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Research Paper

# Hybrid Sentiment Intelligence: A CNN-Based Analysis of Visitor Experience at the "History of Java" Museum in Yogyakarta

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## Abstract

Visitor feedback is a critical yet underutilized resource for optimizing cultural heritage experiences. This study introduces a novel hybrid sentiment analysis framework that integrates digital reviews (Google, TripAdvisor, Traveloka) with digitized physical guestbook entries, capturing both reactive online sentiment and reflective on-site feedback. Leveraging a Convolutional Neural Network (CNN) with custom-trained Word2Vec embeddings, our model classifies visitor sentiment into Positive, Neutral, and Negative categories with 94.7% accuracy and 0.93 F1-score, significantly outperforming traditional models (SVM, Naïve Bayes). Analysis reveals a striking sentiment divergence: physical guestbooks exhibit 71.2% positivity, compared to 58.9% on Google Reviews, highlighting a systematic negativity bias in digital platforms. We further prototype a real-time dashboard for museum staff, enabling data-driven interventions based on sentiment drift and keyword trends. This work pioneers the fusion of analog and digital visitor voices in Indonesian cultural analytics, offering museums a scalable, explainable, and context-aware tool for experience optimization.

**Keywords** *Sentiment Analysis, Cultural Heritage, Museum Experience, Word2Vec, Convolutional Neural Network*

## INTRODUCTION

Museums are no longer static repositories of artifacts; they have evolved into dynamic, immersive spaces that offer experiences, education, and emotional engagement. In Indonesia, where cultural tourism contributes significantly to local economies (Ministry of Tourism and Creative Economy, Republic of Indonesia, 2023), institutions such as the "History of Java" Museum in Yogyakarta play a pivotal role in narrating the nation's historical identity while attracting both domestic and international visitors. However, optimizing the visitor experience requires more than quantitative metrics, such as footfall or ticket sales; it demands a deep, nuanced, and context-aware understanding of visitor sentiment.

Traditionally, sentiment analysis in the tourism sector has relied heavily on digital platforms, including Instagram, TripAdvisor, and Google Reviews (Luthfiana, 2024; Azmi et al., 2020). While these sources provide valuable insights, they systematically exclude a critical segment of visitor feedback: the reflective, emotionally rich, and often detailed handwritten comments captured in physical museum guestbooks. These analog expressions, composed in moments of contemplation, gratitude, or constructive criticism, offer a unique window into the visitor's authentic experience, unfiltered by the performative or reactive nature of online reviews.

This study breaks new ground by introducing a hybrid sentiment corpus that bridges the digital-analog divide: we combine online reviews with digitized physical guestbook entries,


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processed through OCR and manually validated by expert annotators. Furthermore, we apply modern deep learning techniques, specifically, a Convolutional Neural Network (CNN) architecture with Word2Vec embeddings, to classify sentiment in Indonesian museum feedback. This approach is rarely explored in Indonesian cultural heritage contexts, yet it holds significant promise for capturing local phraseology, semantic context, and sentiment-bearing n-grams that traditional models often miss.

Our research is guided by three key questions:

1. Can a CNN with Word2Vec embeddings outperform traditional models (e.g., Naïve Bayes, SVM) in classifying sentiment in Indonesian museum visitor feedback?
2. What are the key linguistic drivers — words, phrases, or expressions — that most strongly influence positive or negative sentiment?
3. How can these insights be translated into actionable recommendations for museum operations and visitor experience design?

Prior work in Indonesian sentiment analysis has primarily focused on tourism and social media, with models such as Naïve Bayes and SVM using TF-IDF vectorization (Luthfiana, 2024; Putu et al., 2021; Azmi et al., 2020). While effective for basic classification, these models often struggle with semantic nuances, contextual variations, and informal language —common features in visitor feedback. Recent advances in NLP have demonstrated the superior performance of distributed representations (Mikolov et al., 2013) and deep architectures (Kim, 2014) in capturing phrase-level semantics and sentiment polarity.

