Journal of Applied Engineering and Technological Science
Vol 5(2) 2024: 955-965

BIG DATA APPROACH TO SENTIMENT ANALYSIS IN MACHINE LEARNING-BASED MICROBLOGS: PERSPECTIVES OF RELIGIOUS MODERATION PUBLIC POLICY IN INDONESIA

Mhd. Furqan[1]*, Ahmad Fakhri Ab. Nasir[2]
Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara, Indonesia[1]
Faculty of Computing, University Malaysia Pahang Al-Sultan Abdullah, Pekan, Malaysia[2]
mhdfurqan@uinsu.ac.id[1], afakhri@umpsa.edu.my[2]

Received : 21 February 2024, Revised: 03 May 2024, Accepted : 05 May 2024
**Corresponding Author*

ABSTRACT
The concept of religious moderation encompasses three key aspects, namely moderate thinking and understanding, moderate behavior, and moderate religious worship. With advancements in information technology, people now have the means to express their opinions through microblogs, pertaining to issues of religious moderation initiated by the Ministry of Religion of Indonesia. This study aims to evaluate public policies introduced by the Ministry of Religion regarding religious moderation such as changes in the halal logo, transfer of authority for halal certification, and regulations on the volume of loudspeakers in the mosque. Public opinions collected as the big data to get the information about public sentiment with those issues. Sentiment analysis was conducted on three primary microblogs such as Twitter, Instagram and YouTube using six machine learning algorithms. These include Naïve Bayes, Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Bagging Classifier, Random Forest, and Gradient Boosting Classifier. The test results showed the highest accuracy is Gradient Boosting reached 82.27%.
Keywords: *Religious moderation, sentiment analysis, microblogs, big data, machine learning.*

1. Introduction

Social media has become an integral part of daily life due to its close association with various activities. These activities include searching for product reviews, sharing information, seeking public opinion, etc. For example, business executives consider social media an indispensable marketing and advertising tool (Asif, 2020). Government decision-makers rely on social media to gauge public sentiment, which can influence future public policies (Barghout, 2015). Social media encompasses various forms, such as microblogs that facilitate easy information sharing through short sentences and digital photos. Additionally, website links allow users to share content like articles or news about current events effortlessly.

Videos able also be embedded on websites or blogs, creating an illusion which they are hosted by the author of the respective platform. The development of big data has provided vast opportunities to sentiment analysis, particularly in microblogging data (Khan & Malviya, 2021). Sentiment analysis involves contextually mining text to identify, extract, and analyze subjective information related for various entities, such as topics, products, and services(Pang & Lee, 2008). The rapid growth of internet-based applications, including web pages, social networks, and blogs, has empowered people to express opinions and comments regarding products, services, and daily activities. Sentiment analysis is a powerful tool to businesses and governments for gauge public opinion on products or services, aiding decision-making processes (Setia & Rahman, 2022).

Numerous opinions and sentiments flood social media platforms every day, prompting the have to a data driven approach for conducting sentiment analysis. This approach, known as microblogging, encompasses various ways in which people express their opinions through textbased comments (Joachims, 1998). The classifier in supervised machine learning that makes use of data that has been manually annotated or that has been labeled with a noisy indication, like emoticons (Maity, 2016). In this context, Support Vector Machines (SVM), Naïve Bayes, and k-Nearest Neighbor (k-NN) are often used classifiers (DeCoste, 2002).

The population of Indonesia is diverse, with members of many ethnic groups, religious affiliations, and cultural traditions. This diversity acts as a socio-cultural asset for the country, playing a critical part in its evolution(Akhmadi, 2008). This diversity serves as a socio-cultural asset for the nation, playing a crucial role in its progress (Davids, 2017). However, diversity can also give rise to attitudes and behaviors that undermine community unity (Yaakub et al., 2019). Promoting inclusive moderation in religious practices, as well as in interactions with others, is a fundamental element of fostering strong communities (Hanapi, 2014). As part of their ongoing efforts, policymakers in the country have implemented a religious moderation program to promote inclusive moderation across all aspects of life (Arifinsyah, 2020). The primary objective of this study was to examine the sentiment surrounding the public policy of religious moderation in Indonesia. Specifically, it investigates recent issues related to halal certification and logos that changed the regularization and form, as well as the circular letter issued by the Ministry of Religion of Indonesia concerning sound regulation in the mosque (Badan Litbang Dan Diklat Kementerian Agama RI, 2020; Tim Kelompok Kerja Moderasi Beragama Kementerian Agama RI, 2020).

Based on the aforementioned context, several research problems emerged, namely effectivity of approach big data for sentiment analysis on microblogs using machine learning and interpreting the results of these analyses within the context of public policy concerning religious moderation in Indonesia.

2. Literature Review

Numerous preliminary studies employed a combination of sentiment and social network analyses in various domains. This application simplifies the collection of online news articles by collecting, preprocessing, and storing them in a local database (A. Sari & Bador, 2022). The stored data can be utilized for various mining processes, including sentiment analysis, topic classification, and text summarization (Breiman, 1999). Another significant advancement was the new approach introduced by Gung Li and Fei Liu called clustering-based sentiment analysis(B. Liu, 2016). It leverages the TF-IDF weighting method, voting mechanism, and term scores to achieve reliable and meaningful grouping results. By employing these techniques, they were able to obtain acceptable and stable clustering outcomes (Feldman & James, 2007). There are two relevant studies related to the sentiment analysis of Twitter data. The first one, titled Big Data Approach for Sentiment Analysis of Twitter Data Using Hadoop Framework and Deep Learning, was authored by Mudassir Khan and Aadarsh Malviya.

