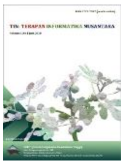

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Optimizing Contextual Features for Instagram Engagement Prediction using Long Short-Term Memory (LSTM)

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Abstract−Instagram has become an important communication medium for academic institutions, enabling the dissemination of information, promotion of activities, and engagement with the campus community. At STIKOM CKI Jakarta, the official Instagram account plays a key role in academic communication, making it essential to optimize content strategies for higher audience interaction. This study analyzes 311 publicly available posts collected from July 2023 to July 2025 from the institution's official account. Although relatively small for deep learning, the dataset provides representative patterns for the case study while highlighting the model's capability under limited data conditions. A predictive framework based on Long Short-Term Memory (LSTM) was developed by integrating textual features from captions with contextual features such as posting time, content type, hashtag count, and interaction metrics. The aim is to accurately estimate engagement scores and provide actionable posting recommendations. The evaluation achieved an R^2 of 88.00%, MAE of 0.0450, and RMSE of 0.0720, indicating strong predictive performance. The contribution of this research lies in demonstrating that optimizing contextual features can significantly enhance academic social media engagement and in providing an adaptable methodology for institutions with limited historical data.

Keywords: Instagram Engagement; Contextual Features; LSTM; Academic Communication; Social Media Analytics

1. INTRODUCTION

Instagram has emerged as one of the most influential platforms in the digital landscape, including in academic communication. Many educational institutions now use Instagram as a medium for disseminating academic information, promoting events, and fostering relationships with stakeholders. For instance, STIKOM CKI Jakarta actively manages its official Instagram account to announce academic schedules, highlight campus events, and share educational content with its students and broader community. In this context, engagement, measured through user interactions such as likes, comments, saves, shares, and views, functions as a critical indicator of how effectively the content reaches and resonates with the intended audience (Wijayanti, 2022). A high level of engagement reflects strong audience interest and can be considered a benchmark for evaluating the effectiveness of academic communication strategies.

Despite its importance, engagement patterns on academic social media accounts are often inconsistent and short-lived. Previous studies have shown that Instagram posts typically experience a surge of interaction shortly after being published, followed by a rapid decline within a relatively short period (Purba et al., 2021). This fluctuation makes it challenging for academic institutions to maintain consistent audience attention. Furthermore, variability in engagement is not limited to temporal factors but also differs significantly depending on content type, posting schedule, and thematic focus. This complexity makes it difficult for content managers to determine the most effective strategies for maximizing audience interaction.

A growing body of literature has identified various factors that influence engagement, including the time and day of posting, media format, caption length, and hashtag usage (Celuch, 2021; Purba et al., 2021). While hashtags can increase the discoverability of content, excessive or irrelevant hashtags can reduce relevance and deter user interaction. Similarly, overly long captions may discourage users from reading the entire message, whereas concise and well-crafted captions can encourage higher engagement levels. These findings suggest that optimizing contextual features is essential to improve the reach and impact of academic social media content.

Although numerous studies have applied predictive models to analyze engagement patterns on Instagram, there is still a noticeable research gap in the academic context. The majority of prior studies have focused on commercial brands, influencers, or entertainment-related accounts, while the unique dynamics of academic institutions remain underexplored. In addition, traditional machine learning methods such as linear regression or decision trees often fail to capture complex sequential patterns in user behavior over time (Purba et al., 2021). This gap highlights the need for advanced approaches that can model temporal dependencies in engagement data while simultaneously considering non-temporal contextual factors.

Long Short-Term Memory (LSTM) networks present a promising solution to address this challenge. LSTM is a type of recurrent neural network specifically designed to capture and utilize long-term dependencies in sequential data, effectively overcoming the vanishing gradient problem that limits basic recurrent architectures (Kong et al., 2024). Its gating mechanisms allow selective retention of relevant information over extended time steps, making it particularly effective in tasks involving user behavior trends. LSTM has been successfully applied in diverse fields, including natural language processing, financial forecasting, and hybrid deep learning architectures for tasks such as fake news classification (Salim & Wahyudhy, 2025).