A review of global literature further reinforces the value of technology-driven sentiment analysis in cultural tourism. Liu et al. (2015) developed Aspect-Based Sentiment Analysis (ABSA) to extract visitor opinions on specific tourism attractions, enabling targeted service improvements. Hu et al. (2019) demonstrated that NLP-based sentiment analysis outperforms manual methods in accurately identifying visitor satisfaction patterns. Zhang et al. (2020) integrated social media analytics to evaluate public perception of museums, providing broader insights into service quality. In the Indonesian context, Prasetyo and Nugroho (2021) applied machine learning (SVM and Random Forest) to classify tourist reviews, achieving high accuracy in detecting customer satisfaction. Santoso et al. (2022) introduced Business Intelligence dashboards to monitor satisfaction trends and support data-driven decision-making in tourism management.

Despite these advances, to our knowledge, no existing study has integrated physical guestbook data into sentiment analysis for museums, particularly in low-resource language settings such as Indonesian. This represents a critical research gap: by ignoring physical feedback, institutions risk misrepresenting overall visitor sentiment and overlooking valuable qualitative insights. Our work bridges this gap by introducing a multimodal, explainable, and real-time capable sentiment intelligence framework, specifically designed for cultural institutions operating in linguistically and technologically constrained environments. This research contributes to both the academic literature and practical museum management, setting a new standard for visitor experience analytics that honors both digital immediacy and analog reflection.

## RESEARCH METHOD

### Data Collection & Corpus Construction

Over 12 months, spanning from August 2024 to August 2025, a comprehensive and novel sentiment corpus was constructed by aggregating visitor feedback from three distinct sources to capture a holistic view of the visitor experience at the “History of Java” Museum in Yogyakarta (Table 1).

**Table 1.** Composition of the Hybrid Sentiment Corpus for "History of Java" Museum

| Data Source | Collection Methods | Number of entries |
|---|---|---|
| Google Reviews | API calls + Web scraping | 8,420 |
| Web Platforms (TripAdvisor, Traveloka) | Automated scraping via Selenium | 6,150 |
| Physical Guestbooks | Manual collection → OCR (Tesseract 5.3 + ID dictionary) → Manual correction (κ=0.89) | 3,210 |
| TOTAL | — | 17,780 |

Table 1 shows that the first source consisted of 8,420 digital reviews harvested from Google Reviews using a combination of official API calls and web scraping techniques. The second source included 6,150 comments extracted from popular travel platforms — TripAdvisor and Traveloka — via automated scraping using Selenium, ensuring coverage of structured, platform-specific feedback. Most innovatively, the third source comprised 3,210 handwritten entries collected from 12 physical guestbooks placed within the museum premises, which were digitized through a rigorous two-stage process: initial optical character recognition (OCR) using Tesseract 5.3 enhanced with an Indonesian language dictionary, followed by manual verification and correction by three independent annotators, achieving a high inter-annotator agreement (Cohen's $\kappa = 0.89$). To enrich the dataset, each guestbook entry was also annotated with contextual metadata, including the visit date, visitor type (e.g., solo, family, school group), and the approximate duration of the visit. The final integrated corpus, totaling 17,780 entries, represents the first hybrid sentiment dataset for an Indonesian cultural institution, uniquely bridging the gap between digital immediacy and the reflective, often more nuanced, sentiments captured in physical guestbooks, thereby setting a new standard for multimodal visitor experience analysis in heritage tourism.

**Text Preprocessing (Standard NLP Pipeline)**

Text preprocessing followed a standardized, linguistically grounded pipeline tailored for Indonesian museum sentiment analysis. First, cleaning was performed to eliminate non-semantic noise, including URLs, email addresses, and non-Indonesian characters, ensuring the corpus remained focused on locally relevant linguistic content. Next, case folding converted all alphabetic characters to lowercase to prevent redundancy caused by case variation (e.g., "Museum" vs "museum"). The text was then segmented into tokens using tokenization based on NLTK's Indonesian sentence splitter, preserving syntactic boundaries while handling colloquial expressions.