In their study, a method for sentiment analysis using Twitter data was proposed. The authors compared their approach with other ones to find the RNN-based method and reported an accuracy, sensitivity, and specificity of 0.9302, 0.9404, and 0.9157, respectively (Khan & Malviya, 2021). The second study, published in 2013 by Tobias Günther, focused in sentiment analysis of microblogs, that has gained significant attention as a thesis topic in recent years (Gunther, 2013). Günther explored the challenges involved in sentiment analysis of microblogs, emphasizing the need for Twitter-specific natural languages processing tools such as dependency parsing and negation scope detectors to achieve optimal results (Bifet & Eibe, 2010). The study suggested strategies to identifying sentiment targets in tweets, including combining online word lists by techniques like Brownian clustering to account for spelling variants. Overall, these methods yield promising results in sentiment analysis of microblog data (B. Liu, 2016).

According to Rodolfo Delmonte and Vincenzo Pallotta, comprehensive linguistic processing is essential for capturing opinions and sentiments expressed in text or dialogue (Brown et al., 1992). While matching search and ontology concepts based on standard lexical sources are useful, a deeper understanding of natural language is still required to address fundamental and pervasive linguistic phenomena (Brown et al., 1992). The authors applied these enhancements to the VENSES system and evaluated the results obtained by comparing them with those reported by the most advanced sentiment analysis and opinion exploration processes. In 2018, Xiaomei Zou, Jing Yang, and Jianpei Zhang conducted a Microblog sentiment analysis study using Social and topic context. They proposed combining social and topic contexts using a Laplacian matrix of graphs constructed from this framework. The proposed model consistently and significantly outperformed the basic method. Neethu MS and Rajasree R S, in their 2013 article “Sentiment Analysis in Twitter using Machine Learning Techniques”, highlighted the vast amount of sentiment data generated through social media platforms such as tweets, status updates, and blog posts. It was asserted that sentiment analysis of this data can be utilized to gauge public opinion about products or services (Sudradat et al., 2021). However, analyzing sentiment on Twitter poses challenges due to slang and misspellings. Neethu MS and Rajasree R S presented a novel vector feature for classifying tweets as positive, negative, or neutral based on the content. The most common technique for sentiment analysis on microblogs is to use manually annotated data or data labeled with a noisy indicator, such emoticons, to train a classifier in supervised machine learning.(Neethu & Rajasree, 2013).

Microblogging platforms provide excellent data collecting for sentiment analysis. Sentiment analysis, often referred to as opinion mining, lexical analysis, or semantic analysis, involves determining the attitude, opinion, or perspective of a speaker or writer(Vapnik, 2014). It entails identifying positive and negative statements within a text and assigning them scores to indicate their level of positivity or negativity (A. Sari & Bador, 2022). There are two main approaches to sentiment analysis in microblogs. One approach involves employing machine learning algorithms to analyze tweets and extract sentiment scores, while the other approach involves analyzing the words used in tweets and studying their frequency to derive sentiment scores (Zou et al., 2018).

Sentiment analysis is the ability of the software to comprehend a writer's or speaker's attitude, viewpoint, or stance.(Purwidiantoro & F, 2018). It is generally called opinion mining and semantic analysis (Gunther, 2013). This process involves identifying positive and negative statements within a text and assigning them a score to indicate their level of positivity or negativity. there for, microblogging services are websites that enable users to share brief text updates, known as tweets, and primarily designed for public and concise expression of thoughts. Microblogging data analysis is the process of collecting and analyzing data from microblogs(B. Liu, 2016).

The first method involves collecting tweets from a user’s selected microblogging site such as Twitter, Instagram, YouTube. With sentiment analysis tools like the Google Cloud Natural Language API to extract sentiments from those tweets (K. Liu et al., 2012). The second method involves scraping tweets from microblogging sites. Sentiment analysis based on machine learning involves the use of algorithms to perform sentiment analysis. In this case, the algorithms are fed with tweets and the sentiment scores are generated (Rizki, 2019). Assuming that the algorithms are well trained, they can be used to generate sentiment scores for other tweets that they have not seen before (Matsumoto et al., 2005). The process of sentiment analysis based on machine learning involves the following steps: collection and pre-processing of tweets, initial step involves gathering tweets from a Twitter account (Lineck, 2017). The Twitter API can be utilized for this purpose, but access to a specific Twitter account is required. When tweets are collected, it often contains unstructured data. To guarantee that it is suitable for additional study, it must be cleaned and prepared. Data cleaning is the process of eliminating special characters, punctuation, and URLs from the tweets. In order for machine learning algorithms to operate effectively, data normalization guarantees uniformity among tweets. Feature engineering involves creating new features from the collected and normalized tweets. Features represent specific aspects of the analyzed data and enabling the extraction of deeper insights based on natural language processing (Kumar & Sebastian, 2012).

