
Sentiment Classification of Instagram Poster Comments on the Documentary Film "Pesta Babi": A Comparative Study of SVM, Random Forest, and Naive Bayes with a Keyword-Based Exploration of Sociocultural Themes

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Abstract

This study analyzes public sentiment in 704 Instagram comments responding to the poster of the Indonesian documentary "Pesta Babi: Kolonialisme di Zaman Kita," which triggered national debate in 2026. Comments were collected through total sampling and sentiment-labeled with AI assistance (partially via an Excel-integrated AI tool, partially via an AI-generated Python script executed in PyCharm), yielding an imbalanced distribution of 514 Positive and 190 Negative comments. After text preprocessing (regex-based tokenization and lowercasing) and binary Bag-of-Words feature extraction with L1 regularization, three algorithms Support Vector Machine, Random Forest, and Naive Bayes were compared using 10-fold cross-validation on the Orange platform. Random Forest achieved the highest overall accuracy (0.786) and AUC (0.858), while Naive Bayes showed the strongest balanced performance on the minority Negative class (MCC = 0.398). A supplementary keyword-based analysis found only 19.7% of comments referenced religious, artistic, or ethical-normative themes, indicating public discourse was dominated by other issues, notably political and funding-related accusations.

A. Introduction

The controversy surrounding the documentary film *Pesta Babi: Kolonialisme di Zaman Kita* deserves to be understood not merely as a debate over the film's content, but as an intersection of media representation, symbolic sensitivity, freedom of expression, and the dynamics of digital public opinion. The film's title itself has been read as a sign that produces layered meaning, since the phrase *Pesta Babi* does not merely refer to a ritual or cultural event, but also functions as an ironic sign that exposes the unequal relationship between indigenous communities, state development discourse, and extractive interests [56]. In film semiotics, titles and representational strategies can indeed become arenas of ideological contestation, since film conveys not only entertainment but also educational value, social critique, and social control through an audiovisual sign system [21]. Because of this, when the film poster foregrounds the word "Babi" (pig) in Indonesia's digital public space [39], the resulting response is highly likely to move beyond the film's agrarian and ecological substance toward a symbolic reading shaped by religious, cultural, and moral norms [46].

In the Indonesian context, social media platforms such as Instagram are not merely information distribution channels, but spaces where social reality is constructed, contested, and negotiated participatively. Digital platforms shape public perception through language, religious symbols, algorithms, and interaction patterns that reinforce both social norms and stereotypes [39]. Social media also creates a hybrid space where local values and global influences meet, so that issues of culture, religion, and identity are easily reframed according to the logic of digital engagement [39]. In the case of religious issues in Indonesia, religious symbols have proven highly susceptible to mediatization in provoking netizen responses, and comment sections become interactive communication arenas that accelerate polarization and the formation of ideological positions [1]. Findings on the transformation of digital religious practice also show that social media simultaneously strengthens religious identity and challenges traditional authority, so that terms, symbols, or images deemed sensitive can trigger a more intense reaction than the actual subject matter being discussed [46].

This situation becomes increasingly important because film controversies in Indonesia frequently intersect with issues of freedom of expression. Legal and social literature shows that freedom of expression on social media in Indonesia is recognized as a fundamental right [22], but its restrictions are often regarded as overly broad, subjective, and prone to being used to silence criticism [36]. In the Southeast Asian context, online repression not only limits direct expression but also encourages self-censorship among users, particularly when the social and political costs of expression are perceived as greater than its benefits [38]. Consequently, the disruption or cancellation of film screenings becomes not only an institutional event but also a trigger for digital discourse on the shrinking of civic space, the legitimacy of censorship, and the public's right to independently interpret cultural works [22], [26].

At the same time, the viral nature of social media often means that restriction efforts actually expand the reach of public attention. Research on the reception of audiovisual controversies shows that clips, emotionally charged phrases, and repeated algorithmic exposure can massively reinforce audience perception,

emotion, and engagement [28]. Social media analytics also show that location, topic, cultural sensitivity, and posting frequency play an important role in shaping public reactions to content [9]. In other words, the *Pesta Babi* film poster can function as an autonomous visual stimulus: it is no longer read merely as a gateway to the Papuan agrarian issue, but as a symbolic object that simultaneously triggers religious, artistic, ethical, and even political judgment [56], [39], [43].

