Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th October 2025. Vol. 5. No. 1; e-ISSN: 2808-4519

Sentiment Analysis of Public Trust Towards Islamic Boarding School on Social Media Using Machine Learning Method

Eko Prasetio Widhi[1]*, Much.Def Putra Sholihin[2], Aziz Musthafa[3], Nurhana Marantika[4]

[1,2,3,4]*University of Darussalam Gontor*
ekoprasetiowidhi@unida.gontor.ac.id [1*], muchdefputrasholihin@gmail.com[2], aziz@unida.gontor.ac.id[3], nurhana@unida.gontor.ac.id[4]

Abstract

This study aims to analyse public sentiment towards Islamic boarding schools on social media using a machine learning approach. A total of 1,905 cleaned comments were collected from two platforms, Twitter (X) and YouTube, and then processed through the CRISP-DM stages, which include business understanding, data preparation, modelling, evaluation, and deployment. Pre-processing steps such as tokenisation, stemming, and labelling were applied to prepare the text data for analysis. The sentiment classification was carried out using five machine learning algorithms: Naïve Bayes, Decision Tree, Neural Network, Support Vector Machine (SVM), and Random Forest. The evaluation results revealed that Random Forest outperformed other models, achieving the highest accuracy (79%), F1-score (79%), precision (80%), and recall (79%), indicating a strong balance in identifying sentiment classes accurately and consistently. Additionally, the research implemented interactive visualisations using Streamlit, enabling the public and stakeholders to understand sentiment trends in a clear, data-driven format. These findings are expected to serve as a strategic foundation for Islamic boarding schools in building a positive image in the digital space and for further development of AI-based opinion monitoring systems.

Keywords: *Semicolon Islamic Boarding School; Machine Learning; Public Trust; Sentiment Analysis; Social Medeia*

1. Introduction

The development of information and communication technology in the digital age has changed the way people interact and express their opinions. Social media has now become a dynamic public space for expression, where public opinion, perceptions, and sentiments on various issues can be easily accessed. This makes social media a rich source of data that can be utilised for social analysis and consideration in policy formulation. One of the issues frequently discussed is related to Islamic boarding schools, which often become a topic of public discourse across various digital platforms[1].

Islamic boarding schools play a strategic role in shaping the character, morals, and religious beliefs of Indonesian society. As traditional educational institutions, Islamic boarding schools have long been bastions of religious values and ethics. Today, Islamic boarding schools continue to adapt to changing times through curriculum development and the integration of life skills relevant to modern needs. The contribution of Islamic boarding schools to the national education system is not only in the religious aspect but also in fostering balanced social skills, leadership, and spirituality.[2].

However, Islamic boarding schools also face major challenges in this era of information openness, especially on social media. The emergence of negative news coverage, social stigma, and biased narratives often shape public perceptions that are unfavourable toward Islamic boarding schools. These perceptions can be positive or negative, depending on how information is disseminated and constructed. A positive image of Islamic boarding schools is crucial, especially for gaining the trust of the community, parents, and prospective students considering an education rooted in Islamic values. [3]

To objectively understand public opinion, data-driven approaches such as sentiment analysis are a relevant solution. Sentiment analysis is a systematic process that uses Natural Language Processing (NLP) and machine learning technologies to classify public expressions into three categories: positive, negative, and neutral. With this approach, educational institutions such as Islamic boarding schools can accurately identify public perceptions and formulate more effective communication strategies.[4]

Machine learning offers the ability to learn historical patterns from data and perform automatic classification with a high degree of accuracy. Various popular algorithms such as Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression are often used in sentiment analysis projects. By comparing the performance of each algorithm, it is possible to determine which model is most effective in classifying public opinion regarding Islamic boarding schools.[5]

Research that specifically analyses the level of public trust in Islamic boarding schools through social media is still very limited. Most previous studies have focused on other topics, such as sentiment analysis of online schools,[6] sentiment analysis of the work of the House of Representatives (DPR) on Twitter using the naïve Bayes classifier method[7] or commercial products. Additionally, there are few studies that directly compare various machine learning algorithms in the context of Islamic boarding schools. This study is unique because it not only compares several algorithms but also uses data from two different social media platforms, Twitter (X) and YouTube, thereby providing a richer and more diverse perspective[8].