Every day, a multitude of viewpoints and opinions social media platforms, requiring the use of data-driven methods for sentiment analysis. This approach called microblogging, encompasses various ways in which people express their opinions through text-based comments (R. Sari, 2020). The prevalent method for sentiment analysis on microblogs involves training a classifier in supervised machine learning using manually annotated data or data labeled with a noisy indicator, such as emoticons (Neethu & Rajasree, 2013). Classifiers commonly employed in this context include SVM, Naïve Bayes, k-NN, and Random Forests (Breiman, 2001; Kurniasari et al., 2020).

In text analysis, feature selection is used to select important features for further analysis. This reduces the number of variables and allows for more accurate results. It also helps to avoid irrelevant or redundant information that may skew the final results (Ho, 1998). In text analysis, feature selection is used to select important features for further analysis.

This reduces the number of variables and allows for more accurate results. It also helps to avoid irrelevant or redundant information that may skew the final results [36]. Feature selection in data science refers to finding pertinent characteristics or features inside a dataset. As a result, there can be fewer variables, (Ben-Hur et al., 2001). When dealing with a large dataset and aiming to find a correlation between a variable and a specific outcome, it is crucial to decrease the number of variables under consideration to avoid missing important information(Gaonkar & Davatzikos, 2013). Feature selection addresses this by removing redundant or irrelevant information and focusing on a smaller set of features. Feature selection addresses this by removing redundant or irrelevant information and focusing on a smaller set of features. Once feature selection is performed, the dataset can be used to create machine learning or predictive models using the selected features(Breiman, 1996). The Scikit-learn package provides a number of useful feature selection methods that can be applied to data (Azhar et al., 2019). Many practical feature selection techniques that can be used with data are available in the Scikit-learn package [40]. Depending on the data and analysis goals, a custom feature selection method can be established in a few easy steps.(Cortes & Vapnik, 1995). Various types of feature selection methods exist, including filter methods, wrapper methods, and embedded methods (Louppe & Geurts, 2012). Any of these methods can be implemented to create a custom feature selection approach. Feature selection method was created for sentiment analysis using Python and Scikit-Learn (Maitra et al., 2015). The necessary packages for the analysis were imported, including pandas, Numpy, and Scipy for data reading and manipulation, as well as Scikit-learn, matplotlib, and seaborn for visualizations and model training, while plot was used for plotting(B. Liu, 2012; Statnikov et al., 2006).

Feature selection played an important role in the data science process, allowing the focus on relevant variables for analysis while disregarding irrelevant ones(Cuingnet et al., 2011). The idea of feature selection and the rationale for developing unique feature selection techniques were covered in this study. It provided guidance on developing such methods for sentiment analysis in Python using Scikit-Learn. This study used a real-data issues to demonstrate the creation of a feature selection method for sentiment analysis using Python.

3. Material and Method

The primary objective of this study was to examine the sentiment surrounding the public policy of religious moderation in Indonesia. Specifically, it investigates recent issues related to halal certification and logos that changed the regularization and form, as well as the circular letter issued by the Ministry of Religion of Indonesia concerning sound regulation in the mosque.

The data used was collected in 2022 from various microblogging platforms including Twitter, YouTube and Instagram with a total of 4500 data collected. Data collection was carried out using Twitter tweets, YouTube comments and Instagram comments, all in Indonesian. The data includes 1500 tweets from Twitter, 1500 comments from YouTube, and 1500 comments from Instagram. This study implemented six different learning algorithms, namely Support Vector Machine, Naïve Bayes, and k-Nearest Neighbor, Bagging Classifier, Random Forest, and Gradient Boosting Classifier, to perform sentiment analysis. By analyzing the results of this sentiment analysis, it becomes possible to understand the opinions of the public regarding the government policy on religious moderation, which is initiated by the Ministry of Religion of Indonesia. Furthermore, this study visualizes the sentiment analysis based on the data obtained from microblogging platforms. The algorithms were implemented using the Python programming language, specifically utilizing Google Collaboratory, and leveraging several available libraries for prediction purposes.

Google Collaboratory have played an essential role in numerous data science workflows. These are instrumental in performing tasks such as data mining, analysis, processing, modeling, and daily experimentation throughout the entire life cycle of data science projects.
The classification method is summarized into several steps as described below:

1. Data collection

For data collection, this study focused on three main microblogging platforms, Youtube, Instagram, and Twitter. It was obtained specifically for three topics, changes in the Halal logo, the transfer of authority for halal certification from MUI to the Ministry of Religion of Indonesia, and the regulation of loudspeaker volume (TOA) in the mosque. These datasets were utilized to address the sentiment classification problem.

Comment data from these movies was retrieved using the API. Data for Instagram was gathered via site scraping, which is how Youtube's data was gathered. Manual searches were conducted to find posts related to the three topics on religious moderation. As for Twitter, the data were obtained legally from Twitter API. Three machine-learning techniques as well as ensemble methods were used in this study's sentiment categorization process to select and evaluate features.

