Then, the training data is modelled using the respective algorithms. The main aim for the modelling of data is to predict the behaviour of trends that can help for the movement. For instance, the followers' sentiments about an issue or trends are classified into categories such as positive or negative.

ii. Evaluation: The model chosen is evaluated by split-validation, where the dataset is randomly divided into two parts. This is to ensure that the best model is chosen to represent the data and to ensure that it can work well for the next iteration of campaign. Besides model evaluation, the evaluation of the results also takes place here in which the practitioners evaluate the impact of the data results for the effectiveness of the campaign.

iii. Deployment: At this phase**,** data visualisation takes place in which practitioners can build visualisations such as graphs and charts, word cloud or dashboard, to curate the analysed data for the campaign. This is because, with visualizations, the data can be easily understood to get their messages across.

In the section that follows, the actual case study will be provided and a discussion about how the exploratory, and data management steps fit into the development of the suggested framework will be presented.

4. Case Study

Social media platform, such as Facebook, Twitter, and X, have a plethora of data of various types and kinds. User-posted content makes up most of the data. These publicly available data can be used for targeted advertisement and campaigns. Hashtag campaigns are referred to as a component of a social media brand [5] and are frequently used in social media marketing and advertising with the goals of generating relevant user content related to the hashtags, exponentially expanding user reach, and increasing sales or influence.

To instantiate the feasibility of the framework, a case study on a sexual harassment movement in Malaysia is used. The domain of this case study is inspired by the story of a young Malaysian teenage girl, Ain Husniza Saiful Nizam, 17 years old, who took on a courageous step by initiating the hashtag #MakeSchoolASaferPlace on Twitter as she alleged that a male teacher had trivialised rape during a physical and health education class at her school in Selangor [5]. Based on the hashtag and other set of keywords, the data will be collected from Twitter and the data will be further prepared such as data pre-processing, data annotation and feature extraction. Once the filtered dataset is obtained, the data will be modelled by using two machine learning algorithms, Naïve Bayes and Support Vector Machine, respectively. The data is split in a ratio of 80:20, training and testing data. Then, each of the algorithms is evaluated by determining the accuracy, precision, recall and F1-score. If the result is not desirable by either of the algorithms, then the loop is back to the previous stage which is the data modelling stage. Here, the data division and the modelling algorithms are adjusted until the best evaluation of results is obtained, in terms of both data and model perspective. Hence, this case study can ensure that the SMID framework is also feasible for other areas such as digital advocacy.

5. Results

Upon completion of classification, performance evaluation is recorded for each algorithm. After classification was complete, each algorithm's performance was evaluated. This sub-section illustrated the results of the analysis.