This research is important because it can provide comprehensive data-based understanding of public perceptions of Islamic boarding schools. The results can be used to help Islamic boarding schools build a positive image in the digital space through evidence-based communication strategies. In addition, this research also provides recommendations on the best classification algorithms that can be adopted in public opinion analysis, particularly of Islamic educational institutions such as Islamic boarding schools.

2.Research Methodology

At this stage of research, it is very important to understand the system development process. CRISP-DM is an industry-neutral and flexible standard, so it can be used with various tools and applications to solve business problems through a data mining approach. This methodology provides an open and customisable framework for integrating data mining into problem-solving strategies, both in business and research environments. CRISP-DM has six stages: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. [10] This framework is used to ensure that the sentiment analysis process of public comments on social media is systematic and comprehensive, from understanding the context to applying the results of the classification model.

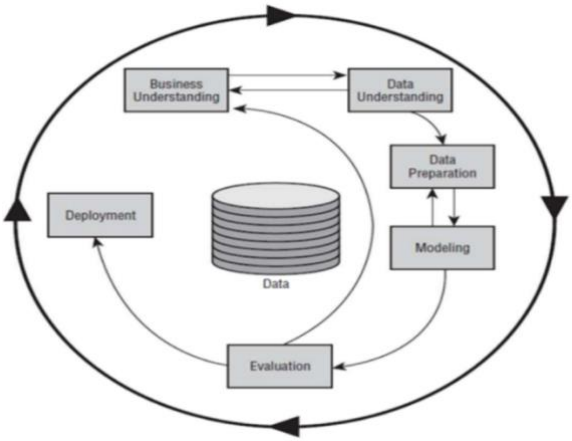

Fig. 1: Model CRISP-DM
(Shafique & Qaiser,2014)

2.1 Business Understanding

This stage aims to understand public perceptions of Islamic boarding schools based on comments on social media, particularly from Twitter (X) and YouTube. The main focus of the research is to analyse and measure public trust in Islamic boarding schools by classifying sentiment into positive, negative, or neutral. The information obtained is important for understanding the image of Islamic boarding schools in the eyes of the public, identifying aspects that are frequently praised or criticised, and providing data-driven recommendations to enhance public trust. This research also maps public opinion on Islamic boarding schools, provides a foundation for developing public communication strategies, and assists in determining the most accurate machine learning model for classifying Indonesian text.

2.2 Data Understanding

The data used in this study was collected from social media platforms Twitter (X) and YouTube, in the form of tweets and video comments containing keywords such as 'pondok pesantren' (Islamic boarding school), "santri" (Islamic boarding school student), or 'mondok' (staying at an Islamic boarding school). Data collection was carried out using scraping techniques via the Twitter API and YouTube Comment Scraper.[11] The data obtained was in the form of short, informal text containing emoticons, abbreviations, and everyday language. An initial exploration was conducted to determine the amount of data, sentiment distribution, and data quality, including the presence of duplicates, non-standard words, and non-text elements such as URLs and hashtags. Term frequency analysis was also used to identify words that frequently appear in positive and negative contexts as a basis for the next modelling stage.

2.3 Data Preparation

Pre-processing is very important in the data refinement process because it will make the model better at recognising data, removing unnecessary noise, and deleting duplicate values. The steps of data pre-processing are case folding, tokenisation, filtering, stemming, and labelling. [12]

2.3.1 Case Folding

Case folding is the process of converting all letters in a text to lowercase, accepting only letters from "a" to "z". Characters other than letters are removed and considered delimiters.[13] Before case folding: 'Pendidikan Pondok PESAntren itu LUAR BIASA!' (The education at the Islamic boarding school is EXTRAORDINARY!), after case folding: 'pendidikan pondok pesantren itu luar biasa' (the education at the Islamic boarding school is extraordinary).

2.2.2 Cleasing
Cleansing is the process of removing unnecessary elements such as URLs, numbers, symbols, and irrelevant punctuation marks. [13] Before cleansing: 'Wow!! This Islamic boarding school is so cool! 😍👍 Visit: https://ponpeskeren.id, or call 08123456789 #PesantrenHebat!!!', after cleansing: 'Wow, this Islamic boarding school is so cool. Visit or call PesantrenHebat'.

2.2.3 Tokenisasi
Tokenisation is the process of breaking down text or documents into small parts, usually phrases or words. .[14] Before tokenisation: 'boarding school education is extraordinary!', after tokenisation: ['education', 'boarding school', 'it', "extraordinary", '!'].

