

Aspect-Based Sentiment Mapping of Google Reviews for Digital Reputation Insights of Private Higher Education Institutions in Padang City

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Abstract. Online reviews provide public feedback for higher education institutions, but overall star ratings cannot explain which institutional aspects shape public perception. This study aims to provide partial and aspect-specific digital reputation insights for five private higher education institutions in Padang City through aspect-based sentiment mapping of textual Google Reviews. Using Outscraper, 1,159 Google Review records were collected. After excluding 794 star-only reviews, 365 textual reviews were retained and transformed into 484 aspect-level records across five aspects: academic and lecturers, campus facilities, administrative services, environment and location, and general/others. The dataset was highly imbalanced, with 443 positive records (91.53%), 35 negative records (7.23%), and 6 neutral records (1.24%). Sentiment classification was evaluated using TF-IDF with Logistic Regression, TF-IDF with SVM, and IndoBERT through 5-fold stratified cross-validation. IndoBERT achieved the strongest performance, with an accuracy of 0.973, balanced accuracy of 0.710, macro F1-score of 0.760, and weighted F1-score of 0.971. The findings show that aspect-based sentiment mapping can support Google Review-based public perception monitoring by producing a university–aspect–sentiment map for the selected institutions. These findings are limited to textual Google Reviews from five selected institutions and should be validated using larger and more balanced datasets.

Keywords: Aspect-Based Sentiment Analysis, Google Reviews, IndoBERT, Imbalanced Sentiment Classification, University Reputation.

1. INTRODUCTION

Digital reputation has become an important asset for higher education institutions because public perception is increasingly shaped by digital interactions, online visibility, and user-generated content. In higher education, digital reputation can be understood as a multidimensional public perception formed through various digital touchpoints, including official websites, social media, online reviews, institutional communication, and other forms of user-generated content [1], [2]. In a competitive higher education environment, prospective students and the public do not only rely on official institutional information, but also consider public opinions shared through digital platforms [3], [4]. In this context, Google Reviews represents one accessible source of public feedback because it contains both star ratings and textual comments from students, alumni, parents, visitors, and the wider community [5], [6]. These reviews can reflect public experiences related to academic services, lecturers, facilities, administrative services, campus environment, and general institutional image [7], [8], [9]. However, Google Reviews cannot represent the complete digital reputation of an institution because it does not capture all digital reputation channels, such as social media discussions, formal student surveys, website analytics, and internal institutional reports [10], [11], [12].

In this study, Google star ratings are treated as general numerical indicators of public perception, while textual reviews provide more detailed information about user experiences. Aspect-based sentiment mapping connects these textual comments to specific institutional aspects and sentiment polarity. Therefore, the resulting university–aspect–sentiment map is interpreted as a Google Review-based digital reputation insight rather than a complete evaluation of institutional reputation.

Although Google Reviews provides valuable public feedback, many higher education institutions still evaluate online reviews manually or only observe the overall rating [13], [14]. This approach is limited because it cannot identify which institutional aspects receive positive, neutral, or negative responses [15], [16]. Through aspect-based sentiment mapping, textual reviews can be transformed into aspect-level sentiment patterns that provide partial insight into digital reputation [17], [18]. General sentiment analysis also has a similar limitation because it usually assigns one sentiment label to an entire review

[19], [20]. In fact, one review may contain different opinions about different aspects, such as praising lecturers while criticizing administrative services or campus facilities [21], [22]. Aspect-Based Sentiment Analysis (ABSA) provides a more detailed approach because it identifies both the aspect discussed in a text and the sentiment polarity attached to that aspect [23], [24], [25].

Previous studies have examined digital opinion analysis on public review platforms using both classical machine learning and deep learning approaches. TF-IDF feature extraction combined with Logistic Regression has been reported to be effective for text-based sentiment classification, achieving an accuracy of 85.11% in review analysis [26]. In addition, TF-IDF combined with Support Vector Machine has shown reliable performance in mapping user review polarity on Google Reviews, with an accuracy of 95% [27]. Beyond classical machine learning approaches, transformer-based architectures such as Indonesian Bidirectional Encoder Representations from Transformers (IndoBERT) have increasingly been applied to Aspect-Based Sentiment Analysis on Google Maps location-based reviews, achieving strong accuracy and precision scores of up to 0.99 [28]. Fine-tuned IndoBERT models have also been used in digital public service review analysis to address informal language ambiguity and perform more specific aspect-level sentiment classification, achieving an overall accuracy of 96% [29]. These studies indicate that automated sentiment mapping of user-generated content on Google Reviews can support digital branding performance measurement and digital reputation monitoring in online environments [30].

However, most previous studies still focus on general sentiment classification and non-higher education domains, such as e-commerce, transportation, public services, tourism, healthcare applications, and public policy discussions. Limited studies have specifically examined Google Review-based digital reputation insights in higher education, especially through university-aspect-sentiment mapping. This creates an important research gap because university reputation is multidimensional and cannot be fully represented by a single positive, neutral, or negative label or by one public review platform alone. A more specific mapping approach is needed to identify which institutional aspects are positively perceived and which aspects require service improvement based on textual Google Reviews.

To address this gap, this study applies aspect-based sentiment mapping of Google Reviews to provide Google Review-based digital reputation insights for private higher education institutions in Padang City. The study uses review data from five private universities: UPI YPTK Padang, Universitas Baiturrahmah, Universitas Ekasakti, Universitas Adzkia, and Bung Hatta University Campus 1. These institutions were selected because they have publicly available Google Reviews, sufficient textual review data, and visible public engagement on Google Maps, making them relevant for examining aspect-specific reputation insights in the local private higher education context. The analysis focuses on five aspects: academic and lecturers, campus facilities, administrative services, environment and location, and general/others.