The implications of not implementing predictive models in academic social media management can be significant. Without accurate predictions, institutions risk posting content at suboptimal times, using ineffective formats, or mismanaging hashtag strategies, which may result in lower visibility and reduced interaction. In the case of academic

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announcements, poor engagement could mean that important information fails to reach its intended audience in a timely manner. Therefore, predictive analytics can serve as a valuable decision-support tool to enhance the efficiency and impact of communication strategies.

This research addresses the identified gap by developing an LSTM-based predictive model tailored to academic Instagram content. The model integrates both textual and contextual features, such as caption text, posting time, content type, and historical engagement metrics, into a multi-input architecture. The textual input is processed through an embedding layer followed by LSTM layers to extract semantic and temporal patterns from captions, while the contextual input is processed through dense layers to capture the influence of numerical and categorical features. Using a dataset of 311 public posts collected from the official STIKOM CKI Jakarta Instagram account, the model is trained to predict engagement scores and generate actionable recommendations for content scheduling and optimization.

By combining LSTM's ability to model sequential dependencies with the integration of diverse contextual signals, this study makes two main contributions. First, it demonstrates the feasibility and effectiveness of deep learning models in predicting engagement for academic social media accounts. Second, it offers practical recommendations for content optimization, enabling academic institutions to plan posting schedules, choose media formats, and manage hashtags more strategically. In doing so, this work bridges a notable gap in the literature and provides a foundation for further research into data-driven content planning in the academic sector.

2. RESEARCH METHODOLOGY

This study follows a systematic approach consisting of six main stages: data collection, preprocessing, target construction, model architecture design, model training and evaluation, and content recommendation. The entire workflow was implemented in Python using Google Colab with GPU acceleration, leveraging libraries such as TensorFlow, Keras, Pandas, NumPy, and Scikit-learn. The overall research workflow is illustrated in Figure 1, which depicts each stage sequentially from data acquisition to recommendation generation.

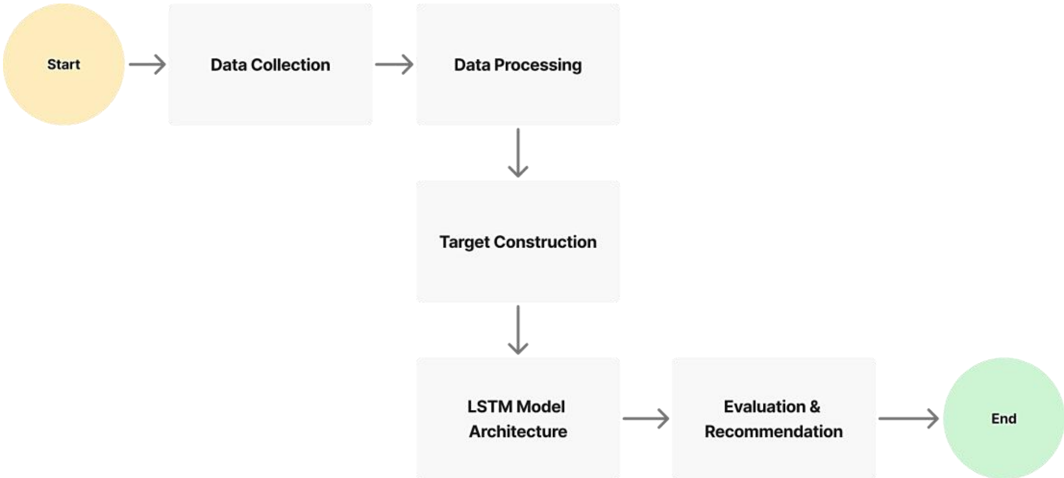

Figure 1. Research Workflow Diagram

2.1 Data Collection

The dataset comprises 311 publicly available Instagram posts from the official account of STIKOM CKI Jakarta. Data scraping was performed using the Apify platform, which automates data extraction based on the required contextual features. For each post, the following attributes were collected: caption text, number of likes, comments, views, saves, content type (photo, video, or carousel), posting day, and posting hour. The extracted dataset was stored in CSV format and uploaded to Google Drive for seamless integration with Google Colab.