2.2.4 Filtering
Filtering is the stage of extracting important words from the term results. You can use a stoplist algorithm (removing less important words) or a wordlist (saving important words). Stoplist/stopwords are non-descriptive words that can be discarded in the bag-of-words approach. Examples of stopwords include 'that,' 'in,' 'from,' 'and,' and so on.[12]. Before filtering, 'boarding school education is extraordinary'; after filtering, 'boarding school education is extraordinary.'

2.2.5 Steming
The stemming stage is the stage of finding the root word of each filtered word. At this stage, various word forms are converted into a common representation or returned to their base form[13] before stemming. Before stemming, the phrase is 'pendidikan pondok pesantren itu luar biasa' (boarding school education is extraordinary), and after stemming, it becomes 'didik pondok pesantren luar biasa' (boarding school education is extraordinary).

2.2.6 Labeling
Labelling is the process of marking a word or sentence into several categories such as positive, negative, and neutral[12]. Positive examples include 'Didik pondok is extraordinary', negative examples include 'buruk didik pondok', and neutral examples include 'Pondok Darussalam'. Labelling is done manually by annotators, or it can also be done semi-automatically using a sentiment dictionary.

After the data has been cleaned and labelled, the next step is to convert the text data into numerical form so that it can be processed by machine learning algorithms. The method used is TF-IDF (Term Frequency - Inverse Document Frequency), which measures how important a word is in a document relative to the entire corpus. [15] Many use feature extraction (TF-IDF) to improve accuracy, calculate synonyms, stem data, or sentence structure. [16] The processed data is then divided into two parts: Training Data (70%) and Testing Data (30%).

2.4 Modeling
After the data was prepared, a classification model was built using several machine learning algorithms, namely Naive Bayes, Support Vector Machine (SVM), Random Forest, Neural Network, and Decision Tree. Each algorithm was trained using training data and validated using testing data. The objective of this stage was to build a sentiment classification model capable of automatically distinguishing public opinion and comparing the performance of different models based on accuracy, in order to determine the most suitable model for analysing Indonesian-language text.

2.5 Evaluation
The model that has been built is then evaluated using several metrics to determine its accuracy in classification. The metrics used include Accuracy, Precision, Recall, and F1-Score. This evaluation aims to measure the model's performance quantitatively while assessing its ability to handle data imbalance and sentiment distribution. The model with the best results was selected based on a combination of these metrics. Regarding the advantages of certain algorithms, such as SVM, which is known to be effective in handling high-dimensional data. [14]

2.6 Deployment
After finding the model with the best accuracy, the next step is to implement the model to automatically classify new comments from social media. The classification results are visualised in the form of pie charts or bar charts. After obtaining the Confusion Matrix, Accuracy, Precision, Recall, and F1-Score, a website is created using Streamlit to display the results of these models, as it is suitable for prototyping and data presentation, since Streamlit is easy to integrate with Python libraries[17].

3. Results and Discussion
3.1 Hasil Dataset
The dataset used in this study consists of 1,970 comments collected from two social media platforms, namely Twitter (X) 1,000 tweets and YouTube 970 comments. This data was collected over the past five years. After preprocessing steps such as removing duplicates, symbols, and irrelevant text, the total valid data for analysis became 1,905 data points. The initial data distribution includes categories based on platform (Twitter vs. YouTube), collection time, and text length. An initial analysis was conducted to examine statistics such as the number of stopwords, punctuation marks, symbols, and other non-text elements before cleaning.

Additionally, text excerpts were sampled for each sentiment category as illustrations. For example, comments with positive keywords such as 'moga' (example: 'moga anak saya masuk pondok pesantren') were classified as positive sentiment because they contained good wishes for the pesantren. Conversely, negative keywords such as "aniayah" (example: 'guru selalu aniayah santri di pondok pesantren') were included in the negative category because they indicated a negative opinion. For the neutral category, ambiguous words such as 'ustadz' are used, which do not directly indicate positive or negative sentiment. The final labelling results show that the data is divided into three sentiment groups with the following distribution: 1,054 positive comments, 391 negative comments, and 460 neutral comments. The public perception of Islamic boarding schools tends to be positive.