The main purpose of this study is to support Google Review-based public perception monitoring by identifying aspect-specific sentiment patterns across selected universities. Model comparison is included as a supporting analytical step to determine which sentiment classification approach performs more reliably on the small and imbalanced aspect-level dataset. Therefore, this study addresses the following research question: How can aspect-based sentiment mapping of Google Reviews reveal university-specific digital reputation patterns across academic, facility, administrative, environmental, and general aspects? The contribution of this study does not lie in proposing a new ABSA method, but in applying aspect-based sentiment mapping to produce a Google Review-based university–aspect–sentiment map for private higher education institutions in Padang City.

2. METHODS

This study used a quantitative computational approach based on Natural Language Processing (NLP) to provide Google Review-based digital reputation insights for private higher education institutions in Padang City. The method was designed to transform unstructured textual reviews into structured information consisting of university name, aspect category, sentiment label, and dominant sentiment. The research workflow consisted of five main stages: input, data filtering and annotation, text preprocessing and model configuration, evaluation, and output. The complete research framework is presented in Figure 1.

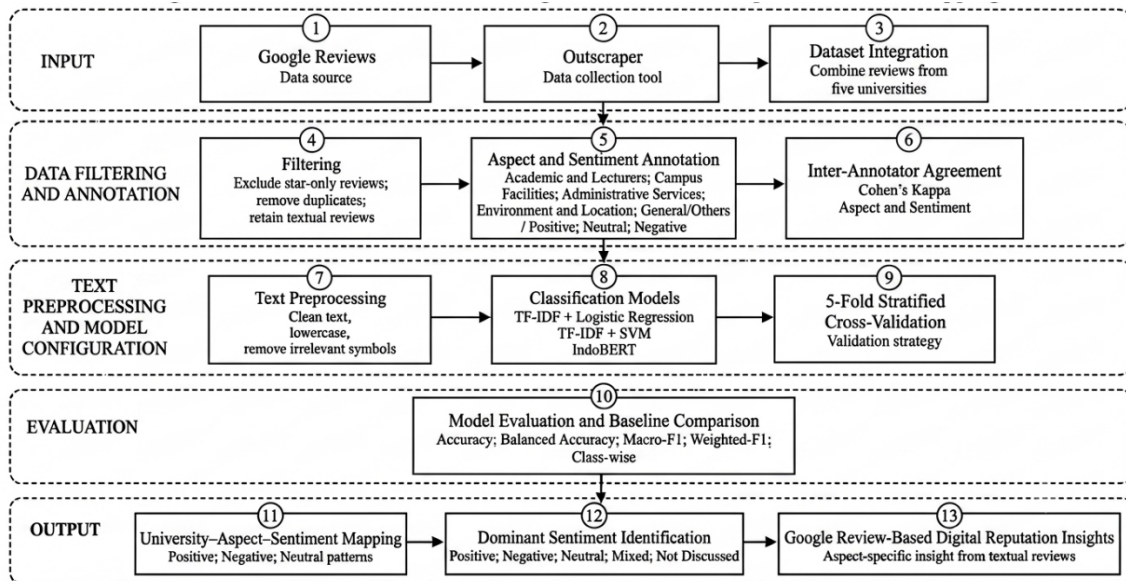


Figure 1. Research Framework

2.1 Input Stage

The input stage consisted of Google Reviews data collected from five private higher education institutions in Padang City, Indonesia. The selected institutions were UPI YPTK Padang, Universitas Baiturrahmah, Universitas Ekasakti, Universitas Adzkia, and Bung Hatta University Campus 1. These institutions were selected because they are private higher education institutions in Padang City with publicly available Google Reviews and sufficient textual review data for aspect-based sentiment mapping.

The data were collected in July 2026 using Outscraper, with the official or commonly used Google Maps names of each institution as search queries. The collection process exported publicly available Google Reviews into spreadsheet format. No strict language filter was applied because Google Reviews may contain Indonesian, English, informal expressions, or mixed-language comments. Reviews were retained if they contained textual comments relevant to university-related experiences. Star-only reviews were excluded because they did not provide textual information needed for aspect and sentiment annotation.

The raw datasets contained several attributes generated by Outscraper, including place information, review metadata, reviewer metadata, and review content. However, this study only used attributes relevant to aspect-based sentiment mapping. Reviewer

identity-related attributes were excluded to maintain data privacy and research ethics. Duplicate records were checked primarily using review_id. When necessary, duplicated entries were also reviewed using the combination of university name, review text, and review date. The main attributes used in this study are presented in Table 1.

Table 1. Relevant Outscraper Attributes Used in This Study

Attribute	Description	Use in This Study
query	Search query used to collect Google Reviews	Identifying the targeted university
Name	Google Maps place name	Identifying the university name
reviews	Total public Google Reviews displayed on Google Maps	Descriptive dataset information
rating	Average Google rating of the institution	Descriptive digital reputation indicator
review_id	Unique identifier of each review	Detecting duplicate review records
review_text	Textual content of the review	Main input for aspect and sentiment analysis
review_rating	Star rating given by the reviewer	Supporting information for review interpretation
review_datetime_utc	Date and time of the review	Review metadata
owner_answer	Response from the institution or owner, if available	Additional metadata, not used for sentiment classification

Table 1 shows the relevant Outscraper attributes used in this study. The main textual input was review_text, while name, reviews, rating, review_rating, and review_datetime_utc were used as supporting metadata. Star ratings were not used as model input because the classification process focused on textual sentiment. Instead, ratings were used only as descriptive context to compare general numerical perception with more specific aspect-level sentiment patterns. Attributes related to reviewer identity, such as author name, author profile link, author ID, and author image, were excluded from the analysis to protect reviewer privacy.