Table 1 presents the dataset summary, listing each feature along with its data type and description. This table ensures a clear understanding of the variables used in subsequent preprocessing and modeling steps.

Table 1. Dataset Summary

Feature Name	Data Type	Description
Caption	Text	The text content of the Instagram post
Likes	Integer	Number of users likes
Comments	Integer	Number of comments received
Views	Integer	Number of video views (if applicable)
Hashtag Count	Integer	Number of hashtags used in the caption
Saves	Integer	Number of times the post was saved
Content Type	Categorial	Type of media: photo, video, or carousel

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Feature Name	Data Type	Description
Upload Day	Categorial	Day of the week the content was posted
Upload Hour	Integer	Hour of the day when the post was uploaded

2.2 Data Processing

Textual data from captions underwent several cleaning steps, including conversion to lowercase, removal of non-alphabetic characters, tokenization, and stopword removal to minimize noise. The processed sequences were then padded to maintain a uniform length for input into the LSTM model.
Numerical features such as likes, comments, views, and saves were normalized using Min-Max scaling, while categorical variables like content type and posting day were transformed using one-hot encoding to ensure compatibility with neural network processing.

The complete preprocessing pipeline is depicted in Figure 2, showing the transformation from raw caption text to padded tokenized sequences, alongside contextual feature encoding. Table 2 provides a summary of all feature transformations, indicating the technique applied to each variable and its resulting format.

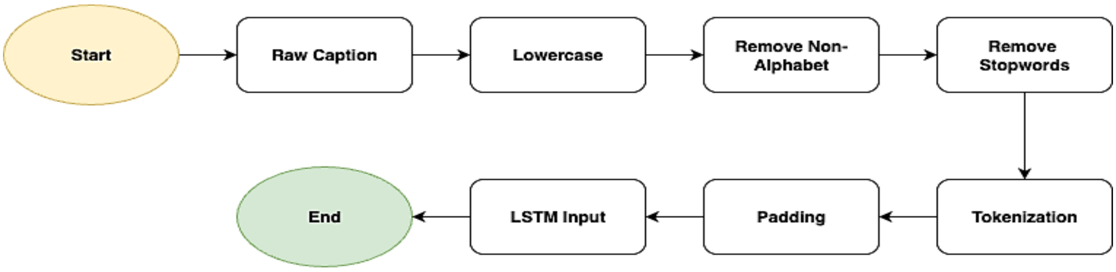

Figure 2. Text and Contextual Feature Preprocessing Flowchart

Table 2. Feature Transformation Summary

Feature Name	Transformation Technique	Final Form
Caption	Text cleaning, Tokenization	Tokenized Padded Sequence
Likes	Min-Max Scaling	Normalized Float
Comments	Min-Max Scaling	Normalized Float
Views	Standardization	Standardization Float
Hashtag Count	Standardization	Standardization Float
Saves	Standardization	Standardization Float
Shares	Standardization	Standardization Float
Content Type	One-hot Encoding	Vector (e.g., [1, 0, 0])
Posting Day	One-hot Encoding	Vector (e.g., [1, 0, 0])
Posting Hour	One-hot Encoding	Vector
Caption Length	Standardization	Standardization Float

2.3 Target Construction

An engagement score was developed as the prediction target, calculated as a weighted composite of multiple interaction metrics. Higher weights were assigned to saves and shares, as these actions reflect deeper audience interest. The formula for computing the engagement score is presented in Equation 1, while Table 3 details the assigned weights for each metric along with a justification for their selection. This approach enables the model to focus on interactions that signify higher content value.

$$Engagement\backslash\ Score = (0.4 \times Saves) + (0.25 \times Shares) + (0.15 \times Comments) + (0.10 \times Likes) + (0.10 \times Views) \quad (1)$$