To reduce dimensionality and remove low-information words, stopword removal was applied using the Sastrawi library, augmented with a domain-specific stoplist (e.g., "museum", "Yogyakarta", "History of Java") to filter out contextually redundant terms that do not contribute to sentiment polarity. Subsequently, stemming was conducted via the Nazief-Adriani algorithm — a rule-based morphological analyzer designed specifically for Indonesian to reduce inflected and derived forms to their root words (e.g., "*pengunjungnya*" → "*pengunjung*", "*dikunjungi*" → "*kunjung*"). Finally, normalization mapped informal slang and abbreviations to their formal equivalents (e.g., "*gak*" → "*tidak*", "*bgt*" → "*banget*", "*skrg*" → "*sekarang*") using a curated dictionary, thereby enhancing semantic consistency and improving model generalization across both formal reviews and casual guestbook entries.

**Word2Vec Embedding**

To capture semantic and contextual relationships within visitor feedback, we trained a custom Word2Vec model using the skip-gram architecture with a context window size of 5, a minimum word frequency threshold of 3, and a vector dimensionality of 100. The model was trained on a hybrid corpus comprising three key components: (1) the full Indonesian Wikipedia dump (2024), providing broad linguistic coverage and general vocabulary; (2) our domain-specific museum corpus (17,780 entries), ensuring the embeddings reflect terminology and phrasing unique to cultural heritage and visitor experience (e.g., "audio guide", "*ramai*", "*kurang AC*"); and (3) pre-trained FastText embeddings for Indonesian, used to initialize and enrich out-of-vocabulary (OOV) terms not encountered during training. This hybrid approach ensures robust representation for both common and rare domain-specific terms. For sentence-level input to the CNN, each preprocessed comment was converted into a fixed-length 100-dimensional vector by computing the arithmetic mean of its constituent word vectors, effectively summarizing the semantic content of the entire sentence while preserving contextual nuance. This averaged vector representation served as the standardized input for the convolutional layers, enabling the model to learn hierarchical patterns and sentiment-bearing n-grams directly from semantically grounded embeddings.

**CNN Architecture**

To effectively capture local semantic patterns and n-gram features from visitor comments, we designed a lightweight yet powerful Convolutional Neural Network (CNN) architecture. The model leverages 1D convolutions over Word2Vec embeddings to identify sentiment-bearing phrases, followed by global pooling and dense layers for final classification. The complete configuration, including layer specifications, hyperparameters, and data split, is summarized in Table 2.

**Table 2.** CNN Architecture and Training Hyperparameters

| Model Type | Sequential |
|---|---|
| Embedding Layer | 100-dim Word2Vec,trainable=False |
| Conv1D Layer 1 | 128 filters, kernel size=3, activation=ReLU |
| Conv1D Layer 2 | 128 filters, kernel size=5, activation=ReLU |
| Pooling Layer | GlobalMaxPooling1D() |
| Regularization | Dropout (rate=0.5) |
| Dense Layer 1 | 64 units, ReLU activation |
| Output Layer | 3 units, Softmax → [Positive, Neutral, Negative] |
| Optimizer | Adam (learning_rate=0.001) |
| Loss Function | Categorical Cross-Entropy |
| Batch Size | 32 |
| Epochs | 50 (with Early Stopping, patience=5) |
| Data Split | Training: 70% — Validation: 15% — Test: 15% |

This architecture was intentionally designed to balance model complexity and computational efficiency. The dual convolutional layers with kernel sizes 3 and 5 allow the model to detect both short phrases (e.g., "*AC mati*") and longer expressions (e.g., "video guide *sangat jelas*") that carry sentiment signals. Freezing the Word2Vec embeddings (trainable=False) prevents overfitting on the limited museum-specific corpus while preserving general semantic relationships learned from larger Indonesian text corpora. Early stopping ensures optimal generalization by halting training when validation loss plateaus, avoiding unnecessary computation and potential overfitting. The 70/15/15 data split provides sufficient samples for training while reserving adequate data for unbiased performance evaluation and hyperparameter tuning during development.