2.2 Data Filtering and Annotation Stage

After data collection, the exported Google Review records were filtered to retain only reviews containing textual comments. In this study, a textual review refers to an original Google Review comment, while an aspect-level record refers to an annotated unit consisting of one aspect category and one sentiment label. Since one textual review may discuss more than one aspect, 365 textual reviews were transformed into 484 aspect-level records.

The annotation process was conducted manually by two annotators from the research team using predefined aspect and sentiment guidelines. The two annotators had backgrounds in information systems research and text-based data analysis. Before annotation, both annotators were briefed using the predefined annotation guideline to ensure a shared understanding of the five aspect categories and three sentiment labels. Annotation was performed after textual review filtering and before text preprocessing for model training. The aspect categories consisted of academic and lecturers, campus facilities, administrative services, environment and location, and general/others. The sentiment categories consisted of positive, neutral, and negative. The aspect labels were manually assigned, while the classification models were evaluated only for sentiment classification. Thus, this study did not perform automatic aspect classification. The annotation guideline used in this study is presented in Table 2.

Table 2. Aspect and Sentiment Annotation Guidelines

Label Type	Category	Annotation Criteria
Aspect	Academic and Lecturers	Reviews discussing lecturers, teaching quality, academic support, learning process, curriculum, or academic experience.
Aspect	Campus Facilities	Reviews discussing classrooms, laboratories, parking areas, buildings, libraries, internet access, or other physical facilities.
Aspect	Administrative Services	Reviews discussing registration, academic administration, staff service, payment process, document handling, or service speed.

Label Type	Category	Annotation Criteria
Aspect	Environment and Location	Reviews discussing campus atmosphere, accessibility, location, cleanliness, comfort, and surrounding environment.
Aspect	General/Others	Reviews containing general impressions, overall opinions, recommendations, or comments that do not clearly belong to the other specific aspects.
Sentiment	Positive	Reviews expressing satisfaction, praise, recommendation, comfort, helpfulness, or favorable experience.
Sentiment	Neutral	Reviews providing factual, unclear, or balanced statements without strong positive or negative polarity.
Sentiment	Negative	Reviews expressing dissatisfaction, complaint, criticism, disappointment, delay, discomfort, or unfavorable experience.

Table 2 shows the guideline used to annotate textual reviews into aspect and sentiment categories. The guideline was used to maintain consistency and to ensure that each aspect-level record contained one aspect category and one sentiment label. Inter-annotator agreement was measured using Cohen's Kappa to assess the consistency between the two annotators. The agreement was calculated separately for aspect-category annotation and sentiment-label annotation. The results of the inter-annotator agreement assessment are presented in Table 3. Table 3 shows that the annotation process achieved a reliable level of agreement between the two annotators. After disagreement cases were resolved through discussion, the final agreed labels were used for model training and evaluation. No third adjudicator was involved in the final resolution process.

Table 3. Inter-Annotator Agreement Results

Item	Description
Number of annotators	2 annotators
Number of records	484 aspect-level records

Item	Description
Agreement metric	Cohen's Kappa
Aspect-category annotation	0.80, indicating substantial agreement
Sentiment-label annotation	0.82, indicating almost perfect agreement
Final resolution	Disagreements were resolved through discussion to produce the final agreed labels.

2.3 Text Preprocessing and Model Configuration

Text preprocessing was conducted before sentiment classification to prepare the textual reviews for machine learning models. The preprocessing steps included removing empty text, deleting duplicate records, converting text into lowercase for TF-IDF-based models, removing URLs, excessive punctuation, irrelevant symbols, and non-informative characters, and standardizing spacing. Emojis and special symbols were removed when they did not contribute to clear sentiment interpretation. Indonesian slang, abbreviations, mixed-language expressions, and misspellings were not aggressively normalized because they may reflect the natural writing style of Google Review users. For IndoBERT, tokenization was handled using the IndoBERT tokenizer after basic text cleaning. Three sentiment classification models were evaluated in this study: TF-IDF with Logistic Regression, TF-IDF with SVM, and IndoBERT. TF-IDF was used to transform textual reviews into numerical features for the classical machine learning models. Logistic Regression and SVM were used as classical baselines, while IndoBERT was evaluated as a contextual Indonesian language model. The model configurations used in this study are presented in Table 4.

Table 4. Model and Preprocessing Configuration

Item	Configuration
Text cleaning	Empty text removal, duplicate removal, URL removal, irrelevant symbol removal, excessive punctuation removal, and spacing normalization
Language handling	Indonesian, English, and mixed-language reviews were retained if they contained meaningful textual content
Slang and abbreviations	Not aggressively normalized to preserve the original user expression in Google Reviews

Item	Configuration
Emojis and symbols	Removed when they did not provide clear textual sentiment information
TF-IDF feature extraction	ngram_range=(1,2), max_features=5000, min_df=2, max_df=0.95, sublinear_tf=True, norm='l2', stop_words=None
Logistic Regression	solver='lbfgs', penalty='l2', C=1.0, class_weight='balanced', max_iter=1000, random_state=42
SVM	kernel='linear', C=1.0, gamma='scale', class_weight='balanced', random_state=42
IndoBERT model	indobenchmark/indobert-base-p1
IndoBERT tokenizer	IndoBERT tokenizer from the same pretrained model
Maximum sequence length	128 tokens
Batch size	16
Epochs	3
Learning rate	0.00002
Random seed	42
Optimizer	AdamW
Scheduler	Linear learning rate scheduler
Loss function	Cross-entropy loss
Class weighting for IndoBERT	Not applied; the effect of class imbalance is discussed as a study limitation
Hardware	NVIDIA Tesla T4 GPU with 16 GB VRAM and CUDA support, Intel(R) Xeon(R) CPU @ 2.20 GHz with 2 cores, and 12.7 GB RAM in a cloud-based Google Colab environment
Validation split	No separate validation split; evaluation used 5-fold stratified cross-validation
Early stopping	Not applied; IndoBERT was trained for a fixed number of three epochs