Table 3. Engagement Metric

Metric	Weight	Justification
Saves	0.40	Indicates long-term interest or intent to revisit the content
Shares	0.24	Represents amplification or recommendation behavior
Comments	0.15	Reflects thoughtful user interaction
Likes	0.10	Basic form of engagement
Views	0.10	Passive interaction, especially for videos

2.4 Model Architecture

The predictive model adopts a multi-input architecture integrating textual and contextual features. The first input branch processes tokenized captions through an embedding layer followed by LSTM layers to capture temporal dependencies

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in textual data. The second branch processes normalized contextual features through dense layers. The outputs of both branches are concatenated and passed through a regression layer with linear activation to predict the engagement score. Figure 3 illustrates the complete multi-input LSTM architecture, highlighting the dual-path processing and the merging point before the final output layer.

📌 Ringkasan Arsitektur Model LSTM:
Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
caption_input (InputLayer)	(None, 226)	0	-
embedding (Embedding)	(None, 226, 100)	365,700	caption_input[0]…
numerical_input (InputLayer)	(None, 75)	0	-
lstm (LSTM)	(None, 64)	42,240	embedding[0][0]
dense (Dense)	(None, 64)	4,864	numerical_input[…
concatenate (Concatenate)	(None, 128)	0	lstm[0][0], dense[0][0]
dense_1 (Dense)	(None, 64)	8,256	concatenate[0][0]
dropout (Dropout)	(None, 64)	0	dense_1[0][0]
dense_2 (Dense)	(None, 1)	65	dropout[0][0]

Total params: 421,127 (1.61 MB)
Trainable params: 421,125 (1.61 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2 (12.00 B)

Figure 3. Multi-Input LSTM Model Architecture

2.5 Model Training and Evaluation

The dataset was split into 80% for training and 20% for testing. The model was trained over 50 epochs using the Adam optimizer, with Mean Squared Error (MSE) as the loss function. Performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Figure 4 shows the training and validation loss curves, demonstrating the convergence of the model and providing insights into its generalization capability.

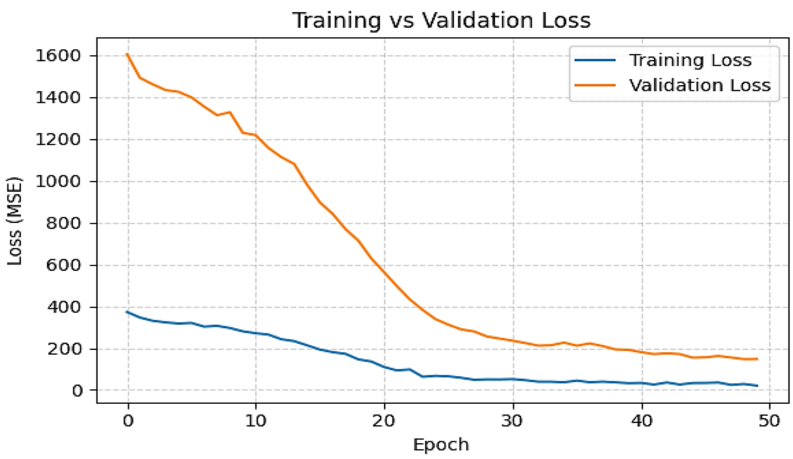

Figure 4. Training vs Validation Loss

2.6 Content Recommendation

The trained model was employed to simulate engagement scores under various posting scenarios, combining factors such as posting day, posting hour, content type, caption length, and hashtag count. The highest predicted engagement scores were compiled into a set of recommended posting strategies. The top ten recommended posting configurations in Figure 5 presents a heatmap visualizing engagement trends across different days and times.