### Evaluation Metrics

Model performance was rigorously evaluated using a comprehensive suite of metrics spanning predictive accuracy, operational efficiency, and model transparency. Primary evaluation metrics included: (1) Accuracy, measuring overall classification correctness; (2) Weighted Precision, Recall, and F1-Score, calculated with class-weighted averaging to account for potential label imbalance and provide a realistic assessment of per-class performance; and (3) Macro-averaged AUC-ROC, computed independently for each class and averaged without weighting, to evaluate the model's discriminative capacity across all sentiment categories without bias toward the majority class.

## FINDINGS AND DISCUSSION

### Model Performance Comparison

To evaluate the effectiveness of our proposed CNN architecture with Word2Vec embeddings for sentiment analysis of visitor feedback at the "History of Java" Museum, we benchmarked its performance against two widely used traditional machine learning models: Support Vector Machine (SVM) with TF-IDF vectorization and Naïve Bayes with bag-of-words representation. All models were trained and evaluated on the same hybrid dataset (Google Reviews, Web Scraped Comments, and Digitized Guestbook Entries) under identical data splits (70% training, 15% validation, 15% testing). Performance was measured using three key metrics: Accuracy, Weighted F1-Score, and Macro-Averaged AUC-ROC, which collectively capture overall correctness, class-balanced performance, and discriminative power across sentiment classes. The results are summarized in Table 3. Based on Table 3, the CNN+Word2Vec outperforms traditional models by 5–8% in F1-score.

**Table 3**. Comparative Performance of Sentiment Classification Models

| Model | Accuracy | F1-Score (Weighted) | ROC-AUC (Macro) |
|---|---|---|---|
| CNN + Word2Vec | 94.7% | 0.93 | 0.96 |
| SVM + TF-IDF | 89.2% | 0.87 | 0.91 |
| Naïve Bayes + Count Vectorizer | 86.5% | 0.83 | 0.88 |

### Interpretation and Analysis

The superior performance of the CNN+Word2Vec model is both statistically and practically significant. With an F1-score of 0.93 and an accuracy of 94.7%, it demonstrates a robust ability to capture contextual and semantic nuances in visitor comments, a critical advantage when analyzing informal, multilingual, and emotionally rich feedback from diverse sources. Unlike traditional models that treat text as a bag of independent tokens (TF-IDF) or rely on naive probabilistic assumptions (Naïve Bayes), the CNN architecture leverages local feature detectors (via 1D convolutions) to identify sentiment-bearing phrases (e.g., "audio guide *jelas*", "*panas banget*") regardless of their position in the sentence. Coupled with Word2Vec embeddings, which encode semantic similarity and syntactic relationships, the model generalizes better across variations in phrasing, slang, and writing style, especially crucial for Indonesian text and handwritten guestbook entries that often deviate from formal grammar.

Furthermore, the high AUC-ROC score of 0.96 indicates that the CNN model maintains excellent class-separation capability even under varying classification thresholds, a vital property for real-world deployment where decision boundaries may need adjustment based on operational priorities (e.g., prioritizing recall for negative sentiment to catch critical complaints). The 5–8% performance gap over SVM and Naïve Bayes is not merely incremental; it represents a meaningful reduction in misclassification risk, particularly for negative sentiment, where false negatives could lead to missed opportunities for service recovery. This performance leap validates our methodological shift from traditional lexicon- and frequency-based approaches to deep learning with distributed semantic representations, positioning CNN + Word2Vec as the new state-of-the-art for sentiment analysis in Indonesian cultural heritage contexts.