The Indonesian Ministry of Religion initiated the evaluation on three subjects pertaining to religious moderation in Indonesia. The dataset for this analysis was obtained from three primary microblogging platforms, YouTube, Instagram, and Twitter. The topics included changes in the Halal logo, the transfer of authority for halal certification from the MUI to the Ministry of Religion, and the regulation of loudspeaker volume (TOA) in the mosque. The findings indicate that each system component plays a crucial role, and the suggested ensemble technique can potentially enhance the sentiment classification metric for the microblog dataset on religious moderation.

2. Pre-processing.

This technique is crucial for eliminating noise, inconsistent information, and incomplete data from the dataset. This involves employing methods such as tokenization, removing stop words, and performing stemming to ensure data quality and consistency.

3. Feature Extraction and selection.

A feature vector is created during this stage, which represents binary values (1 or 0) denoting the existence or nonexistence of particular characters in the document. A feature receives a score of 1 if it appears in the document and 0 if it does not.

4. In the classification phase

Supervised machine learning classifiers were trained using both simple techniques (Naïve Bayes, SVM, and k-NN) and ensemble methods (bagging classifier, random forest, and gradient boosting).

The experiments were conducted using Python and the efficient scikit-learn library. The performance of the supervised machine learning algorithms was evaluated based on the elements of the confusion matrix, which includes True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The accuracy with equation (1)(2)(3)(4).

$$Accuracy = \frac{(TP+TN+TN)}{(TP+TN+FP+FN+TN+FP+FN+TN+TP)} x\ 100\% \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{3}$$

$$F1-Score = 2\ x\ \frac{(Precision\ x\ Recall)}{(Precision+Recall)} \tag{4}$$

The performance scores of the six studied classifiers were determined by evaluating the approximation matrix, precision, recall, F-score, and ROC. These measures were used to estimate the performance of the classifiers and assess their effectiveness. The system was tested on the following datasets collected from three microblogs (Youtube, Instagram, and Twitter) relating to different topics:

- Dataset from Youtube on the topic of changing the halal logo.

- Dataset from Youtube on the topic of changing the authority of halal certification.
- Dataset from Youtube on the topic of setting the loudspeaker volume (TOA) in the mosque.
- Dataset from Instagram on the topic of changing the halal logo.
- Dataset from Instagram on the topic of changing the authority of halal certification.
- Dataset from Instagram on the topic of setting the loudspeaker volume (TOA) in the mosque.
- Dataset from Twitter on the topic of changing the halal logo.
- Dataset from Twitter on the topic of changing the authority of halal certification.
- Dataset from Twitter on the topic of setting the loudspeaker volume (TOA) in the mosque.
- Dataset from the combination of the three microblogs on the topic of changing the halal logo.
- Dataset from the combination of the three microblogs on the topic of changing the authority of halal certification.
- Dataset from a combination of the three microblogs on the topic of setting the volume of loudspeakers (TOA) in the mosque.

4. Result And Discussion

All datasets were tested using the following:

a. Single classifier (Naïve Bayes, SVM, and k-NN)
   The performance of the three classifiers is shown in Table 1. In general, from the three classifiers, the best performance is given by SVM, in terms of accuracy, precision, recall and F-measure.
b. Ensemble classifier (Bagging Classifier, Random Forest, and Gradient Boosting).
   The performance of the three classifiers is shown in Table 2.

Table 1- Comparison of accuracy, precision, recall and F-measure for Single Classifier

Dataset	Classifier											
	Naïve Bayes				SVM				k-NN			
	Å	℘	ℜ	F-measure	Å	℘	ℜ	F-measure	Å	℘	ℜ	F-measure
YouTube Halal logo	42.15%	0.45	0.50	0.62	75.24%	0.75	0.89	0.62	68.31%	0.69	0.69	0.67
YouTube Halal Certification	53.15%	0.53	0.58	0.63	56.75%	0.56	0.61	0.67	48.64%	0.49	0.52	0.59
YouTube TOA in the mosque	61%	0.61	0.64	0.68	62%	0.62	0.65	0.63	50%	0.50	0.54	0.59
Instagram Halal logo	67.32%	0.67	0.71	0.74	75.24%	0.75	0.78	0.81	58.41%	0.58	0.61	0.64
Instagram Halal Certification	58.90%	0.59	0.63	0.66	58.90%	0.59	0.64	0.68	64.38%	0.64	0.69	0.72
Instagram TOA in the mosque	66.42%	0.66	0.69	0.72	69.34%	0.69	0.72	0.76	67.88%	0.68	0.72	0.75
Twitter Halal logo	67.32%	0.67	0.71	0.74	68.31%	0.68	0.72	0.76	57.42%	0.57	0.71	0.74
Twitter Halal Certification	70.29%	0.71	0.74	0.77	70.29%	0.71	0.74	0.78	60.39%	0.61	0.64	0.67
Twitter TOA in the mosque	60%	0.60	0.64	0.67	59%	0.59	0.63	0.67	47%	0.47	0.51	0.54
Halal logo	58.20%	0.58	0.61	0.64	58.70%	0.59	0.63	0.69	57.21%	0.57	0.61	0.64
Halal certification	54.92%	0.55	0.59	0.62	51.05%	0.51	0.56	0.62	40.85%	0.41	0.45	0.48
TOA in Mosque	52.66%	0.53	0.56	0.59	52.95%	0.53	0.56	0.61	52.36%	0.53	0.56	0.59

In this section, various contrast experiments are shown to validate the usefulness of the ensemble algorithm. Tables 1 and 2 detail the results of the various approaches used for the test corpus. As a training feature for each classifier, corpus feature extraction is used. Then the polarity and quantity are evaluated.