Table 4 summarizes the preprocessing and model configurations used in this study. The same labeled aspect-level dataset was used for all classification models to ensure a fair

comparison. The TF-IDF-based models used numerical word-level features, while IndoBERT used contextual token representations. IndoBERT training was conducted using an NVIDIA Tesla T4 GPU with 16 GB VRAM and CUDA support, supported by an Intel(R) Xeon(R) CPU @ 2.20 GHz with 2 cores and 12.7 GB RAM in a cloud-based Google Colab environment. The random seed was set to 42 to improve reproducibility. Early stopping was not applied because IndoBERT was trained for a fixed number of three epochs. Since the dataset was small and highly imbalanced, class weighting was applied to the classical machine learning models, while IndoBERT was evaluated using its contextual token representation. The effect of class imbalance is considered in the interpretation of model performance, especially for the minority neutral class.

2.4 Evaluation Stage

The evaluation stage was conducted to compare the performance of the sentiment classification models [31], [32], [33], [34]. Model validation was performed using 5-fold stratified cross-validation to preserve the proportion of positive, negative, and neutral sentiment classes across folds as much as possible. Model performance was evaluated using accuracy, balanced accuracy, macro F1-score, weighted precision, weighted recall, weighted F1-score, class-wise precision, class-wise recall, class-wise F1-score, and confusion matrices. This evaluation setting was used to provide a more stable comparison than a single train-test split, particularly because the dataset was small and highly imbalanced. For the TF-IDF-based models, text preprocessing and TF-IDF vectorization were fitted only on the training data within each fold and then applied to the corresponding test data. This procedure was used to avoid information leakage from the test fold into the training process. For IndoBERT, tokenization was also performed within each fold after the training and test partitions were created.

2.5 Output Stage

Aligned with the framework's concluding workflow (steps 11, 12, and 13), the output phase comprised university–aspect–sentiment mapping, dominant sentiment identification, and the derivation of Google Review-based digital reputation insights. Sentiment predictions generated across the five evaluated aspect dimensions were aggregated based on institutional identity, aspect class, and sentiment orientation. This granular consolidation produced a systematic mapping of positive, neutral, and negative sentiment densities. The dominant sentiment profile for each university–aspect intersection was defined by

the highest categorical frequency. To ensure analytical completeness, university–aspect pairs with zero records were marked as 'Not Discussed,' while those exhibiting equal maximum frequencies were denoted as 'Mixed.' This mapped synthesis provides targeted, aspect-specific strengths and optimization strategies from textual reviews, avoiding over-generalization of the universities' broader digital reputation. Google star ratings were used only as descriptive metadata and were not used as model input. They were compared with the aspect-based textual sentiment results at the institutional level to examine whether high overall star ratings were consistent with the sentiment patterns found in textual reviews.

2.6 Data Availability Statement

The anonymized aspect-level dataset may be made available from the corresponding author upon reasonable request. Reviewer identity-related metadata were removed to protect user privacy.

3. RESULTS AND DISCUSSION

3.1 Dataset Filtering

The dataset used in this study was collected from Google Reviews of five private higher education institutions in Padang City. A total of 1,159 review records were exported using Outscraper. However, not all exported records contained textual comments. Since aspect-based sentiment mapping requires textual information to identify aspect categories and sentiment polarity, star-only reviews were excluded from the textual analysis. The dataset filtering results are presented in Table 5.

Table 5. Dataset Filtering Results

University	Exported Reviews	Textual Reviews Used	Star-Only Reviews Excluded	Textual Reviews (%)
Universitas Adzkia	182	66	116	36.3
Universitas Baiturrahmah	250	73	177	29.2

University	Exported Reviews	Textual Reviews Used	Star-Only Reviews Excluded	Textual Reviews (%)
Bung Hatta University Campus 1	227	79	148	34.8
Universitas Ekasakti	250	61	189	24.4
UPI YPTK Padang	250	86	164	34.4
Total	1,159	365	794	31.5

Table 5 shows that 365 of the 1,159 exported records contained textual comments and were used for aspect-based sentiment mapping. This means that only 31.5% of the exported Google Review records were suitable for textual analysis, while 794 records were excluded because they contained star ratings without textual comments. The excluded star-only reviews were not treated as invalid feedback; rather, they were excluded because they did not provide sufficient textual information for aspect and sentiment annotation. This filtering result indicates that Google star ratings can provide a general numerical signal of public perception, but textual reviews are needed to identify which institutional aspects are praised, criticized, or described neutrally.

3.2 Model Performance Comparison

Model performance comparison was conducted to evaluate the ability of three sentiment classification models to classify sentiment in 484 aspect-level Google Review records. The evaluated models consisted of TF-IDF with Support Vector Machine, TF-IDF with Logistic Regression, and IndoBERT. Because the dataset was highly imbalanced, model evaluation was conducted using 5-fold stratified cross-validation to preserve the proportion of positive, negative, and neutral sentiment classes across folds. The fold distribution is presented in Table 6.