This complexity is precisely what makes conventional sentiment analysis based on global positive-negative polarity inadequate. In general, sentiment analysis is indeed useful for extracting opinions, emotions, and public impressions from large, unstructured textual data [55], [54], [32]. However, a number of studies emphasize that global sentiment scores often fail to capture stance, or position toward a specific target, which can produce misleading conclusions when the text is political, ideological, or controversial in nature [10]. More recent studies of digital controversy also show that the intensity of debate is shaped not only by sentiment but also by positional antagonism, sarcasm, and offensive language [53]. Therefore, if research stops at classifying comments as merely "positive" or "negative," it will be unable to answer what theme actually dominates the debate over this film's poster.

On this basis, this study requires a more contextual approach through sociocultural indicators, specifically religious-cultural sensitivity, artistic-expressive freedom, and ethical-normative considerations. This approach aligns with the development of sentiment analysis increasingly moving toward aspect-, theme-, or dimension-based classification rather than mere general polarity [2]. In the context of film and media in Indonesia, previous research shows that public response to audiovisual works is often shaped by social issues, moral narratives, netizen ideology, and media framing, rather than by artistic quality alone [7], [48], [43]. Even in controversies over religious dramas in Indonesia and Malaysia, public response has proven divided between reading the work as artistic critique and concern over the distortion of religious authority [28]. This reinforces the assumption that the three sociocultural indicators proposed in this study are indeed relevant as an initial analytical framework, while still leaving room for other, more dominant themes to emerge from keyword-based exploration.

Methodologically, Indonesian-language Instagram comments present real challenges, being short, informal, ambiguous, rich in abbreviations, mixed-code, and heavily laden with emotional context. Both literature reviews and empirical studies consistently show that large-scale social media data is unstructured and difficult to analyze using traditional methods [55], [54], [32]. In Indonesian, this difficulty is compounded by non-standard spelling, slang, hashtags, mentions, short context, and semantic ambiguity [41], [21], [6]. Preprocessing stages such as cleaning, case folding, tokenization, stopword removal, stemming, and normalization are therefore not additional technical steps but prerequisites for obtaining a more reliable sentiment signal [41], [49], [37], [35]. TF-IDF-based feature transformation also remains a strong choice for Indonesian text, having been repeatedly used as an effective numerical representation in social media sentiment studies [45], [49], [6], [20].

The selection of Support Vector Machine (SVM), Random Forest, and Naive Bayes algorithms in this study also has strong empirical grounding, although the

literature shows no single model consistently outperforms across all datasets. Several Indonesian studies have found Random Forest to be the best-performing model, for instance in cases of Pertamina socio-political sentiment, Ruangguru reviews, and KIP-K discourse, with accuracies of 88.9%, 97.16%, and 100% respectively after certain optimizations [31], [24], [3]. Other studies show SVM outperforming on mental health stigma, Telegram reviews, marketplace sentiment, political issues, and documentary film text, with accuracies of 86.11%, 93.4%, higher than Naive Bayes on marketplace data, 71.6%, and 91.1% on Dirty Vote [19], [13], [17], [37], [44]. Yet Naive Bayes remains competitive in several studies, including sentiment analysis of the film *Pengepungan di Bukit Duri* with 83.67% accuracy, a Twitter-based Dirty Vote study reaching 90% accuracy after grid search, and an Anti-LGBT campaign study with 86.43% accuracy [7], [8], [24]. This variation confirms that model performance is heavily influenced by data structure, class distribution, preprocessing quality, and labeling strategy, meaning that a direct algorithm comparison on the Pesta Babi comment dataset is indeed necessary rather than assumed from other studies [31], [41], [45].