Table 2 - Comparison of accuracy, precision, recall and F-measure for Ensemble Classifier

Dataset	Classifier											
	Bagging Classifier				Random Forest				Gradient Boosting			
	Å	℘	ℜ	F-measure	Å	℘	ℜ	F-measure	Å	℘	ℜ	F-measure
YouTube Halal logo	71.28%	0.74	0.82	0.61	**73.26%**	0.73	0.73	0.85	69.30%	**0.78**	**0.85**	**0.81**
YouTube Halal Certification	**61.35%**	**0.61**	**0.63**	**0.72**	60.45%	0.60	0.62	0.71	56.84%	0.57	0.59	0.69
YouTube TOA in the mosque	70%	0.70	0.73	0.77	**71%**	**0.71**	**0.74**	**0.78**	69%	0.69	0.72	0.77
Instagram Halal logo	76.33%	0.76	0.79	0.82	76.33%	0.76	0.81	0.84	**82.27%**	**0.82**	**0.85**	**0.88**
Instagram Halal Certification	68.90%	0.69	0.73	0.76	**68.90%**	**0.69**	**0.73**	**0.76**	67.53%	0.68	0.63	0.66
Instagram TOA in the mosque	**74.96%**	**0.75**	**0.79**	**0.72**	**74.96%**	**0.75**	**0.79**	**0.72**	71.31%	0.71	0.75	0.78
Twitter Halal logo	69.40%	0.69	0.72	0.75	73.36%	0.73	0.77	0.81	**74.35%**	**0.74**	**0.77**	**0.81**
Twitter Halal Certification	**81.28%**	**0.83**	**0.86**	**0.89**	79.31%	0.81	0.84	0.87	**81.28%**	**0.83**	**0.86**	**0.89**
Twitter TOA in the mosque	**63%**	**0.63**	**0.67**	**0.71**	57%	0.57	0.61	0.64	63%	0.63	0.66	0.69
Halal Logo	67.71%	0.68	0.72	0.75	67.21%	0.67	0.71	0.74	**69.70%**	**0.71**	**0.74**	**0.77**
Halal Certification	58.6%	0.59	0.53	0.66	52.25%	0.52	0.56	0.59	**60.35%**	**0.61**	**0.66**	**0.69**
TOA in the mosque	**61.47%**	**0.61**	**0.64**	**0.67**	60%	0.60	0.63	0.67	60%	0.60	0.63	0.66

Semantic rules play a crucial role in determining the sentiment tendency of a text document. The first three approaches involve calculating the final scores using these rules. Initially, a comparison was made between the single algorithm on each platform. Subsequently, the three datasets from the three microblogs were combined for each topic and evaluated. Table 1 shows that, in general, SVM exhibits the highest accuracy compared to the other two classifiers.

The implementation of the chosen ensemble classifier results in a notable improvement in accuracy. Table 2 shows the enhanced accuracy achieved by each method across various platforms and topics.