Table 6. Stratified 5-Fold Cross-Validation Data Distribution

Plot	Train Positive	Train Negative	Train Neutral	Train Total	Test Positive	Test Negative	Test Neutral	Test Total
1	354	28	5	387	89	7	1	97
2	354	28	5	387	89	7	1	97

Fold	Train Positive	Train Negative	Train Neutral	Train Total	Test Positive	Test Negative	Test Neutral	Test Total
3	354	28	5	387	89	7	1	97
4	355	28	4	387	88	7	2	97
5	355	28	5	388	88	7	1	96

Table 6 shows that stratification maintained the class distribution across the five folds as consistently as possible. Each test fold contained approximately 96 to 97 records, while the training folds contained 387 to 388 records. The positive class remained dominant across all folds, followed by negative and neutral sentiment. This distribution reflects the overall imbalance of the dataset, where positive sentiment accounted for most aspect-level records. A majority-class baseline was included to provide a reference point for model comparison. The baseline assigned all records to the dominant class, namely positive sentiment. The overall performance comparison is presented in Table 7.

Table 7. Mean and Standard Deviation of Model Performance Across Five Folds

Model Architecture	Accuracy	Balanced Accuracy	Macro F1-score	Weighted Precision	Weighted Recall	Weighted F1-score
Majority-Class Baseline	0.915 ± 0.000	0.333 ± 0.000	0.319 ± 0.000	0.838 ± 0.000	0.915 ± 0.000	0.875 ± 0.000
TF-IDF + SVM	0.928 ± 0.010	0.461 ± 0.012	0.479 ± 0.015	0.908 ± 0.011	0.928 ± 0.010	0.916 ± 0.013
TF-IDF + Logistic Regression	0.940 ± 0.008	0.474 ± 0.011	0.508 ± 0.014	0.923 ± 0.009	0.940 ± 0.008	0.927 ± 0.010
IndoBERT	0.973 ± 0.005	0.710 ± 0.021	0.760 ± 0.024	0.971 ± 0.006	0.973 ± 0.005	0.971 ± 0.007

Table 7 presents the mean and standard deviation of model performance across the five stratified cross-validation folds. IndoBERT achieved the strongest average performance across all main evaluation metrics, with an accuracy of 0.973 ± 0.005 , balanced accuracy of 0.710 ± 0.021 , macro F1-score of 0.760 ± 0.024 , and weighted F1-score of 0.971 ± 0.007 . TF-IDF with Logistic Regression remained the best-performing classical machine learning

model, followed by TF-IDF with SVM. However, the performance should be interpreted cautiously because the dataset was small and highly imbalanced.

The majority-class baseline achieved a relatively high accuracy of 0.915 ± 0.000 because positive sentiment dominated the dataset. However, its balanced accuracy and macro F1-score remained low, at 0.333 ± 0.000 and 0.319 ± 0.000 , respectively. This result confirms that accuracy alone is not sufficient for evaluating model performance on a highly imbalanced dataset. To further examine model performance across sentiment classes, class-wise precision, recall, and F1-score were analyzed. The results are presented in Table 8.

Table 8. Class-Wise Performance Metrics

Model	Sentiment Class	Precision	Recall	F1-score
TF-IDF + SVM	Positive	0.946	0.982	0.963
TF-IDF + SVM	Negative	0.583	0.400	0.475
TF-IDF + SVM	Neutral	0.000	0.000	0.000
TF-IDF + Logistic Regression	Positive	0.946	0.993	0.969
TF-IDF + Logistic Regression	Negative	0.789	0.429	0.556
TF-IDF + Logistic Regression	Neutral	0.000	0.000	0.000
IndoBERT	Positive	0.980	0.995	0.988
IndoBERT	Negative	0.903	0.800	0.848
IndoBERT	Neutral	0.667	0.333	0.444

Table 8 shows that all models performed strongly on the positive class. However, the performance differences became clearer for the minority classes. TF-IDF with SVM and TF-IDF with Logistic Regression failed to correctly identify the neutral class, as shown by their neutral-class precision, recall, and F1-score of 0.000. In contrast, IndoBERT showed better minority-class performance, particularly for negative sentiment, with a precision of 0.903, recall of 0.800, and F1-score of 0.848. IndoBERT also identified part of the neutral class, although this result should be interpreted cautiously because the dataset contained only six neutral records. In addition to the overall and class-wise performance metrics, confusion matrices were used to examine the classification behavior of each model across positive, negative, and neutral sentiment classes. The confusion matrices represent aggregated predictions across the five stratified cross-validation folds. The

total number of predictions in each confusion matrix is 484, corresponding to the total number of aspect-level records used in the evaluation.

1) TF-IDF + SVM

Figure 2 shows that TF-IDF with SVM performed well in identifying positive sentiment, with 435 positive records correctly classified. However, the model had limited performance on negative sentiment and failed to correctly identify neutral sentiment.

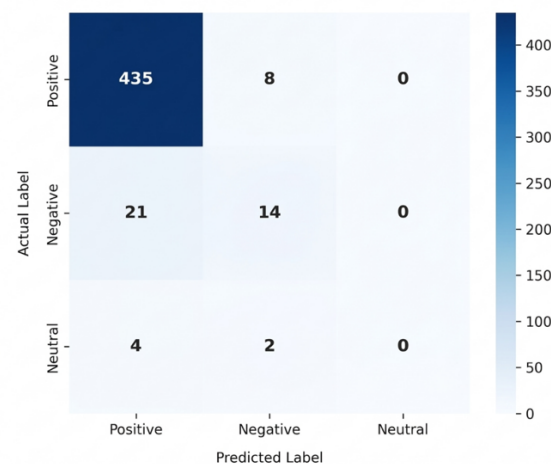


Figure 2. Confusion Matrix of TF-IDF + SVM

2) TF-IDF + Logistic Regression

Figure 3 shows that TF-IDF with Logistic Regression correctly classified 440 positive records and 15 negative records. However, similar to SVM, it did not correctly classify any neutral records.