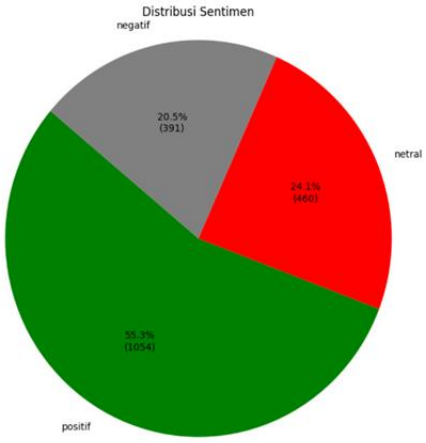

Fig. 2: Sentiment Distribution

3.2 Data Preprocessing Results

In the preprocessing stage, its role is very important in text data analysis because it aims to clean the data from various irrelevant elements or so-called noisy elements, such as symbols, numbers, URLs, punctuation marks, and common words (stopwords) that do not provide significant meaning. This process includes steps such as case folding, cleansing, tokenisation, filtering, stemming, and labelling, all of which aim to produce clean, consistent, and structured data. As a result, the machine learning models used in subsequent stages can operate optimally because they receive more accurate and interference-free input data.

Table 2: Tokenization

No	Pre-processing stages	
	Comments	Stages
1.	Pendidikan Pondok PESAntren itu LUAR BIASA@---	Social Media Comments
2	pendidikan pondok pesantren itu luar biasa@---	Case folding
3	pendidikan pondok pesantren itu luar biasa	Clasing
4	[“pendidikan”, “pondok”,”pesantren”, “itu”, “luar”, “biasa”]	Tokenezing
5	pendidikan pondok pesantren luar biasa	Filtering
6	didik pondok pesantrenluar biasa	Steming
7	didik pondok pesantren luar biasa	Labeling (Positif)
8	Didik pondok pesantren buruk	Labeling (Negatif)
9	Didik pondok pesantren	Labeling (Netral)

3.2.1 WordCloud Sentimen

WordCloud digunakan untuk memvisualisasikan kata-kata yang paling sering muncul dalam setiap kategori sentiment terhadap pesantren positif,negative dan netral.[18] WordCloud **Fig. 3.** WordCloud Positif menampilkan sentimen positif, yang diwarnai oleh kata-kata seperti semoga, alhamdulillah, bangga, gontor, dan sukses, mencerminkan rasa syukur, kebanggaan, serta dukungan terhadap pesantren. Gambar **Fig. 4.** WordCloud Negatif menggambarkan sentimen negatif, dengan kata-kata seperti pencabulan, cabul, pelecehan, korban, dan kasus, yang menunjukkan adanya opini atau pemberitaan negatif terkait kejadian tidak menyenangkan di lingkungan pesantren. **Fig. 5.** WordCloud Netral menunjukkan WordCloud untuk sentimen netral, di mana kata-kata seperti pondok, pesantren, santri, ustadz, dan nahdlatul ulama mendominasi, menandakan konteks umum tanpa penilaian emosional. Melalui WordCloud ini, dapat dipahami persepsi masyarakat berdasarkan kata-kata kunci yang sering muncul dalam komentar.

Fig. 3. WordCloud Positif.

Fig 4. WordCloud Negatif

Fig. 5. WordCloud Netral

3.3 Model Training Results

The figures show a comparison of the performance of five classification models—SVM, Naive Bayes, Decision Tree, Random Forest, and Neural Network—based on four main evaluation metrics: accuracy, F1-score, precision, and recall. The SVM model demonstrates high performance with an accuracy of 78%, F1-score of 76%, precision of 78%, and recall of 78%, making it a consistent and competitive model. On the other hand, Naive Bayes recorded the lowest performance with an accuracy of only 61%, F1-score of 51%, precision of 65%, and recall of 61%, indicating weaknesses in prediction balance. Decision Tree produced fairly good performance with an accuracy of 77%, F1-score of 77%, precision of 78%, and recall of 77%, demonstrating stability across all metrics. Random Forest was the best-performing model, recording an accuracy of 79%, an F1-score of 79%, a precision of 80%, and a recall of 79%, making it the most reliable and balanced model. Meanwhile, the Neural Network achieved an accuracy of 76%, an F1-score of 75%, precision of 75%, and recall of 76%, with stable performance but slightly lower than Decision Tree and SVM.