Class imbalance is an additional reason this comparative study matters. Methodological literature consistently shows that skewed class distribution can degrade classification performance, induce prediction bias, and cause overfitting, particularly in high-dimensional text data [51], [34], [20]. In a study of the South Sumatra gubernatorial election, Decision Tree and Random Forest appeared to perform well on imbalanced data but showed signs of overfitting, while SVM improved after data balancing [40]. Other studies show SMOTE and ADASYN can improve accuracy, with linear SVM often performing very well on balanced TF-IDF data [34]. Because comments on a controversial poster commonly skew toward one sentiment tendency or a particular theme, this study needs to assess algorithm performance under real, imbalanced data conditions to ensure its results are more practically relevant [41], [20].

Based on the discussion above, this study occupies a clear gap at two levels simultaneously. At the substantive level, this study seeks to explain whether public debate over the Pesta Babi poster is genuinely driven by religious-cultural, artistic freedom, and ethical issues, or instead by other themes that emerge more dominantly in digital conversation. At the methodological level, this study examines which model among SVM, Random Forest, and Naive Bayes is most adaptive to short, informal, ambiguous, and potentially class-imbalanced Indonesian-language Instagram comments [31], [3], [4]. This background thus supports two main contributions: first, extending sentiment analysis from general polarity toward a sharper sociocultural reading; and second, providing an empirical basis for selecting the most appropriate classification algorithm for studies of digital public opinion on controversial film issues in Indonesia [55], [2], [4].

B. Research Method

This study employs a quantitative comparative design, since its primary goal is to compare the performance of several machine learning algorithms on a binary sentiment classification task applied to Instagram comments [5], [47], [27]. This is supplemented by a keyword-frequency analysis that is explicitly exploratory-

descriptive in nature, intended to provide thematic context beyond what binary polarity alone can capture [29], [30].

Data source and sampling. Data were drawn from comments on the official Instagram upload of the "Pesta Babi" film poster, consistent with prior sentiment studies that treat Instagram comments as a source of user-generated textual opinion (50), (42), (33). A total sampling technique was used capturing the entire population of comments on the target post emphasizing full coverage of one specific digital object rather than partial comment selection (42), (33). After initial cleaning, 704 valid comments were used as the unit of analysis; this focus on short user-generated text is consistent with common practice in social media sentiment analysis (29), (27).

Sentiment labeling in this study was performed with AI assistance rather than full manual annotation. Approximately 200 comments were labeled using an AI-integrated tool within Excel, and the remainder were labeled using a Python script produced through AI collaboration and executed in PyCharm two distinct automated pipelines whose agreement was not independently tested. This absence of an inter-method agreement check results in a weaker ground-truth basis than studies employing dual human coders or manual validation [25]], and is treated as a methodological limitation rather than a strength of the labeling procedure.

Preprocessing was performed in Orange's Text Mining module through regex-based tokenization, punctuation/symbol filtering, and lowercase transformation, consistent with standard social media text-cleaning stages prior to classification [5], [50], [30]. Stopword removal was not applied in the final preprocessing configuration used to generate the reported results.

Feature extraction used a Bag-of-Words representation with binary term frequency. This choice is consistent with a number of comparative sentiment studies that use BoW as the vectorization basis for SVM, Random Forest, and Naive Bayes [5], [48] Model testing. Three algorithms were evaluated: Support Vector Machine, Random Forest, and Naive Bayes, among the most frequently compared models in text sentiment classification [47], [30]. Evaluation used 10-fold stratified cross-validation, consistent with comparable studies that use k-fold cross-validation to assess performance stability across data folds [5], [42], [11]. Model performance was assessed using AUC, Accuracy (CA), F1-score, Precision, and Recall, metrics commonly reported together in sentiment studies to capture both model discrimination and classification error trade-offs [48], [33].