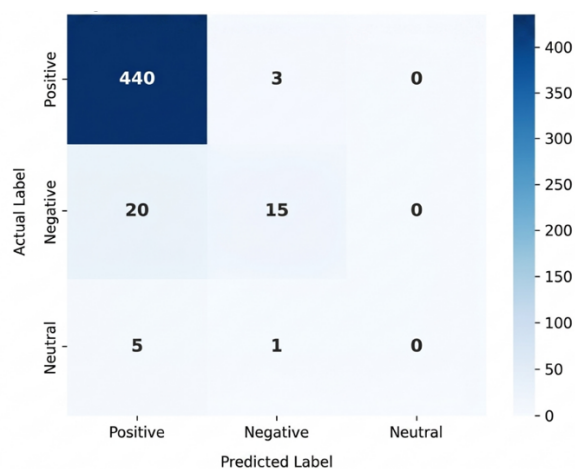


Figure 3. Confusion Matrix of TF-IDF + Logistic Regression

3) IndoBERT

Figure 4 shows that IndoBERT produced the strongest classification pattern. It correctly classified 441 positive records, 28 negative records, and 2 neutral records, making it the only model that identified part of the neutral class. Overall, the confusion matrix analysis supports the results in Table 7 and Table 8. IndoBERT achieved the strongest overall performance, particularly in detecting minority-class sentiment. TF-IDF with Logistic Regression remained the best classical machine learning model, while TF-IDF with SVM showed weaker performance on negative and neutral sentiment. These findings indicate that contextual representation in IndoBERT provided an advantage for sentiment classification on the imbalanced aspect-level Google Review dataset.

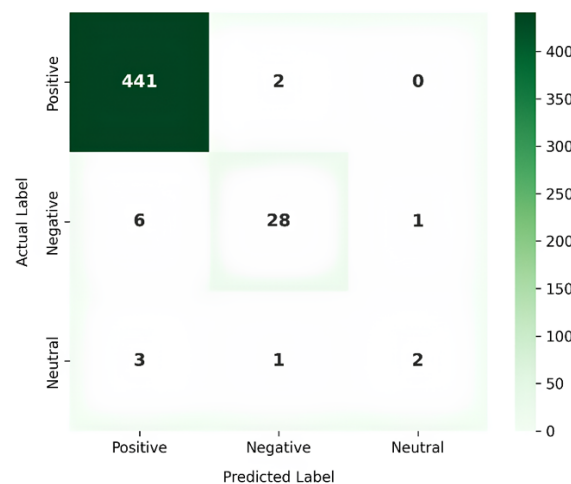


Figure 4. Confusion Matrix of IndoBERT

3.3 Error Analysis

The error analysis shows that most misclassifications occurred in the negative and neutral classes. For the TF-IDF-based models, several negative records were predicted as positive, indicating that word-frequency features were less effective in capturing contextual cues of dissatisfaction when the text contained general or polite expressions. The neutral class was the most difficult to identify because it contained only six records and often consisted of factual or ambiguous statements without strong sentiment polarity. As a result, TF-IDF with SVM and TF-IDF with Logistic Regression failed to correctly identify neutral records. IndoBERT reduced several minority-class errors because its contextual representation was better able to capture sentence-level meaning,

but its neutral-class performance should still be interpreted cautiously due to the very small number of neutral records.

3.4 Sentiment Distribution by University

After the annotation process, 365 textual Google Reviews were transformed into 484 aspect-level records because one review could discuss more than one institutional aspect. The sentiment distribution by university is presented in Table 9.

Table 9. Sentiment Distribution by University

University	Google Star Rating	Positive, n (%)	Neutral, n (%)	Negative, n (%)	Total
Universitas Adzkia	4.7	80 (90.91%)	2 (2.27%)	6 (6.82%)	88
Universitas Baiturrahmah	4.6	95 (95.96%)	0 (0.00%)	4 (4.04%)	99
Bung Hatta University Campus 1	4.6	80 (91.95%)	4 (4.60%)	3 (3.45%)	87
Universitas Ekasakti	4.5	77 (82.80%)	0 (0.00%)	16 (17.20%)	93
UPI YPTK Padang	4.7	111 (94.87%)	0 (0.00%)	6 (5.13%)	117
Total	-	443 (91.53%)	6 (1.24%)	35 (7.23%)	484

Table 9 shows that positive sentiment dominated the textual Google Review records across all five universities. Overall, 443 of 484 aspect-level records were positive (91.53%), while 35 were negative (7.23%) and only 6 were neutral (1.24%), indicating a highly imbalanced dataset. At the university level, Universitas Baiturrahmah had the highest proportion of positive sentiment (95.96%), followed by UPI YPTK Padang (94.87%), Bung Hatta University Campus 1 (91.95%), and Universitas Adzkia (90.91%). Although positive sentiment also dominated Universitas Ekasakti, this university recorded the highest proportion of negative sentiment, with 16 records or 17.20%. Therefore, this negative pattern should be interpreted as an indication of specific issues in textual reviews rather than as a complete assessment of institutional reputation.

The comparison between Google star ratings and textual sentiment shows that all selected institutions had high overall star ratings, ranging from 4.5 to 4.7. This pattern is

generally consistent with the dominance of positive textual sentiment across all universities. However, the aspect-based textual sentiment results provide more specific information than star ratings alone. For example, Universitas Ekasakti had a high Google star rating of 4.5, but its textual reviews showed the highest proportion of negative sentiment at 17.20%. This indicates that star ratings provide a broad positive signal, while textual aspect-based sentiment mapping can reveal more specific issues within the review content.

3.5 Aspect-Based Sentiment and University Mapping

Aspect-based sentiment mapping was conducted to identify how textual Google Reviews described five institutional aspects: academic and lecturers, campus facilities, administrative services, environment and location, and general/others. The aspect-based sentiment distribution is presented in Table 10.