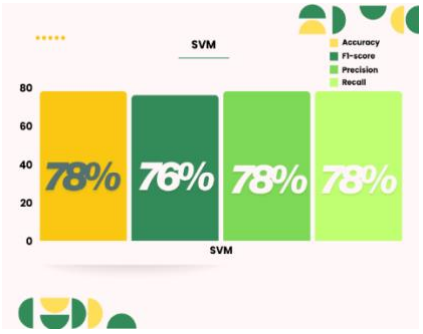

Fig. 6. SVM Model

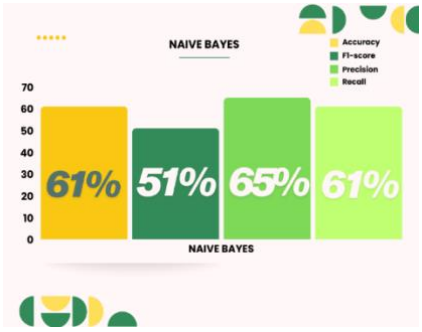

Fig. 7. Naïve Bayes Model

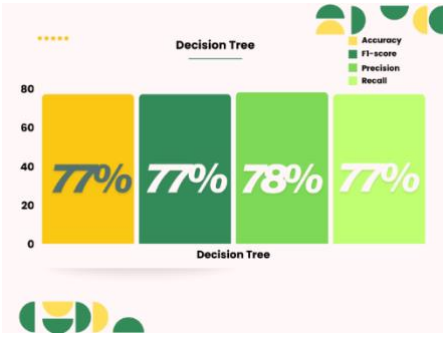

Fig. 8. Decision Tree Model

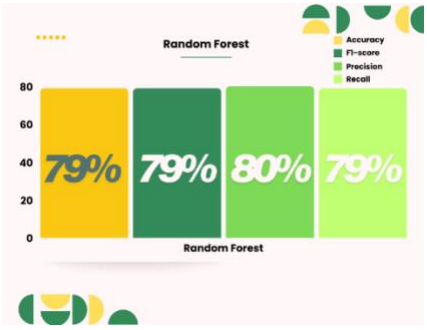

Fig. 9. Random Forest Model

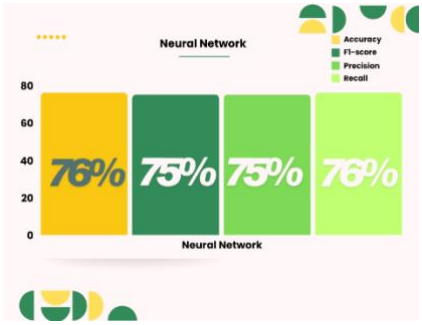

Fig. 10. Neurol Network Model

3.4 Best Model

The performance comparison results of all models are displayed in a bar chart. Based on the evaluation results, the highest accuracy metric was achieved by Random Forest at 79%, followed by SVM at 78%. The best F1-score was also achieved by Random Forest at 79%, indicating a good balance between precision and recall. Meanwhile, the highest precision value of 80% is also achieved by Random Forest, indicating its accuracy in predicting relevant classes. On the other hand, the best recall of 79% is again achieved by Random Forest, reinforcing its position as the most reliable model in identifying all relevant labels. Thus, Random Forest consistently excels in all evaluation metrics, making it the best classification model in this study..

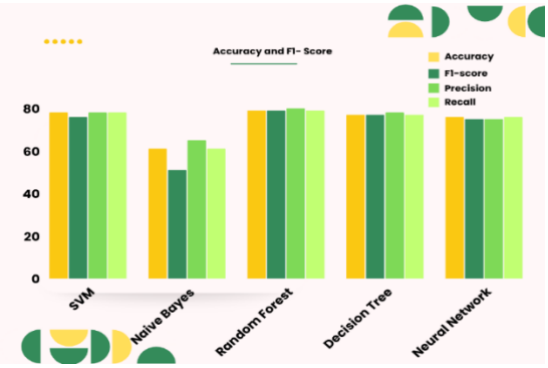

Fig. 11. Comparison of evaluation metrics

3.5 Visualisation Implementation

After determining the accuracy of each model, visualisation will be developed using Streamlit because it is easier to integrate with Python libraries,[17] and to simplify code development using Visual Studio Code tools.