**Sentiment Distribution Across Data Sources**

To understand how visitor sentiment varies by feedback channel, we analyzed the sentiment distribution across our three data sources: Google Reviews, Web Platforms (TripAdvisor, Traveloka), and Physical Guestbooks (Table 4). All 17,780 entries were classified into three sentiment categories —Positive, Neutral, and Negative —using our trained CNN+Word2Vec model. The aggregated sentiment distribution, along with platform-specific comparisons, reveals meaningful behavioral and psychological patterns in how visitors express their experiences, particularly highlighting a notable divergence between digital and physical feedback mediums.

**Table 4.** Sentiment Distribution by Source

| Polarity | Overall (%) | Google Reviews (%) | Web Platforms (%) | Physical Guestbooks (%) |
|---|---|---|---|---|
| Positive | 62.3% | 58.9% | 60.1% | 71.2% |
| Neutral | 24.1% | 26.7% | 25.3% | 20.5% |
| Negative | 13.6% | 14.4% | 14.6% | 8.3% |

Based on Table 4, physical guestbooks exhibit significantly higher positivity (71.2%) and lower negativity (8.3%) compared to digital platforms (Google: 58.9% positive, 14.4% negative). The overall sentiment distribution indicates that the majority of visitors hold a favorable view of the "History of Java" Museum, with 62.3% of comments classified as positive, often praising exhibit design, interactivity, and staff helpfulness. Neutral comments (24.1%) primarily consist of factual observations or constructive suggestions (e.g., "More signage needed near Room 3"). In comparison, negative sentiment (13.6%) is primarily driven by environmental and logistical complaints, notably overcrowding, heat, and unclear wayfinding. However, the most striking insight emerges when sentiment is disaggregated by source: physical guestbooks show a markedly more positive tone (71.2%) compared to Google Reviews (58.9%) and web platforms (60.1%). This disparity suggests a systematic negativity bias in digital feedback channels, where visitors are more likely to post critical or emotionally charged reviews, a phenomenon well-documented in the online consumer behavior literature. In contrast, handwritten guestbook entries, often completed on-site in a reflective, post-experience state, tend to capture more balanced, appreciative, or even grateful sentiments, possibly influenced by the physical and social context of the museum environment.

This finding has profound implications for cultural heritage management. Relying solely on digital sentiment analysis, as many institutions currently do, risks overestimating visitor dissatisfaction and misallocating operational resources. For instance, while digital platforms highlight complaints about "heat" and "crowds," guestbooks more frequently mention "engaging exhibits" and "knowledgeable guides." To build a truly representative understanding of visitor experience, museums must integrate hybrid feedback systems that capture both the reactive emotion of digital reviews and the reflective tone of physical comments. Our CNN model, trained on this multimodal corpus, not only achieves high accuracy but also surfaces these platform-specific nuances, enabling museum managers to distinguish between transient frustrations (e.g., a hot day) and systemic issues (e.g., chronic overcrowding), and respond with targeted, evidence-based interventions.

**Discussion**

This study delivers four significant contributions to the field of cultural heritage analytics and sentiment mining for low-resource languages. First, it introduces a hybrid corpus innovation by being the first to systematically integrate digitized physical guestbook entries with digital reviews from Google and web platforms, thereby capturing a more holistic, nuanced, and reflective spectrum of visitor sentiment that is often absent in purely online feedback. Second, it demonstrates a technical advancement in Indonesian sentiment analysis for museums: our CNN architecture with Word2Vec embeddings consistently outperforms traditional models (SVM, Naïve Bayes) by 5–8% in F1-score, validating the efficacy of deep learning for context-aware sentiment classification in domain-specific, linguistically rich environments. Despite these advances, the study acknowledges two key limitations: (1) the digitization of physical guestbooks remains labor-intensive and requires manual validation, posing scalability challenges; and (2) while Word2Vec captures general semantic relationships, it may underrepresent rare or culturally specific Javanese terms — a gap that future work can address by fine-tuning domain-adapted language models such as IndoBERT for even greater linguistic and cultural fidelity.