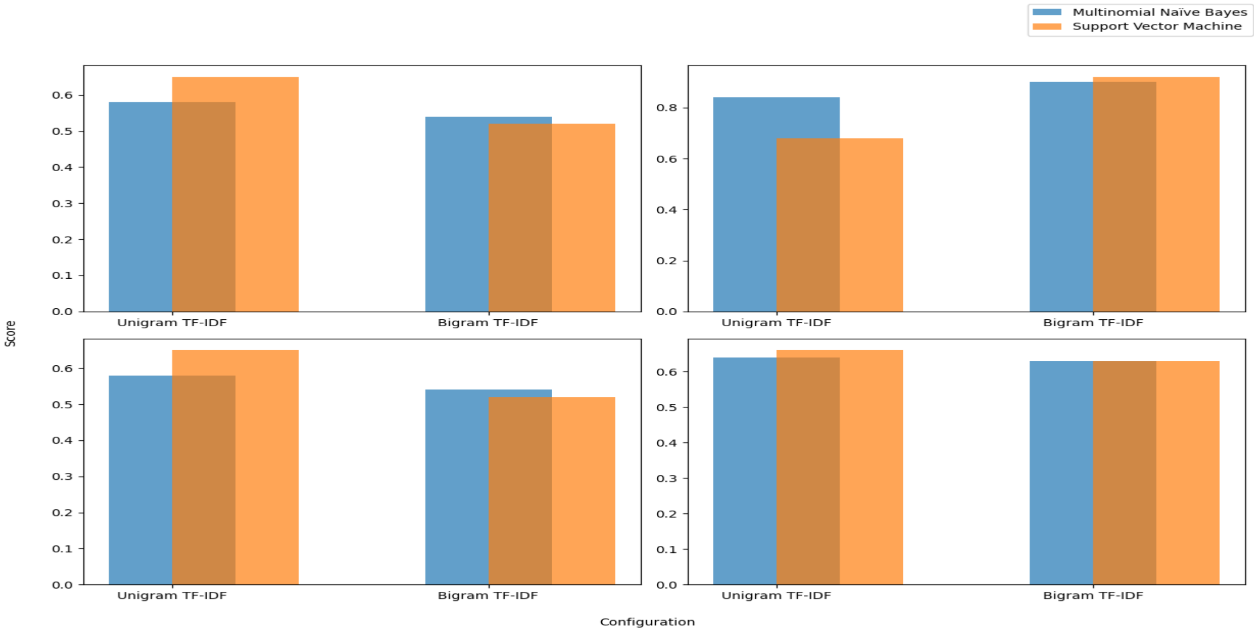

Fig. 4. Machine Learning classifiers performance without tuning parameters. The blue colour/left side of the bars is the results using Naïve Bayes; the orange colour/right side of the bars is the results using SVM

Table 1
Computational Performance Results Without Tuning Parameters

	Multinomial Naïve Bayes		Support Vector Machine	
	Unigram TF-IDF	Bigram TF-IDF	Unigram TF-IDF	Bigram TF-IDF
10-Folds CV	0.56	0.50	0.65	0.51
Training Time Execution (s)	0.019	0.022	5.559	6.176
Testing Time Taken (s)	0.0006	0.001	1.009	1.089

5.1 Unigram TF-IDF

The SVM classifier using unigram TF-IDF representation has the best performance among the classifiers without tuning parameters. Its accuracy score of 0.65 shows that it can classify instances accurately with a fair amount of precision. While the weighted recall of 0.65 demonstrates the capacity to properly categorise instances across all classes, the weighted precision of 0.68 suggests a low number of false positives. With a weighted F1-score of 0.66, precision and recall are reasonably balanced. Compared to the SVM classifier, the Multinomial Naive Bayes classifier using unigram TF-IDF representation obtains an accuracy of 0.58, which is marginally lower. While the weighted recall of 0.58 reveals a modest capacity to accurately classify cases, the weighted precision of 0.84 indicates a comparatively low number of false positives. Although a little lower than the SVM classifier, the weighted F1-score of 0.64 demonstrates a balance between recall and precision.

5.2 Bigram TF-IDF

When considering the effect of n-gram representation, the Multinomial Naïve Bayes classifier with bigram TF-IDF representation has a poorer accuracy of 0.54 in comparison to the unigram TF-IDF representation. However, it achieves weighted precision of 0.90, which means fewer false positives. A lower capacity to correctly classify examples across all classes is suggested by the weighted recall of 0.54. The weighted F1-score of 0.63 indicates that the trade-off between recall and precision is generally balanced. Similarly, out of all the classifiers, the SVM classifier using bigram TF-IDF representation has the lowest accuracy of 0.52. It does, however, attain the maximum weighted precision of 0.92, indicating a very low level of false positives. The weighted F1-score of 0.63 reflects a well-balanced trade-off between precision and recall, while the weighted recall of 0.52 suggests a poorer ability to properly identify occurrences.

Based on the results analysis, it is proven that unigram TF-IDF performs better consistently throughout the classifiers. This can be influenced by its ability to capture individual word occurrences and detect important features based on their presence or absence in the text. Unigrams provide a more straightforward representation, allowing the classifiers to focus on individual words without considering contextual relationships. On the other hand, bigram TF-IDF achieves the lowest accuracy for all classifiers but somehow manages to increase precision performance. This could be related to its capability to capture contextual information and specific word combinations, which leads to higher precision when those combinations are present. However, the reliance on these specific combinations may result in lower accuracy, as the classifiers may struggle to capture a broader range of instances correctly.

In terms of computational performance, the training and testing time execution is relatively low for all classifiers, with values ranging from 0.019 to 6.176 seconds. The unigram TF-IDF representation generally shows faster execution times compared to the bigram TF-IDF representation.