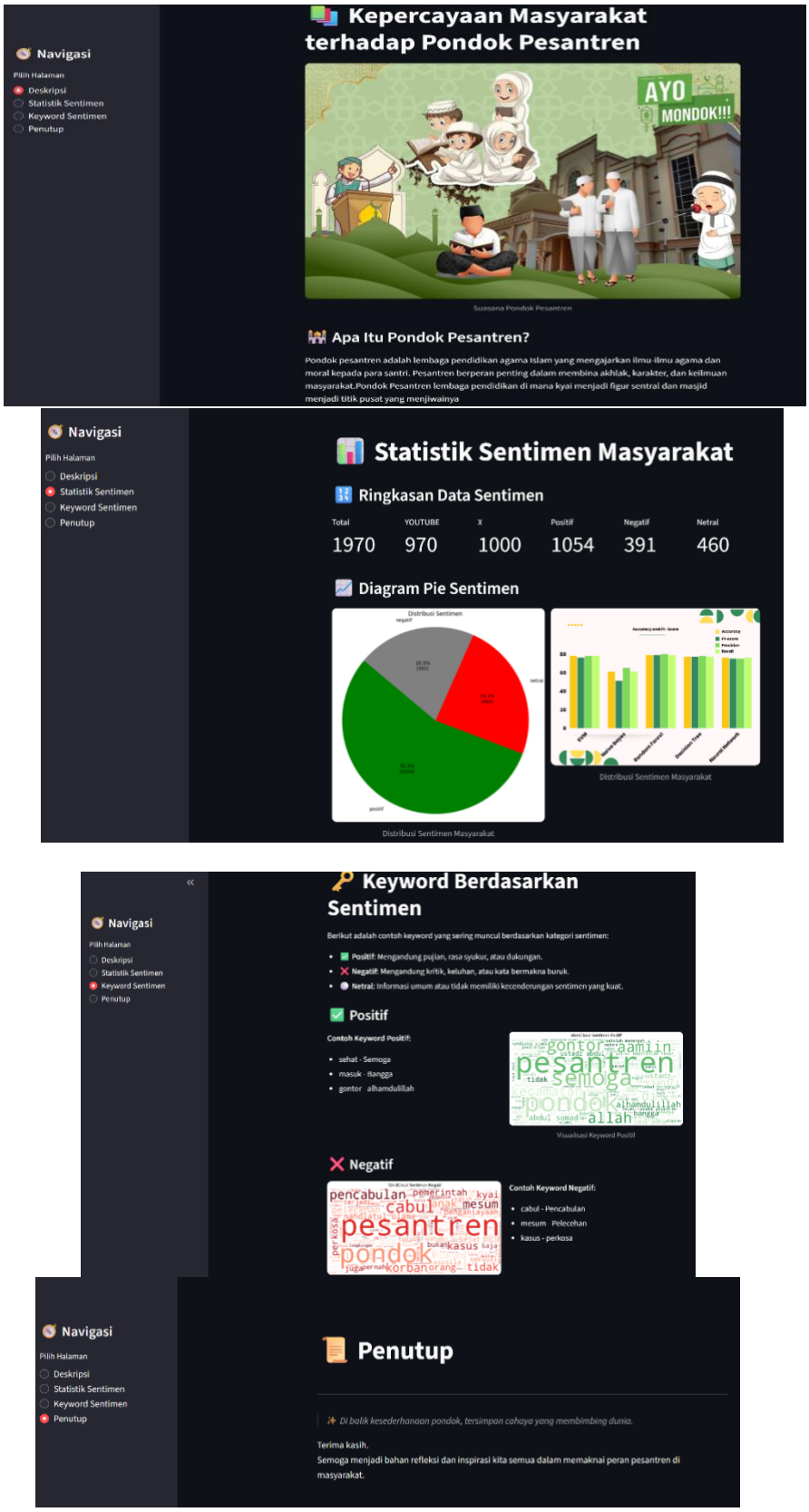

Fig. 12 Streamlit

This Streamlit website has four pages: Description, Sentiment Statistics, Sentiment Keywords, and Conclusion. The first page displays the title 'Public Trust in Islamic Boarding Schools' and provides a description of Islamic boarding schools and their important role in shaping the character and morals of society. The Sentiment Statistics page displays a summary of data collected from social media platforms Twitter (X) and YouTube, including the total number of comments, the total number of positive, negative, and neutral comments, the percentage of public comments regarding Islamic boarding schools, and the

accuracy and F1-Score of each machine learning model used in this study. The next page displays keywords and word clouds for the three sentiments, highlighting the words that frequently appear in the comments. In the conclusion section, the final relaxation of the entire analysis is presented, including expressions of gratitude and hopes that this research may be beneficial.

3.6 Discussion of Findings

This discussion contains interpretations of sentiment analysis results in the context of social and cultural Islamic boarding schools in Indonesia. The findings show that most comments on social media regarding Islamic boarding schools are positive, indicating a strong level of public trust. Furthermore, these results are linked to previous literature and studies that show the important role of Islamic boarding schools in shaping the morals and character of society.