Table 10. Aspect-Based Sentiment Distribution

Aspect	Positive, n (%)	Neutral, n (%)	Negative, n (%)	Total
Academic and Lecturers	75 (90.36%)	0 (0.00%)	8 (9.64%)	83
Campus Facilities	97 (90.65%)	2 (1.87%)	8 (7.48%)	107
Administrative Services	9 (52.94%)	1 (5.88%)	7 (41.18%)	17
Environment and Location	121 (94.53%)	1 (0.78%)	6 (4.69%)	128
General/Others	141 (94.63%)	2 (1.34%)	6 (4.03%)	149
Total	443 (91.53%)	6 (1.24%)	35 (7.23%)	484

Table 10 shows that positive sentiment dominated all aspect categories. The General/Others category had the highest number of aspect-level records, with 149 records, followed by Environment and Location with 128 records and Campus Facilities with 107 records. These findings indicate that many Google Review comments reflected broad institutional impressions, campus atmosphere, accessibility, and physical facilities. Administrative Services showed a relatively higher proportion of negative sentiment, with 7 negative records out of 17 records or 41.18%. However, this finding should be interpreted cautiously because the number of records in this aspect was small. Therefore, the result should be treated as an indication for further monitoring rather than as definitive evidence of administrative service quality.

Table 11. University Aspect-Sentiment Mapping.

University	Aspect	Positive	Neutral	Negative	Total	Dominant Sentiment
Universitas Adzkia	Academic and Lecturers	22	0	2	24	Positive
	Campus Facilities	9	1	0	10	Positive
	Administrative Services	0	0	0	0	Not Discussed
	Environment and Location	28	1	2	31	Positive
	General/Others	21	0	2	23	Positive
Universitas Baiturrahmah	Academic and Lecturers	12	0	1	13	Positive
	Campus Facilities	25	0	0	25	Positive
	Administrative Services	3	0	0	3	Positive
	Environment and Location	28	0	1	29	Positive
	General/Others	27	0	2	29	Positive
Bung Hatta University Campus 1	Academic and Lecturers	10	0	0	10	Positive
	Campus Facilities	20	1	1	22	Positive
	Administrative Services	1	1	0	2	Mixed
	Environment and Location	18	0	1	19	Positive
	General/Others	31	2	1	34	Positive
Universitas Ekasakti	Academic and Lecturers	17	0	3	20	Positive
	Campus Facilities	11	0	5	16	Positive
	Administrative Services	5	0	6	11	Negative

University	Aspect	Positive	Neutral	Negative	Total	Dominant Sentiment
UPI YPTK Padang	Environment and Location	15	0	1	16	Positive
	General/Others	29	0	1	30	Positive
	Academic and Lecturers	14	0	2	16	Positive
	Campus Facilities	32	0	2	34	Positive
	Administrative Services	0	0	1	1	Negative
	Environment and Location	32	0	1	33	Positive
	General/Others	33	0	0	33	Positive
Total	-	44	6	35	48	-
		3			4	

Table 11 shows that positive sentiment dominated most university–aspect combinations. UPI YPTK Padang recorded the highest number of positive aspect-level records, particularly in Campus Facilities, Environment and Location, and General/Others. Universitas Baiturrahmah also showed consistently positive sentiment across all discussed aspects. However, Administrative Services appeared as the most sensitive aspect, especially at Universitas Ekasakti, where negative sentiment was more visible. This finding should be interpreted cautiously because the number of administrative-service records was limited. Overall, the mapping indicates that textual Google Reviews provide useful aspect-specific insights, but they should not be generalized as a complete assessment of institutional digital reputation.

3.6 Examples of Anonymized Review Quotes

The examples presented in Table 12 are paraphrased anonymized examples derived from the review annotation process. They are included to illustrate how review content was assigned to aspect and sentiment categories while avoiding the disclosure of reviewer identity or identifiable textual traces.

Table 12. Examples of Anonymized Review Quotes

No.	Aspect Dimension	Sentiment Class	Anonymized Review Quote	Annotation Rationale
1	Academic and Lecturers	Positive	"The lecturers are highly competent, friendly, and their teaching methods are easy to understand."	Indicates satisfaction with lecturer competence and teaching clarity.
		Negative	"Some lecturers rarely attend classes and only provide assignments without proper explanations."	Indicates dissatisfaction with lecturer attendance and limited explanation.
		Neutral	"The learning process runs normally, similar to the standard higher education system."	Describes the learning process in a neutral and standard manner.
2	Campus Facilities	Positive	"The campus building is impressive, the classrooms are air-conditioned, and the laboratories are very well equipped."	Indicates positive perception of classrooms, buildings, and laboratories.
		Negative	"The motorcycle parking area is very limited, and some toilets on several floors are frequently damaged."	Indicates criticism of parking space and physical facilities.
		Neutral	"The campus infrastructure is adequate for students' daily needs."	Describes facilities as functionally adequate without strong sentiment.
3	Administra tive Services	Positive	"The processing of scholarship documents and financial	Indicates satisfaction with administrative service efficiency.

No.	Aspect Dimension	Sentiment Class	Anonymized Review Quote	Annotation Rationale
4	Environment and Location		administration is handled quickly."	
		Negative	"The administrative service counter is very slow, and the staff are less friendly."	Indicates dissatisfaction with service speed and staff attitude.
		Neutral	"The diploma legalization process requires a standard waiting time as usual."	Describes an ordinary administrative process without strong polarity.
		Positive	"The campus location is very strategic on the main road and easily accessible by public transportation."	Indicates positive perception of accessibility and strategic location.
		Negative	"The surrounding campus area is quite noisy during the day because it is near a busy intersection."	Indicates discomfort related to surrounding noise and traffic.
		Neutral	"The campus is located in an area close to student housing."	Provides factual location information without clear positive or negative polarity.
5	General/Others	Positive	"I highly recommend this campus for those who want to continue their studies."	Indicates a general positive recommendation without referring to a specific aspect.
		Negative	"I am very disappointed studying here because it does not meet my initial expectations."	Indicates general dissatisfaction without specifying a

No.	Aspect Dimension	Sentiment Class	Anonymized Review Quote	Annotation Rationale
				particular institutional aspect.
		Neutral	"I only visited this campus to attend a seminar yesterday."	Indicates a neutral visitor experience without evaluative sentiment.