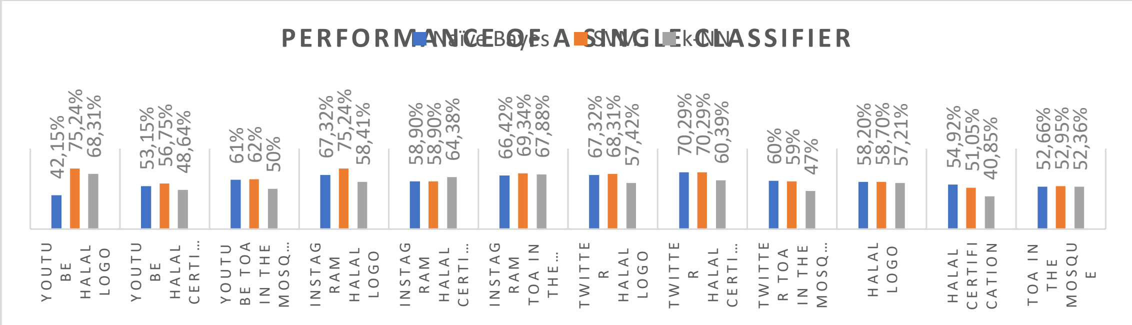

Fig. 1. Performance of a single classifier

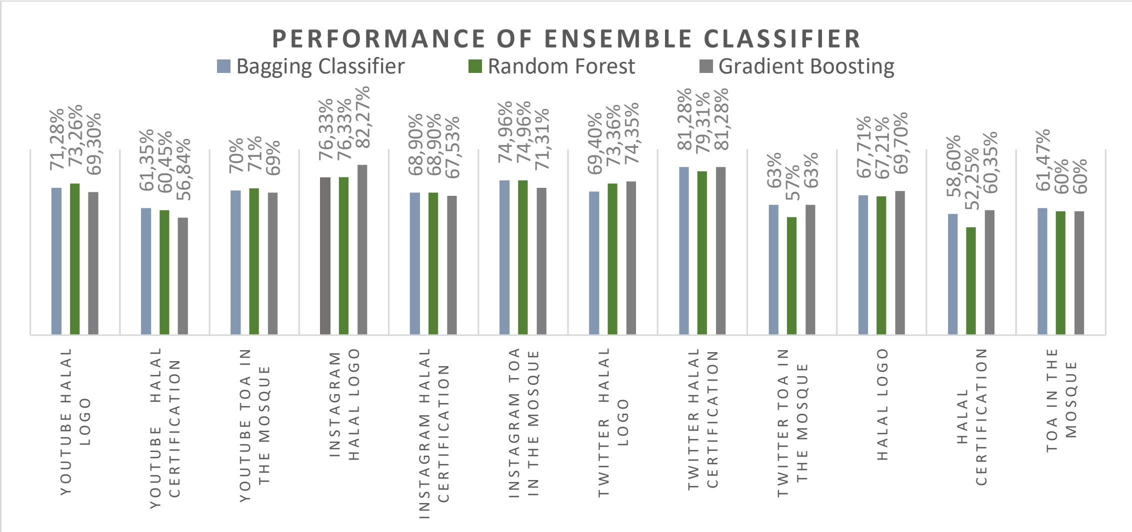

Fig. 2. Performance of ensemble classifier

In summary, the suggested ensemble method shows enhanced accuracy compared to ML techniques SVM, Naïve Bayes, and k-NN for both positive and negative corpora. The results emphasized the significance of each system component and highlighted the effectiveness of the ensemble technique in boosting the sentiment classification metric in the microblog dataset focused on religious moderation.

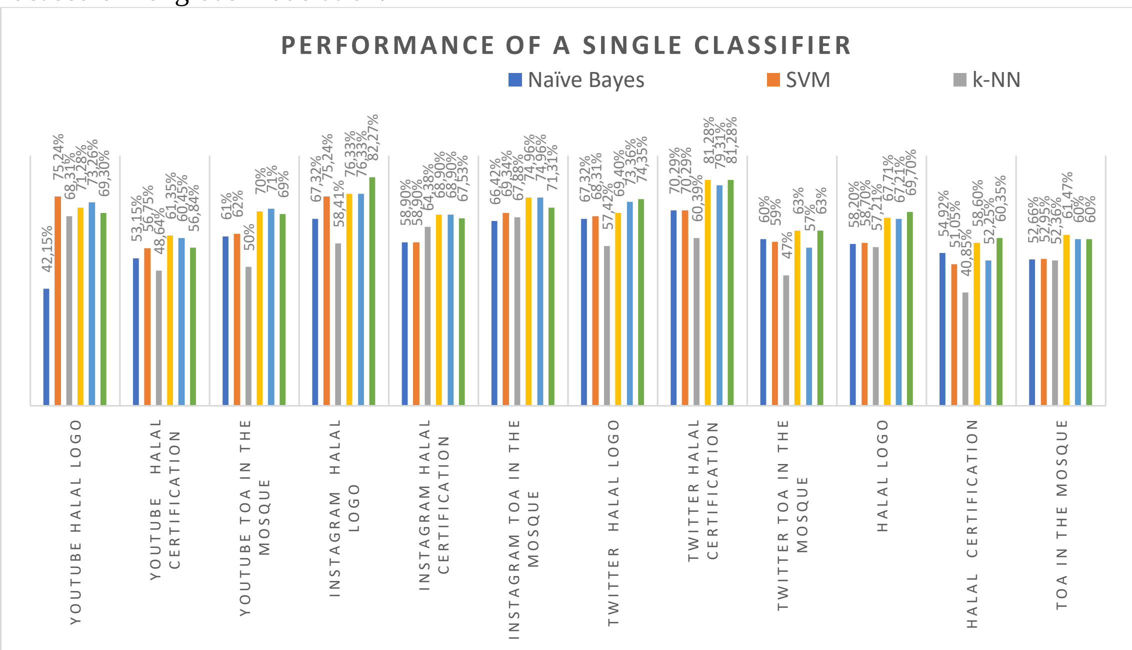

Fig. 3. Comparison of the performance of a single classifier with an ensemble classifier

5. Conclusion

Previous studies based on machine learning encountered challenges in achieving accuracy due to the unstructured nature of social media, relying heavily on a strong match between training and test data. Sentiment analysis was conducted on three primary microblogs such as Twitter, Instagram and YouTube using six machine learning algorithms. These include machine learning algorithm namely Naïve Bayes, Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), ensemble method namely Bagging Classifier, Random Forest, and Gradient Boosting Classifier. The test results showed the highest accuracy is Gradient Boosting reached 82.27% as the ensemble method. The experimental results indicated that the ensemble approach showed promising performance in sentiment classification, although there was still room for improvement. To attain optimal outcomes, the creation of a standard corpus was suggested.