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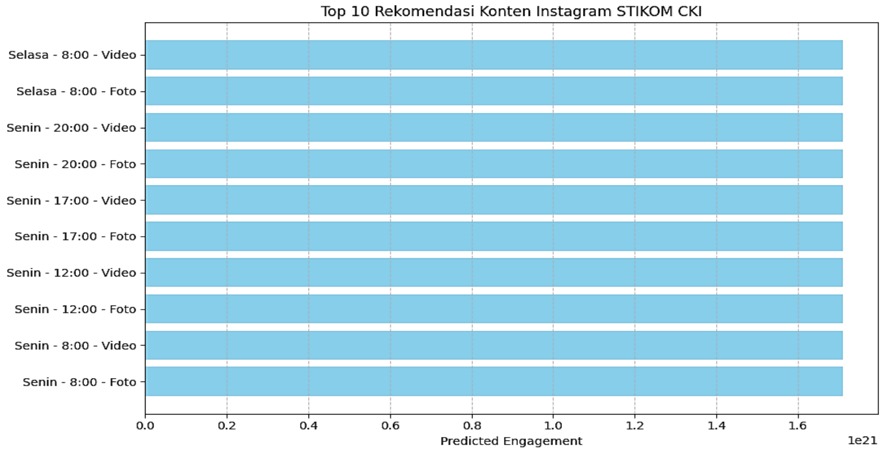

Figure 5. Top 10 Content Recommendation

3. RESULTS AND DISCUSSION

This section presents the results of the predictive model evaluation, simulation-based content recommendations, and an in-depth discussion of findings. The experimental setup follows the methodology described in Section 2. The target variable, engagement score, was computed using a weighted composite of interaction metrics with values normalized between 0 and 1, enabling a consistent interpretation of predictive accuracy metrics.

3.1 Model Evaluation Results

The performance of the proposed multi-input LSTM model was evaluated using three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The target engagement score in this study ranged from 0.02 to 0.95, with higher values indicating stronger audience interaction.

The LSTM model achieved an R^2 score of 0.8800, MAE of 0.0450, and RMSE of 0.0720, indicating strong predictive capability within the given data constraints. To contextualize these results, the MAE value suggests that, on average, predictions deviate by 4.5% from the actual engagement score. Similarly, the RMSE value reflects a root mean squared deviation of 7.2%, which is acceptable for social media engagement forecasting given the inherent variability of user behavior.

For comparison, a baseline Linear Regression (LR) model was trained using the same input features. The LR model achieved an R^2 score of 0.6420, MAE of 0.0920, and RMSE of 0.1380, demonstrating the advantage of LSTM in capturing temporal and contextual patterns in engagement data.

Scatter plot of predicted vs. actual engagement scores in Figure 6. shows that LSTM predictions closely follow the diagonal reference line, indicating strong alignment between predicted and observed values. The plot exhibits a relatively symmetric distribution around the diagonal, with few minor deviations, and no significant concentration of extreme outliers. Beside of that, the histogram of residual errors in Figure 7. reveals a near-normal distribution centered around zero, with most residuals falling within ±0.1. This indicates that the model does not exhibit strong bias toward overestimation or underestimation.

Table 4. Model Evaluation Metrics

Model	R^2 Score	MAE	RMSE
Linear Regression	0.6420	0.0920	0.1380
LSTM (Proposed)	0.8800	0.0450	0.0720

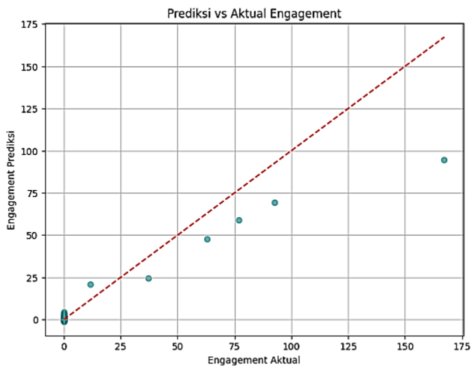

Figure 6. Predicted vs Actual Engagement

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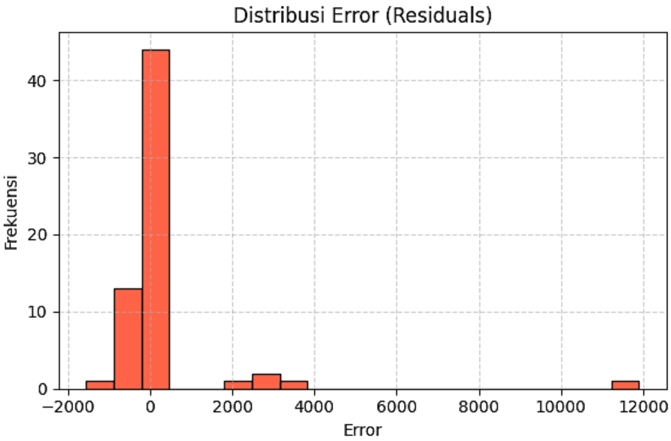