Table 12 demonstrates that the annotation process considered both the aspect discussed in the review and the sentiment expressed by the reviewer. The General/Others category was used for broad comments that did not clearly refer to a specific institutional aspect, while the other categories were assigned when the review explicitly discussed academic, facility, administrative, or environmental issues.

3.7 Google Review-Based Digital Reputation Insights

The results suggest that textual Google Reviews provide generally positive Google Review-based digital reputation insights for the five selected private higher education institutions in Padang City. Of the 484 aspect-level records, 443 records or 91.53% were classified as positive, while 35 records or 7.23% were negative and 6 records or 1.24% were neutral. However, these findings should not be interpreted as a complete evaluation of institutional digital reputation because Google Reviews represent only one public feedback channel. Therefore, the findings should not be generalized beyond the selected institutions, data source, and city context. The model evaluation showed that IndoBERT achieved the strongest overall performance among the evaluated models.

Aspect-based mapping provides more specific insight than overall star ratings because it identifies which institutional aspects were discussed positively, negatively, or neutrally. General/Others, Environment and Location, and Campus Facilities were the most frequently represented aspect categories, with positive sentiment dominating these categories. The dominance of General/Others indicates that many Google Review comments expressed broad institutional impressions rather than specific service or academic experiences. Administrative Services appeared as the most sensitive aspect, particularly for Universitas Ekasakti. However, this finding should be interpreted

cautiously because the number of administrative-service records was limited to 17 records. The negative administrative-service result for UPI YPTK Padang should also not be generalized because it was based on only one record. Therefore, negative sentiment in this aspect should be treated as an indication for further monitoring rather than definitive evidence of overall administrative service quality. Overall, star ratings provide a broad numerical signal, while textual aspect-based sentiment mapping provides more detailed information about the aspects being praised or criticized. The comparison between these two forms of information shows that a high overall star rating does not necessarily represent uniformly positive textual perceptions across specific institutional aspects. The findings therefore provide a more granular view of Google Review-based digital reputation while remaining limited to the perceptions represented in the available textual reviews.

3.8 Discussion

The findings demonstrate that aspect-based sentiment analysis provides a more comprehensive approach to understanding higher education digital reputation than relying solely on overall rating scores. While star ratings provide a general indication of public perception, they do not reveal the specific institutional aspects underlying user opinions. By integrating aspect identification and sentiment classification, this study provides more detailed insights from user-generated online reviews.

The superior performance of IndoBERT compared with TF-IDF-based approaches highlights the importance of contextual language representation for Indonesian user-generated reviews. Traditional frequency-based approaches may face limitations in handling informal expressions and contextual meanings, whereas transformer-based models can better capture semantic relationships within text. However, this finding should be interpreted cautiously because the dataset was highly imbalanced, particularly in the neutral category, which contained only six records.

The aspect-level findings further show that General/Others represented broad institutional impressions, while Administrative Services showed a comparatively higher negative tendency, particularly at Universitas Ekasakti. However, the limited number of records prevents this pattern from being interpreted as definitive evidence of overall service quality. The study is limited to textual Google Reviews from selected private

higher education institutions in Padang City and does not include other digital feedback platforms or temporal analysis. Future research should consider larger and more balanced datasets, multiple digital platforms, temporal analysis, and expert or stakeholder validation.

4. CONCLUSION

This study applied aspect-based sentiment mapping to textual Google Reviews to provide partial digital reputation insights for five selected private higher education institutions in Padang City. From 1,159 exported records, 365 textual reviews were retained and transformed into 484 aspect-level records. The dataset was highly imbalanced, with 443 positive, 35 negative, and 6 neutral records. The results showed that positive sentiment dominated the analyzed textual reviews, indicating generally favorable public perceptions within the scope of the selected Google Review data. Using 5-fold stratified cross-validation, IndoBERT achieved the strongest average performance, with an accuracy of 0.973 ± 0.005 , balanced accuracy of 0.710 ± 0.021 , macro F1-score of 0.760 ± 0.024 , and weighted F1-score of 0.971 ± 0.007 . TF-IDF with Logistic Regression remained the best-performing classical machine learning model, followed by TF-IDF with SVM. These findings provide preliminary evidence that aspect-based sentiment mapping can offer more detailed insight than star ratings alone. However, the model performance should be validated further using larger and more balanced datasets.

The aspect-based results showed that General/Others, Environment and Location, and Campus Facilities were the most positively represented aspects. Administrative Services showed a relatively higher negative tendency, but this finding should be interpreted cautiously because it was based on limited records. Therefore, it should be treated as an indication for further monitoring rather than definitive evidence of overall service quality. This study is limited to textual Google Reviews from five private higher education institutions in one city and should not be interpreted as a complete evaluation of higher education digital reputation. The analysis excluded 794 star-only reviews because they did not contain textual information for annotation. In addition, expert validation is still needed to assess whether the aspect-sentiment mapping is practically useful for institutional decision-making. Future research should include more universities, additional review sources, temporal analysis, expert validation, star-only review

integration, and imbalance-handling strategies to produce broader and more reliable digital reputation insights.

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