Acknowledgment

Thank you very much to the Universitas Islam Negeri Sumatera Utara in carrying out the research programs for the 2022 fiscal year on contract number 328 of 2022

References

Akhmadi, A. (2008). Moderasi Beragama dalam Keragaman Indonesia. *Jurnal Diklat Keagamaan*, *13*(2), 45–55. https://bdksurabaya.e-journal.id/bdksurabaya/article/view/82

Arifinsyah. (2020). The Urgency of Religious Moderation in Preventing Radicalism in Indonesia. *ESENSIA*, *21*(1). https://doi.org/10.14421/esensia.v21i1.2199

Asif, M. (2020). Sentiment analysis of extremism in social media from textual information. *Telematics and Informatics*, 48. https://doi.org/10.1016/j.tele.2020.101345

Azhar, Masruroh, S. U., Wardhani, L. K., & Okfalisa. (2019). Perbandingan Kinerja Algoritma Naive Bayes dan K-NN Pendekatan Lexicon pada Analisis Sentimen di Media Twitter. *Seminar Nasional Fisika Universitas Riau IV (SNFUR-4)*, 1–6. https://snf.fmipa.unri.ac.id/wp-content/uploads/2019/09/25.-OFMI-3011.pdf

Badan Litbang Dan Diklat Kementerian Agama RI. (2020). *Religious Moderation*. Kementerian Agama RI.

Barghout, L. (2015). Spatial-Taxon Information Granules as Used in Iterative Fuzzy-Decision-Making for Image Segmentation. *Granular Computing and Decision-Making*, *10*, 285–318. https://doi.org/10.1007/978-3-319-16829-6_12

Ben-Hur, A., Horn, D., Siegelmann, H., & Vapnik, V. (2001). Support vector clustering. *Journal of Machine Learning Research*, *2*, 125–137. https://doi.org/10.1162/15324430260185565

Bifet, A., & Eibe, F. (2010). Sentiment knowledge discovery in twitter streaming data. *In Discovery Science*, 1–15. https://doi.org/10.1007/978-3-642-16184-1_1

Breiman, L. (1996). Bagging predictors. *Machine Learning*, *24*(2), 123–140. http://dx.doi.org/10.1007/BF00058655

Breiman, L. (1999). Pasting small votes for classification in large databases and on-line. *Machine Learning*, *36*(1), 85–103. https://doi.org/10.1023/A:1007563306331

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1023/A:1010950718922

Brown, P. F., Desouza, P. V, Mercer, R. L., Pietra, V., & Lai, J. C. (1992). Class-based n-gram models of natural language. *Computational Linguistics*, *18*(2), 467–479. https://aclanthology.org/J92-4003.pdf

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273. https://doi.org/10.1023/A:1022627411411

Cuingnet, R., Rosso, C., Chupin, M., Lehéricy, S., Dormont, D., Benali, H., Samson, Y., & Colliot, O. (2011). Spatial regularization of SVM for the detection of diffusion alterations associated with stroke outcome. *Medical Image Analysis*, *15*(5), 729–737. https://doi.org/10.1016/j.media.2011.05.007

Davids, N. (2017). Islam, Moderation, Radicalism, and Justly Balanced Communities. *Journal of Muslim Minority Affairs*, *37*(3), 309–320. https://doi.org/10.1080/13602004.2017.1384672

DeCoste, D. (2002). Training Invariant Support Vector Machines. *Machine Learning*, *46*, 161–190. https://doi.org/10.1023/A:1012454411458

Feldman, R., & James, S. (2007). *The Text Mining Handbook*. Cambridge. https://doi.org/10.1017/CBO9780511546914

Gaonkar, B., & Davatzikos, C. (2013). Analytic estimation of statistical significance maps for support vector machine based multi-variate image analysis and classification. *NeuroImage*, *78*, 270–283. https://doi.org/10.1016/j.neuroimage.2013.03.066

Gunther, T. (2013). *Sentiment Analysis of Microblogs*. https://www.researchgate.net/publication/258521310_Sentiment_Analysis_of_Microblogs

Hanapi, M. S. (2014). The Wasatiyah (Moderation) Concept in Islamic Epistemology: A Case Study of Its Implementation in Malaysia. *International Journal of Humanities and Social Science*, *4*(9), 51–62. https://doi.org/10.5901/mjss.2015.v6n4s2p66

Ho, T. (1998). The random subspace method for constructing decision forests. *Pattern Analysis and Machine Intelligence*, *20*(8), 832–844. https://doi.org/10.1109/34.709601

Joachims, T. (1998). Text categorization with Support Vector Machines: Learning with many relevant features. *Machine Learning*, *1398*, 137–142. https://doi.org/10.17877/DE290R-5097

Khan, M., & Malviya, A. (2021). Big Data Approach for Sentiment Analysis of Twitter Data using Hadoop Framework and Deep Learning. *Emerging Trends in Information Technology and Engineering*. https://doi.org/10.1109/ic-ETITE47903.2020.201

Kumar, A., & Sebastian, T. M. (2012). Sentiment analysis on twitter. *IJCSI International Journal of Computer Science Issues*, *9*(3), 372–378. https://dx.doi.org/10.2139/ssrn.3920078

Kurniasari, I., Kusrini, & Al-Fatta, H. (2020). Analisis Sentimen Komentar Facebook Berbasis Lexicon dan Support Vector Machine. *Jurnal Sains Dan Teknologi*, 40–44. https://ejournal.unwaha.ac.id/index.php/saintek/article/download/855/545/2208