Pesantren are considered to be able to utilise social media strategically to strengthen their positive image and build public trust, including through the publication of positive activities, transparent communication approaches, and the delivery of contextual Islamic values. In addition, the selection of the right machine learning algorithm is highly relevant to the context of Indonesian-language data. The results indicate that the Random Forest algorithm is better able to handle the complexity of informal text and the variety of languages used on Indonesian social media compared to other algorithms.

This study provides several significant strategic implications. For pesantren administrators, the results of this study can be used as input in designing more effective public communication strategies to build and maintain a positive image on social media. From a technological development perspective, this study supports initiatives to build an artificial intelligence (AI)-based public opinion monitoring system that can help Islamic educational institutions understand public perceptions in real time. Additionally, this study opens opportunities for future researchers to explore topics related to education and technology in greater depth, particularly in the fields of sentiment analysis, natural language processing (NLP), and digital literacy within the context of Indonesia's local culture.

4. Conclusion

This study focuses on comparing existing machine learning algorithms with data taken from social media (such as Twitter and YouTube) to detect public sentiment towards Islamic boarding schools. Of the five algorithms applied in this sentiment analysis, there are traditional machine learning models such as Naïve Bayes, and Decision Tree, as well as modern machine learning models commonly used today, such as Support Vector Machine Learning (SVM), Random Forest, and Neural Network. From the comparison of each algorithm that has been tested, each algorithm has its own characteristics, as each algorithm has its own advantages and disadvantages in data processing. Random Forest has higher accuracy and F1-Score than other algorithms, with an accuracy and F1-Score of 77%.

Preprocessing is an important stage because it will determine the accuracy of the models to be used, as many comments are not yet understood by computers, making this stage very important[18] for cleaning the data so that it is ready for modelling. TF-IDF is also important for improving the quality of detection results. Within TF-IDF itself, it provides an evaluation of each algorithm based on accuracy metrics, recall, precision, and F1-score.

The visualisation of the results of algorithm comparisons in Streamlit makes it easy to see the results of each algorithm tested, as the display is more user-friendly and integrated with the Python library. As a result, laypeople will find it easier to understand the results of each machine learning algorithm model. It can also be further developed with even better innovations.

References

[1] A. N. Alfifa, V. Fahira, R. Batubara, K. Sakinah, J. Manik, and R. A. Yoes, "Media Sosial dan Pembentukan Opini Publik (Analisis Studi Kasus Echo Chamber Pada Interaksi Komentar di Akun Instagram @Turnbackhoaxid Dalam Konteks Post-Truth)," *J. Penelit. Ilmu-Ilmu Sos.*, vol. 2, no. 6, pp. 162–169, 2025, [Online]. Available: https://ojs.daarulhuda.or.id/index.php/Socius/article/view/1130

[2] Alisia Zahro'atul Baroroh and Abdul Khobir, "Peran Pondok Pesantren dalam Membentuk Karakter Anak Muda di Era Modern," *J. Ekon. Akuntansi, dan Perpajak.*, vol. 2, no. 1, pp. 01–13, 2024, doi: 10.61132/jeap.v2i1.721.

[3] S. Rahmatullah, Fahrurrozi, and A. Malik, "COMMUNICATION STRATEGY OF AS-SUNNAH ISLAMIC BOARDING SCHOOL IN RESTORING ITS IMAGE AFTER IDENTITY CONFLICT IN BAGIK NYAKE," *Wasilatuna J. Komun. dan Penyiaran Islam*, vol. 6, no. 02, pp. 127–142, Oct. 2023, doi: 10.38073/wasilatuna.v6i02.1016.

[4] S. Fanissa, M. A. Fauzi, and S. Adinugroho, "Analisis Sentimen Pariwisata di Kota Malang Menggunakan Metode Naive Bayes dan Seleksi Fitur Query Expansion Ranking," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 8, pp. 2766–2770, 2018, [Online]. Available: http://j-ptiik.ub.ac.id

[5] S. Ulum, M. Mispani, J. Jaenullah, and M. Thohir, "The Public Perception of Islamic Education at Wali Songo Islamic Boarding School Sukajadi Village, Bumiratu Nuban District," *Bull. Pedagog. Res.*, vol. 1, no. 2, p. 187, Feb. 2021, doi: 10.51278/bpr.v1i2.190.