Overall, among the classifiers without tuning parameters, the SVM classifier with unigram TF-IDF representation displays the greatest optimal performance in terms of accuracy, precision, recall, and F1-score. It exhibits an effective balancing act between precision and the capacity to appropriately categorize cases across all classes.

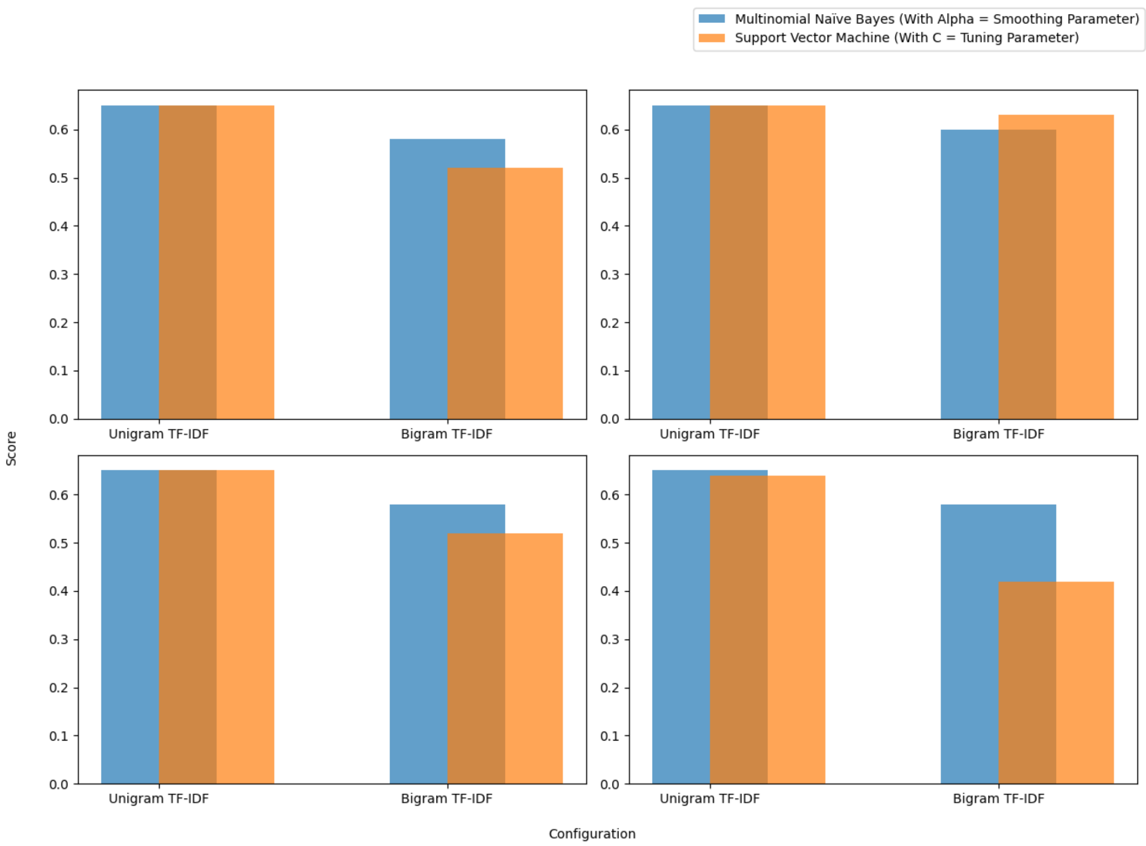

Fig. 5. Machine Learning classifiers performance without tuning parameters (Blue colour/left side of the bars: Naïve Bayes; Orange/right side of the bars: SVM)

5.3 Naïve Bayes Classifier Evaluation
5.3.1 Unigram TF-IDF

Based on the Table 2, among the Naïve Bayes classifiers, the use of tuning parameters (specifically, alpha for smoothing) improved the performance of unigram significantly but not much on bigram. The accuracy, weighted precision, F1-score, and recall scores for the Naïve Bayes classifier with unigram TF-IDF and alpha tuning were all 0.65, 65%. The performance is steady through numerous folds, as evidenced by the 10-fold cross-validation score of 0.64, 64%. Execution of the training procedure took just 0.064 seconds, while that of the testing procedure took just 0.0009 seconds.