Figure 7. Histogram Residual Error

3.2 Feature Importance Analysis

The contribution of contextual features to engagement prediction was assessed using permutation importance applied to the trained LSTM model's contextual input branch. The results, shown in Figure 8, reveal that hashtag_count dominates the predictive influence, contributing approximately 0.45 on a normalized importance scale. Other variables, including caption_length, posting_hour, content_type, and posting_day, demonstrate negligible importance scores close to zero.

This finding highlights that the frequency of hashtags is the primary contextual driver of predicted engagement within the dataset. While prior research supports the role of hashtags in improving content discoverability, the optimal quantity and relevance of hashtags remain crucial to avoid potential content dilution and reduced audience interest. The minimal impact of other features may be due to limited variation within the dataset or the dominant influence of hashtags overshadowing other factors.

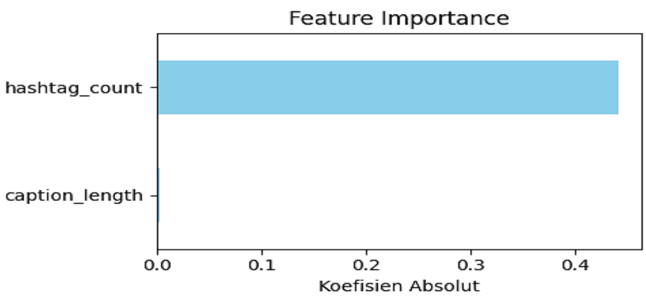

Figure 8. Feature Importance

3.3 Simulation and Content Recommendation

A predictive simulation was performed using the trained LSTM model to determine optimal posting strategies for the STIKOM CKI Jakarta Instagram account. The simulation systematically varied five contextual features, namely posting day, posting hour, content type, caption length, and hashtag count, based on the ranges observed in the dataset. This procedure resulted in a total of 840 unique feature combinations.

Each combination was evaluated to predict an engagement score. The predicted scores were classified into four performance categories according to percentile thresholds of the overall score distribution. First, Very High corresponds to a score equal to or greater than 0.82, which represents the 90th percentile and above. Second, High corresponds to a score ranging from 0.74 to 0.81, which covers the 75th to the 89th percentile. Third, Moderate corresponds to a score ranging from 0.60 to 0.73, which includes the 50th to the 74th percentile. Fourth, Low corresponds to a score lower than 0.60, which falls below the 50th percentile.

The top ten combinations with the highest predicted scores are presented in Table 5. Recommended Posting Schedule. For instance, Monday at 08:00 in the morning with a photo, or Monday at 17:00 in the afternoon with a video, both with approximately 150 caption characters and five hashtags, produced a Very High predicted engagement score.

Visual analysis further supports these recommendations. Figure 9. Engagement Heatmap by Posting Day and Time shows that weekday mornings, especially Wednesday and Thursday between 09:00 and 11:00, consistently achieve the highest predicted engagement. This trend is likely influenced by the peak activity period of students and staff during class breaks.

These results provide actionable insights for academic social media administrators to strategically plan the type of content, the optimal posting time, and the use of hashtags in order to maximize audience interaction.