[6] N. L. P. C. Savitri, R. A. Rahman, R. Venyutzky, and N. A. Rakhmawati, "Analisis Klasifikasi Sentimen Terhadap Sekolah Daring pada Twitter Menggunakan Supervised Machine Learning," *J. Tek. Inform. dan Sist. Inf.*, vol. 7, no. 1, pp. 47–58, 2021, doi: 10.28932/jutisi.v7i1.3216.

[7] D. Duei Putri, G. F. Nama, and W. E. Sulistiono, "Analisis Sentimen Kinerja Dewan Perwakilan Rakyat (DPR) Pada Twitter Menggunakan Metode Naive Bayes Classifier," *J. Inform. dan Tek. Elektro Terap.*, vol. 10, no. 1, pp. 34–40, 2022, doi: 10.23960/jitet.v10i1.2262.

[8] E. Ditendra, S. Suryani, S. Romelah, M. H. Arsyiddik Tanjung, and M. Sarah, "Perbandingan Algoritma Klasifikasi untuk Analisis Sentimen Islam Nusantara di Indonesia," *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 2, no. 1, pp. 71–77, May 2022, doi: 10.57152/malcom.v2i1.199.

[9] A. Lathifah, Z. Arham, N. Hasanati, Zulfiandri, and E. Nurmiati, "Cross-Industry Standard Process For Data Mining (CRISP-DM) For Discovering Association Rules in Graduate Tracer Study Data of Islamic Higher Education Institution," in *2023 11th International Conference on Cyber and IT Service Management (CITSM)*, IEEE, Nov. 2023, pp. 1–6. doi: 10.1109/CITSM60085.2023.10455691.

[10] U. Shafique and H. Qaiser, "A Comparative Study of Data Mining Process Models (KDD , CRISP-DM and SEMMA)," *Int. J. Innov. Sci. Res.*, vol. 12, no. 1, pp. 217–222, 2014, [Online]. Available: http://www.ijisr.issr-journals.org/

[11] K. Purwandari, R. B. Perdana, J. W. C. Sigalingging, R. Rahutomo, and B. Pardamean, "Automatic Smart Crawling on Twitter for Weather Information in Indonesia," *Procedia Comput. Sci.*, vol. 227, pp. 795–804, 2023, doi: 10.1016/j.procs.2023.10.585.

[12] B. Gunawan, H. Pratiwi, Sasty, and E. Pratama, Esyudha, "Sistem Analisis Sentimen pada Ulasan Produk Menggunakan Metode Naive Bayes," *J. Edukasi dan Penelit. Inform.*, vol. 2, no. 1, pp. 95–103, 2023.

[13] N. W. A. S. Aprilia and A. R. Isnain, "Analisis Sentimen Terhadap Media Sosial Twitter dengan Kasus Kampanye Anti-Korupsi di Indonesia

Menggunakan Naive Bayes," *J. Media Inform. Budidarma*, vol. 8, no. 2, p. 695, 2024, doi: 10.30865/mib.v8i2.7582.
[14] C. A. Sugianto and T. H. Apandi, "Pengaruh Tokenisasi Kata N-Grams Spam SMS Menggunakan Support Vector Machine," *Citisee 2017*, pp. 5–9, 2017, [Online]. Available: osf.io/69bxn/
[15] L. Havrlant and V. Kreinovich, "A simple probabilistic explanation of term frequency-inverse document frequency (tf-idf) heuristic (and variations motivated by this explanation)," *Int. J. Gen. Syst.*, vol. 46, no. 1, pp. 27–36, Jan. 2017, doi: 10.1080/03081079.2017.1291635.
[16] A. S. Alammary, "Arabic Questions Classification Using Modified TF-IDF," *IEEE Access*, vol. 9, pp. 95109–95122, 2021, doi: 10.1109/ACCESS.2021.3094115.
[17] B. L. Kumaran and N. V. Ravindran, "NLP based Text Summarization Techniques for News Articles," in *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, IEEE, Mar. 2024, pp. 1–6. doi: 10.1109/IATMSI60426.2024.10503001.
[18] A. Hermawan, I. Jowensen, J. Junaedi, and Edy, "Implementasi Text-Mining untuk Analisis Sentimen pada Twitter dengan Algoritma Support Vector Machine," *JST (Jurnal Sains dan Teknol.*, vol. 12, no. 1, pp. 129–137, 2023, doi: 10.23887/jstundiksha.v12i1.52358.