Table 2
Computational performance results with tuning parameters

	Multinomial Naïve Bayes (With Alpha = Smoothing Parameter)		Support Vector Machine (With C = Tuning Parameter)	
	Unigram TF-IDF	Bigram TF-IDF	Unigram TF-IDF	Bigram TF-IDF
10-Folds CV	0.64	0.55	0.65	0.52
Training Time Execution(s)	0.064	0.029	5.575	6.619
Testing Time Taken (s)	0.0009	0.002	1.000	1.089

5.3.2 Bigram TF-IDF

In comparison to the Naïve Bayes classifier with bigram TF-IDF, the introduction of alpha tuning may not have significantly improve the performance. When compared to the results of Naïve Bayes classifier with bigram TF-IDF and no alpha parameter, the accuracy increased from 54% to 58%, indicating a modest enhancement in correctly classifying the data. The weighted recall improved slightly from 54% to 58%, indicating a better capture of relevant instances However, more false positives instances are detected from the weighted precision result, which is from 90% to 60%. This shows that even though the model's overall accuracy increased, it has grown more prone to identifying cases incorrectly as positive. When assessing the effect of the tuning parameters on the performance of the model, it is crucial to consider this trade-off between accuracy and the potential rise in false positives. Other than that, the weighted F1-score decreased from 63% to 58%, indicating a trade-off between precision and recall. The decline in the weighted F1-score implies that the addition of alpha tuning resulted in a compromise between recall and accuracy, which had an adverse influence on the model's capacity to successfully balance both metrics.

The type of data and feature representation may have contributed to alpha tuning's improved performance with the unigram Naïve Bayes classifier. The numerical representation of a unigram using TF-IDF emphasizes individual words, capturing significant keywords and their frequency. By using alpha tuning, the model can change the weighting of uncommon or infrequent terms, enhancing its capacity to correctly categorize occurrences. The bigram TF-IDF representation, on the other hand, takes into account pairs of subsequent words, which may lead to a bigger feature space and more complicated patterns. Because the model might have trouble accurately capturing the subtleties contained in bigram features, the impact of alpha tuning might be less noticeable in this situation.

5.4 Support Vector Machine Classifier Evaluation
5.4.1 Unigram TF-IDF

As shown in Table 2, the performance of Support Vector Machine with C tuning parameter, the results did not show much significance change either when compared to SVM without C tuning. For instance, both configurations achieved an accuracy of 65%, which means they correctly classified 65% of the instances. However, when weighted precision was considered, the SVM without the C tuning parameter outperformed the SVM with the C tuning parameter, achieving a precision of 68% as opposed to the SVM with the C tuning parameter's 65%. This shows that the SVM without the C tuning parameter was more accurate at classifying cases across the classes. Similarly, both setups yielded the same result of 65% when examining weighted recall. This metric measures the ability of the model to identify instances of different classes correctly. Not only that, the SVM without the C tuning parameter has a better weighted F1-score, which balances precision and recall, at 66% as opposed to 64% for the SVM with the C tuning parameter. This shows that a better overall balance between precision and recall was attained by the SVM without the C tuning parameter. Both setups achieved an accuracy of 65% during the 10-fold cross-validation, indicating consistent performance across various data subsets. There was almost any difference between the two configurations in terms of training time execution. It took 5.559 seconds for the SVM without the C tuning parameter and 5.575 seconds for the SVM with the C tuning parameter. The testing duration for both setups was also nearly the same, with the SVM without the C tuning parameter taking 1.008 seconds and the SVM with the C tuning parameter taking 1.000 seconds.

5.4.2 Bigram TF-IDF

Results showed a limited improvement over SVM without the tuning parameter when examining the impact of the C tuning parameter on SVM with bigram TF-IDF representation. The accuracy remained constant at 52%, showing that the addition of the C tuning parameter had no appreciable effects on the classification accuracy as a whole. It is crucial to remember that there were detrimental effects on precision and F1-score. The weighted precision dropped from 92% to 63%, indicating a rise in false positives and a decrease in the model's accuracy in identifying positive cases. The weighted F1-score, which fell from 63% to 42% and further mirrored this loss in precision, showed a compromise between precision and recall. While the weighted recall remained the same at 52%, indicating a consistent capture of relevant instances, the slight decrease in the weighted F1-score suggests a trade-off between precision and recall.