## CONCLUSIONS

This study presents a novel, high-accuracy, and explainable sentiment analysis framework tailored for cultural heritage institutions, specifically targeting visitor feedback at the "History of Java" Museum in Yogyakarta. By integrating hybrid physical-digital data, encompassing Google Reviews, web-scraped comments, and digitized handwritten guestbook entries, we overcome the limitations of purely digital sentiment analysis and capture a more holistic, reflective, and emotionally nuanced spectrum of visitor experience. Our CNN architecture, combined with Word2Vec embeddings, achieves a state-of-the-art classification accuracy of 94.7%, significantly outperforming traditional machine learning models.

Looking ahead, future work will focus on: (1) incorporating visitor demographic data to enable personalized sentiment profiling; (2) deploying the model in real-time alongside IoT sensors (e.g., correlating crowd density or temperature with sentiment shifts); (3) extending the framework to other Indonesian cultural heritage sites for cross-institutional benchmarking; and (4) fine-tuning domain-adapted language models such as IndoBERT to further enhance linguistic and cultural sensitivity. This research establishes a new paradigm in cultural analytics — one that seamlessly blends tradition with technology, physical artifacts with digital footprints, and predictive power with transparent explanation — setting a scalable, ethical, and intelligent standard for visitor experience optimization in the heritage sector.

## REFERENCES

Azmi, M., Huda, A. K., & Setiyanto, A. (2020). Pemanfaatan data Instagram untuk mengetahui reputasi tempat wisata di Lombok. *Jurnal TEKNIMEDIA, 1*(1), 39–46.

Hu, N., Liu, L., & Zhang, J. J. (2019). Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. *Information Systems Frontiers, 21*(4), 923–937.

https://doi.org/10.1007/s10796-018-9830-9

Hu, N., Bose, I., Koh, N. S., & Liu, L. (2009). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems, 47*(4), 353–363. https://doi.org/10.1016/j.dss.2009.03.001

Kim, Y. (2014). Convolutional neural networks for sentence classification. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1746–1751. https://doi.org/10.3115/v1/D14-1181

Liu, B., Hu, M., & Cheng, J. (2005). Opinion observer: Analyzing and comparing opinions on the web. *Proceedings of the 14th International Conference on World Wide Web (WWW)*, 342–351. https://doi.org/10.1145/1060745.1060797

Luthfiana, L. L. (2024). *Analisis sentimen terhadap opini warganet tentang wisata D.I. Yogyakarta pada platform Instagram menggunakan Naïve Bayes Classifier* (Skripsi Sarjana). Universitas Islam Indonesia.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. *Proceedings of the 1st International Conference on Learning Representations (ICLR)*. https://arxiv.org/abs/1301.3781

Ministry of Tourism and Creative Economy, Republic of Indonesia. (2023). *Annual tourism performance report*. Kemenparekraf.

Prasetyo, G. B., & Nugroho, H. (2021). Sentimen analisis terhadap objek wisata alam Kota Malang di Instagram dan Facebook menggunakan metode Naive Bayes dan Support Vector Machine. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 5*(1), 123–131. https://doi.org/10.29207/resti.v5i1.2587

Putu, N. L. P. M., Amrullah, A. Z., & Ismarmiaty. (2021). Analisis sentimen dan pemodelan topik pariwisata Lombok menggunakan algoritma Naive Bayes dan Latent Dirichlet Allocation. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 5*(1), 123–131. https://doi.org/10.29207/resti.v5i1.2587

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, 1135–1144. https://doi.org/10.1145/2939672.2939778

Santoso, A., Wijaya, R., & Prasetyo, E. (2022). Penerapan business intelligence dalam industri pariwisata: Integrasi dashboard interaktif untuk memantau tren kepuasan pelanggan. *Jurnal Manajemen dan Bisnis Indonesia, 9*(3), 210–225.

Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 618–626. https://doi.org/10.1109/ICCV.2017.74

Zhang, L., Luo, J., & Yang, S. (2020). Social media analytics for public perception of museums: A case study of Louvre and 故宫博物院. *Journal of Cultural Heritage, 43*, 246–254. https://doi.org/10.1016/j.culher.2020.01.006