Lineck, S. (2017). It's All About Informatioan? The Following Behaviour of Professor and Ph.D Students in Computer on Twitter. *The Journal of Web Sciences*, *3*(1), 1–15. https://10.1561/106.00000008

Liu, B. (2012). *Sentiment Analysis and Subjectivity*. Graeme Hirst Morgan & Claypool Publisher. https://www.cs.uic.edu/~liub/FBS/SentimentAnalysis-and-OpinionMining.pdf

Liu, B. (2016). *Sentiment Analysis and Opinion Mining*. Graeme Hirst Morgan & Claypool Publisher. https://www.cs.uic.edu/~liub/FBS/SentimentAnalysis-and-OpinionMining.pdf

Liu, K., Li, W., & Goo, M. (2012). Emoticon smoothed language models for twitter sentiment analysis. *In Twenty-Sixth AAAI Conference on Artificial Intelligence*. https://doi.org/10.1609/aaai.v26i1.8353

Louppe, G., & Geurts, P. (2012). Ensembles on Random Patches. *Machine Learning and Knowledge Discovery in Databases*, 346–361. https://doi.org/10.1007/978-3-642-33460-3_28

Maitra, D. S., Bhattacharya, U., & Parui, S. K. (2015). CNN based common approach to handwritten character recognition of multiple scripts. *13th International Conference on Document Analysis and Recognition (ICDAR)*. https://doi.org/10.1109/ICDAR.2015.7333916

Maity, A. (2016). *Supervised Classification of RADARSAT-2 Polarimetric Data for Different Land Features*. https://doi.org/10.5281/zenodo.832427

Matsumoto, S., Takamura, H., & Okumura, M. (2005). Sentiment classification using word sub-sequences and dependency sub-trees. *In Advances in Knowledge Discovery and Data Mining*, 301–311. https://doi.org/10.1007/11430919_37

Neethu, M., & Rajasree, R. (2013). Sentiment Analysis in Twitter using Machine Learning Techniques. *International Conference on Computing, Communications and Networking Technologies*. https://doi.org/10.1109/ICCCNT.2013.6726818

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, *2*(1), 135. https://doi.org/10.1561/1500000011

Purwidiantoro, M. H., & F, K. D. (2018). Pengaruh Penggunaan Media Sosial Terhadap Pengembangan Usaha Kecil Menengah (UKM). *Ekacida*, *1*(1), 31. https://journal.amikomsolo.ac.id/index.php/ekacida/article/download/19/11

Rizki, M. M. (2019). Analisis Sentimen Terhadap Produk Otomotif dari Twitter Menggunakan Kombinasi Algoritma K-Nearest Neighbor dan Pendekatan Lexicon (Studi Kasus : Mobil Toyota). *Universitas Islam Negeri Syarif Hidayatullah*. https://repository.uinjkt.ac.id/dspace/bitstream/123456789/48643/1/MAHDI%20MUHAMMAD%20RIZKI-FST.pdf

Sari, A., & Bador. (2022). Sentiment analysis for cruises in Saudi Arabia on social media platforms using machine learning algorithms. *Journal of Big Data*, *9*, 21. https://doi.org/10.1186/s40537-022-00568-5

Sari, R. (2020). Analisis Sentimen Pada Review Objek Wisata Dunia Fantasi Menggunakan Algoritma K-Nearest Neighbor (K-NN). *Evolusi : Jurnal Sains Dan Manajemen*, 10–17. https://doi.org/10.31294/evolusi.v8i1.7371

Setia, P., & Rahman, M. T. (2022). Socializing Religious Moderation and Peace in the Indonesian Lanscape. *Jurnal Iman Dan Spiritualitas*, *2*(3), 333–340. https://doi.org/10.15575/jis.v2i3.17916

Statnikov, A., Hardin, D., & Aliferis, C. (2006). *Using SVM weight-based methods to identify causally relevant and non-causally relevant variables*. http://ccdlab.org/paper-pdfs/NIPS_2006.pdf

Sudradat, T., Supiana, & Zakiah, Q. Y. (2021). Higher Education, Nation Character, and Religious Moderation Program: A Public Policy Perspective. *Journal of Asian Social Science Research*, *3*(1), 73–92. https://doi.org/10.15575/jassr.v3i1.35

Tim Kelompok Kerja Moderasi Beragama Kementerian Agama RI. (2020). *Peta Jalan (Roadmap) Penguatan Moderasi Beragama Tahun 2020-2024*. Kementerian Agama RI.

Vapnik, V. (2014). Invited Speaker. *Information Processing and Management*.

Yaakub, M. B., Othman, K., & Nazi, N. (2019). Islamic Moderation (wasatiyah) Manifestation of Practices: An Elaboration of Its Degree of Effectiveness. *Humanities and Social Sciences Reviews*, *7*(1), 171–179. https://doi.org/10.18510/hssr.2019.7121

Zou, X., Yang, J., & Zhang, J. (2018). *Microblog Sentiment Analysis using Social and Topic Context*. https://doi.org/10.1371/journal.pone.0191163