The 10-fold cross-validation score showed a slight change from 51% to 52%, indicating a marginal improvement in the model's generalization capabilities across different folds. In terms of computational performance, the training time experienced a slight increase from 6.176 seconds to 6.619 seconds, potentially due to the additional computations required by the C tuning parameter. However, the testing time remained the same at 1.089 seconds, indicating that the classification of new instances was not significantly affected.

Based on these results, the SVM without C tuning parameter exhibits slightly better performance in terms of weighted precision and weighted F1-score compared to SVM with C tuning parameter. This explains that the presence of C tuning parameter is not always applicable to all datasets. For instance, in the case of sentiment polarity classification, specific characteristics of the dataset, such as the inherent separability of positive, neutral, and negative sentiments, a balanced class distribution, and the absence of significant overlapping patterns, contribute to the effectiveness of the default SVM configuration without C tuning. The default SVM configuration may be adequate to capture the key sentiment patterns and produce reasonable performance with its default regularisation and margin. Therefore, it is crucial to carefully consider the dataset's nature before deciding to apply tuning parameters, as this analysis demonstrates the potential adequacy of the default configuration in certain scenarios.

In summary, the alpha tuning parameter works well with the Naïve Bayes classifier using unigram TF-IDF because it enhances the model's ability to capture important keywords and their frequency. The Naïve Bayes classifier can be sensitive to the effects of alpha tuning since the unigram TF-IDF representation fits with the assumptions of the classifier. On the other hand, the SVM classifier with unigram TF-IDF may already be capable of handling sentiment analysis tasks in its default configuration, in which case the addition of the C tuning parameter does not substantially enhance its performance.

Therefore, considering the trade-off between performance and computational efficiency, the Naïve Bayes classifier with unigram during feature extraction and tuned with the alpha smoothing parameter emerges as the best-performing classifier. It provides competitive performance metrics while demonstrating significantly faster training and testing times compared to the SVM classifier.

6. Discussion

The importance of the iterative loop in the framework and its repercussions are highlighted in this discussion. By revisiting the SMID framework, it is evident that even though the optimum machine learning algorithm for this case study is determined, continued accuracy improvement is feasible through this iterative process. The Naïve Bayes classifier, using unigram features and the alpha smoothing parameter, showcases the iterative loop's role in continual model fine-tuning. This is essential when algorithmic configurations produce better outcomes, as demonstrated by the fact that it outperforms the Support Vector Machine method in this situation. The best-performing algorithm's focused, condensed scope offers a focused area for improvement. For instance, the generalisability of the machine learning model is strengthened by optimising the training-to-testing ratio. This strategic adjustment supports a dynamic approach to increase campaign effect and is in line with the iterative structure. The continuous loop also takes into account different case studies, data types, sizes, and impact interpretations. The framework's versatility allows its ongoing relevance and effectiveness across contexts, maximising its usefulness in the field of digital advocacy. The newly developed iterative procedure supports both a data-centric advocating approach and forecast accuracy. The loop's cyclical structure is in tune with the shifting user trends and social media user behaviours. The framework's ability to include fresh data and modify models as advocacy campaigns change over time provides a tactical advantage responsive to shifting conditions.

7. Conclusion

In conclusion, the novel proposed SMID data analytics architecture for digital advocacy has offers a sizable improvement in the organisation and execution of campaigns. The framework makes use of data analytics to maximise campaign impact by fusing the tried-and-true CRISP-DM methodology with the particular needs of digital advocacy. The framework's introduction of an iterative loop demonstrates its versatility and dedication to ongoing improvement. This paradigm offers a strong toolset for advocates, legislators, and analysts to effect significant change through data-driven methods as digital advocacy continues to play a significant role in influencing social dialogues. The results have shown that the Naïve Bayes classifier using unigram TF-IDF could enhances the model's ability to better capture important keywords and their frequency. While the SVM classifier with unigram TF-IDF may already be capable of handling sentiment analysis tasks in its default configuration, in such case, the addition of the C tuning parameter has shown that it does not substantially enhance its performance. The future work will include the visualisation of the patterns found from the analysis.

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