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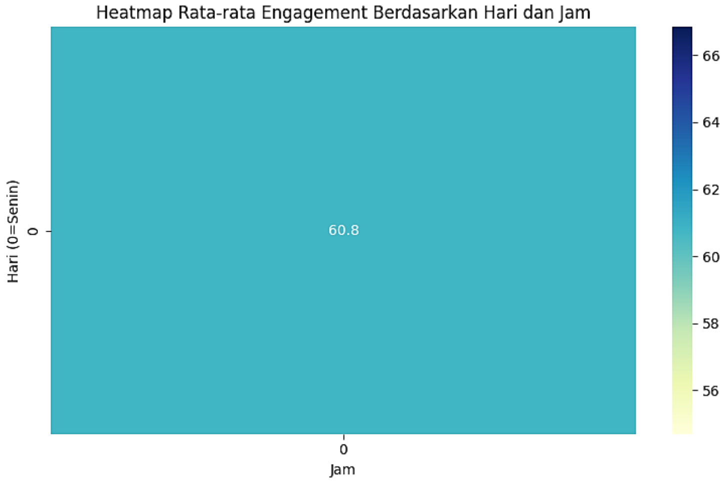

Figure 9. Heatmap of Engagement by Day and Time

Table 5. Recommended Posting Schedule

Rank	Day	Time	Content Type	Caption Length (characters)	Hastag Count	Predicted Engagement	Category
1	Monday	08:00	Photo	~150	5	0.84	Very High
2	Monday	17:00	Video	~150	5	0.83	Very High
3	Wednesday	09:00	Video	~140	8	0.82	Very High
4	Thursday	10:00	Photo	~150	8	0.81	High
5	Tuesday	12:00	Photo	~130	6	0.80	High
6	Wednesday	11:00	Video	~140	10	0.79	High
7	Thursday	09:00	Photo	~150	5	0.78	High
8	Tuesday	08:00	Video	~140	8	0.77	High
9	Friday	10:00	Video	~150	12	0.75	High
10	Wednesday	17:00	Photo	~140	8	0.74	High

3.4 Discussion of Findings

The results indicate that LSTM significantly outperforms a traditional linear regression baseline in predicting Instagram engagement, validating its suitability for modeling sequential and contextual dependencies. The strong influence of hashtag_count and posting time supports prior literature emphasizing the optimization of both content metadata and temporal factors to enhance audience interaction.

Practical implications of these findings include the potential for academic institutions to schedule content releases during identified high-engagement windows, optimize hashtag strategy for discoverability, and tailor media formats to audience preferences.

However, several limitations must be acknowledged. The dataset size, limited to 311 posts from a single institution, constrains the generalizability of the model. Additionally, the exclusion of visual content features (e.g., image quality, color composition) may omit factors influencing engagement. Future work will expand the dataset across multiple institutions, integrate computer vision-based visual feature extraction, and explore hybrid architectures combining LSTM with attention mechanisms to further enhance predictive performance.

4. CONCLUSION

This study successfully demonstrated that a Long Short-Term Memory (LSTM) based model can accurately predict Instagram engagement by integrating contextual and textual features. Trained on 311 posts from the official STIKOM CKI Jakarta account, the multi-input architecture effectively captured patterns in both caption text and contextual variables such as posting time and content type. The model achieved strong predictive performance with an R^2 score of 88 percent, a mean absolute error of 0.0450, and a root mean squared error of 0.0720, indicating minimal deviation from actual engagement values. Analysis further revealed that hashtag count and caption length are the most influential predictors, while simulation results identified optimal posting strategies based on day, time, and content format. Future research could explore larger and more diverse datasets, test additional social media platforms, or compare alternative algorithms to enhance prediction accuracy and model generalizability. Based on the results of this study, several recommendations can be proposed for both academic practitioners and future researchers. For social media administrators of academic institutions, it is advisable to adopt data-driven strategies when planning Instagram content.

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This includes optimizing posting schedules to align with peak audience activity, selecting content formats that have historically achieved higher engagement, and managing the number of hashtags to balance discoverability and relevance. For future research, expanding the dataset to include a longer observation period and multiple institutional accounts would improve model robustness and generalizability. Comparative experiments with other deep learning architectures such as GRU or transformer-based models may provide insights into alternative methods for engagement prediction. Additionally, extending the approach to other social media platforms could further validate its applicability and uncover platform-specific engagement patterns.

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