On the use of MCC. The Matthews Correlation Coefficient was included as a supplementary metric, but its use requires a careful, non-overstated justification. Several studies consider MCC more informative than accuracy and F1 in binary classification because it only scores high when prediction is accurate across all cells of the confusion matrix, including on imbalanced data [15], [16]. However, this is not fully settled in the literature: while some simulation studies find MCC, alongside G-Mean and Cohen's Kappa, generally performs well for model selection on imbalanced data, other studies report that MCC can drop sharply under severe class imbalance, and therefore recommend treating it as a complementary metric rather than the sole basis for model selection [18], [52], [57]. Given the class imbalance in this dataset 73% Positive versus 27% Negative relying on accuracy alone risks an overly optimistic reading, since the model may default toward the

majority class [15], [18], [52], [12] ; MCC and F1 are therefore reported alongside accuracy rather than in place of it.

Thematic exploration. The keyword-frequency analysis is positioned as an exploratory step, not a validated thematic classification, since it only checks for the presence of substrings from a predefined term list assumed to represent sociocultural themes [29]. This positioning matters because comparative literature shows no single automated method consistently outperforms across all datasets, and text classification or tagging outcomes depend heavily on method, sample size, and data characteristics [29], [25]. Retaining this exploratory step is nonetheless substantively justified: binary sentiment classification only answers the direction of opinion, while keyword analysis helps identify which issue most frequently triggers public reaction [29], [30], [33] . To keep this consistent with the study's stated aims, it should be stated explicitly that keyword-frequency results were not used to train any model, were not tested as a classifier, and serve only as a descriptive reading against three hypothesized themes religious-cultural, artistic-expressive, and ethical-normative leaving the core comparative aim (SVM vs. Random Forest vs. Naive Bayes on Instagram comment classification) unchanged.

Table 1. Model Configuration Parameters

No	Model	Key parameters
1	SVM	SVMLinear kernel, C = 1.00, tolerance = 0.0010, iteration limit = 100
2	Random Forest	Random Forest100 trees, min. subset size = 5, no depth limit
3	Naive Bayes	Naive BayesDefault parameters (no tuning applied)

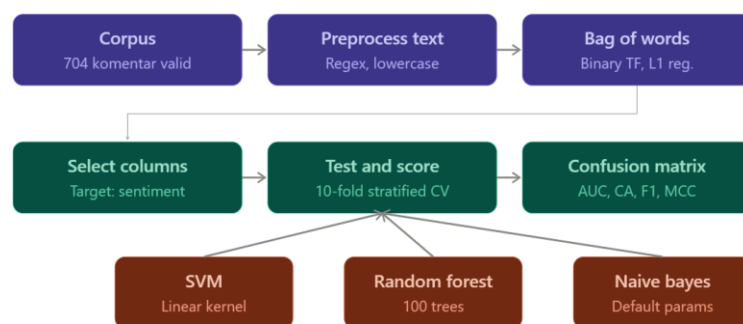


Figure1. Research workflow in Orange, from corpus input to model evaluation

C. Result and Discussion

Classification performance. As shown in Figure 1, comments were processed through a pipeline of preprocessing, binary Bag-of-Words feature extraction, and three parallel learners evaluated via 10-fold stratified cross-validation. Table 2 summarizes the resulting performance across the three algorithms, using the configuration parameters listed in Table 1.

Table 2. Model performance comparison

Model	AUC	CA	F1	Precision	Recall	MCC
SVM	0.825	0.768	0.738	0.749	0.768	0.328
Random Forest	0.858	0.786	0.740	0.797	0.786	0.383
Naive Bayes	0.839	0.778	0.768	0.765	0.778	0.398

Random Forest achieved the highest overall accuracy and AUC, outperforming SVM with 92.4% probability and Naive Bayes with 95.7% probability based on pairwise AUC comparison. However, confusion matrix analysis reveals a class-level trade-off: of 190 actual Negative comments, Naive Bayes correctly identified 45.2%, compared to 38.1% for Random Forest and 32.7% for SVM. This is reflected in MCC, where Naive Bayes scored highest (0.398) despite trailing Random Forest on AUC and CA indicating Naive Bayes handled the minority class more robustly, while Random Forest's higher accuracy is partly driven by the majority (Positive) class.

These accuracy figures (77–79% CA) sit notably below several previously reported comparisons of the same three algorithms on Indonesian social media text, where Random Forest and SVM have reached 88.9–100% and 86–93% respectively [31], [3], [24], [19], [13]. This gap is unlikely to be attributable to the algorithms themselves, and more plausibly reflects three compounding methodological factors already noted as limitations: binary Bag-of-Words rather than TF-IDF weighting, the absence of stopwords removal in preprocessing, and most importantly sentiment labels generated through two unreconciled AI-assisted pipelines rather than validated human annotation [25]. Since ground-truth quality bounds achievable classifier accuracy, some portion of the performance ceiling observed here may reflect noise in the labels themselves rather than a genuine limit on how separable the two classes are.

This labeling noise is plausible on inspection of individual comments. For instance, the comment "Hidup soros, hidup penghianat bangsa, jaya jaya jaya" ("Long live Soros, long live the nation's traitor, glory glory glory") was labeled Negative, correctly capturing its sarcastic intent but its surface vocabulary ("hidup," "jaya") is lexically celebratory. A binary Bag-of-Words representation, which treats word presence independently of ironic framing, is structurally prone to misreading comments of this kind [10], [53] and sarcasm of this form likely contributes to the moderate MCC ceiling observed across all three models rather than being a weakness specific to any single algorithm.

The keyword-based analysis found that only 139 of 704 comments (19.7%) contained terms associated with the three hypothesized sociocultural themes: Religious/Cultural (70 comments, 9.9%; 32 Negative/38 Positive),

Artistic/Expressive (92 comments, 13.1%; 42 Negative/50 Positive), and Ethical/Normative (9 comments, 1.3%; 6 Negative/3 Positive) categories are not mutually exclusive. The remaining 565 comments (80.3%) contained none of these keywords; manual review of this majority subset indicated it was dominated by political accusations, most frequently allegations that the film's production was

foreign-funded (e.g., repeated references to "George Soros"), alongside general expressions of support unrelated to religion, art, or ethics.

This finding is worth connecting back to the framing in the Introduction rather than left as a standalone statistic. The controversy was hypothesized to travel through symbolic-religious and civic-space channels disrupted screenings amplifying attention through a Streisand Effect (Ong, 2019; Fernando et al., 2022; Gede et al., 2024). The data offer a direct, if small-scale, illustration of that specific mechanism: one comment reads "Karena dilarang malah jd smakin antusias buat nonton" ("Being banned only made me more eager to watch it"), labeled Positive. That the dominant public reaction skewed toward political-funding suspicion rather than the three sociocultural indicators originally hypothesized suggests the controversy, at least as expressed in this comment section, was driven less by the poster's religious symbolism per se than by a broader politicized narrative about the film's legitimacy and backers a pattern more consistent with the civic-space and self-censorship literature (38) than with the religious-mediatization literature (46) that motivated the original three-indicator framework.

Three limitations should be disclosed explicitly: (1) sentiment labels were generated with AI assistance rather than validated human annotation, and no inter-method agreement check was performed between the Excel-based and PyCharm-based labeling approaches this is the most likely single driver of the accuracy gap relative to prior studies discussed above; (2) the sociocultural theme analysis relies on a simple, unvalidated keyword-matching heuristic rather than a trained classifier or manual coding scheme, and cannot distinguish sarcasm, negation, or indirect reference; (3) total sampling from a single Instagram post limits generalizability to broader Indonesian public opinion on the film.

D. Conclusion

Comparative evaluation of three machine learning algorithms on 704 Indonesian-language Instagram comments found no single best-performing model across all metrics: Random Forest achieved the highest overall accuracy and AUC, while Naive Bayes provided more balanced detection of the minority Negative class, reflected in its higher MCC. This indicates that algorithm choice for imbalanced, informal Indonesian social media sentiment classification should be guided by which class matters more for the analytical purpose, rather than accuracy alone. A supplementary keyword-based exploration found that public reaction to the film's poster was dominated by themes outside the three sociocultural categories hypothesized at the outset, suggesting the controversy centered more on political and funding-related suspicion than on religious, artistic, or ethical concerns specifically.

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F. References

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