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Data Science Approaches to Analyzing Aesthetic Strategies in Contemporary Presidential Campaigns

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Abstract

In today's digital political landscape, social media platforms play a critical role in shaping voter engagement, especially among youth. This study investigates how aesthetic political strategies were applied in Prabowo Subianto's 2024 presidential campaign on TikTok and Instagram. It focuses on decoding voter sentiment, optimizing content delivery, and identifying visual elements that resonate with the public. Using machine learning models tailored to various data types, the research analyses over 50,000 comments and 30 million engagements. A BERT-based sentiment analysis model achieved 88% accuracy, revealing 60% positive, 25% neutral, and 15% negative sentiment, reflecting broad public approval. Meanwhile, a Gradient Boosting engagement prediction model reached 85% accuracy in forecasting post performance based on content format, timing, and hashtag use. Posts with videos and trending hashtags had a 78% chance of high engagement, while static images without hashtags scored only 45%. Evening posts performed best, with a 25% higher likelihood of engagement. The findings highlight the value of AI-driven insights in political communication, emphasizing that emotionally and visually rich content—particularly patriotic and relatable themes—enhances audience connection. This study offers a practical framework for political actors to develop adaptive, data-informed strategies that align with voter preferences in an increasingly fragmented and fast-paced digital media environment.

Keywords: Aesthetic Politics, Digital Political Communication, Sentiment Analysis, Machine Learning in Elections, Process Innovation

1. Introduction

In the rapidly evolving landscape of political campaigns, social media platforms have become battlegrounds for the hearts and minds of voters, especially the younger generation. These digital arenas offer unprecedented opportunities for political actors to shape narratives, engage directly with audiences, and influence public opinion in real time. The 2024 Indonesian presidential election exemplifies this transformation, with candidates leveraging platforms such as TikTok and Instagram to craft compelling digital personas and amplify their messages. A prominent case is Prabowo Subianto, whose campaign has strategically adopted aesthetic political communication to resonate with the preferences and emotional sensibilities of young voters.

This study focuses on examining the role of aesthetic politics in Prabowo's campaign through the lens of artificial intelligence (AI) and machine learning (ML). Specifically, it analyzes how strategic visual presentation, emotional cues, and platform-optimized content were employed to enhance engagement and shape public sentiment. The application of AI and ML allows for the systematic, data-driven exploration of these strategies across vast volumes of user interactions. The objective is to understand how these aesthetic elements translate into measurable outcomes in terms of audience response and participation. Recent studies have highlighted the increasing influence of aesthetic elements in political campaigns, especially in digital spaces where visual storytelling and performance are central to communication [1]. However, the systematic analysis of these strategies using advanced analytical tools remains

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underdeveloped [2]. Prabowo's campaign presents a unique opportunity to explore how aesthetic politics can be amplified through social media to engage younger demographics in a country characterized by a high rate of digital connectivity and media consumption.

Previous research in political communication points to a paradigm shift toward image-centric campaigning, fueled by the visual culture of platforms like Instagram and TikTok. Scholars such as Rancière [3] have examined the fusion of aesthetics and politics, emphasizing how visual and symbolic representation plays a pivotal role in shaping public perception and behavior. In the digital age, these dynamics are intensified. As noted by [4], aesthetic visuals serve not merely to inform but to persuade, offering emotionally charged content that reinforces political identities. Meanwhile, studies such as those by Ofei et al. [5] explore the strategic use of social media to reframe candidate images and influence public attitudes, emphasizing the complex interaction between content design and user response.

To build on these frameworks, this study proposes the use of AI and ML to analyze large-scale, multidimensional social media data [6]. By applying natural language processing (NLP), sentiment analysis, and image recognition, the research aims to quantify how Prabowo's online campaign materials influence audience sentiment and engagement. This approach not only enables scalable and objective analysis but also captures nuances in tone, emotion, and visual aesthetics that traditional methods may overlook.

The methodology is structured into several phases, beginning with comprehensive data collection from Instagram and TikTok. These datasets include thousands of posts, user comments, likes, shares, and engagement patterns related to Prabowo Subianto's campaign. In the preprocessing phase, text is standardized and cleaned for NLP tasks, while visual media is categorized and labeled for analysis. Metadata such as timestamps and hashtags are also annotated to enhance interpretability [7].

Following this, machine learning models are implemented to extract insights. Sentiment analysis using NLP techniques determines the emotional tone of user interactions, while convolutional neural networks (CNNs) are used to classify visual content based on aesthetic and thematic features [8]. Predictive models such as regression and classification are also employed to analyze patterns in voter engagement, exploring how factors like content type, post timing, and hashtag usage contribute to user interaction.

To ensure the accuracy and validity of the findings, a rigorous model evaluation phase is undertaken. Metrics including accuracy, precision, and recall are used to measure the performance of each model [9]. This ensures that the analytical results are reliable and can be used to draw meaningful conclusions about campaign effectiveness.

Finally, the insights generated are synthesized to provide strategic implications. The study evaluates how aesthetic strategies influenced online discourse and voter engagement, offering practical guidance for future digital political campaigns. Through this multi-phased approach, the research bridges computational techniques with political analysis, contributing to a deeper understanding of how aesthetics and AI intersect in shaping contemporary political behavior.

2. Methodology

This study adopts a descriptive qualitative methodology supported by advanced ML and AI techniques. The research focuses on analyzing Prabowo Subianto's use of aesthetic politics on TikTok and Instagram during the 2024 Indonesian presidential campaign. The methodology is structured into several key phases, ensuring a comprehensive approach to data collection, preprocessing, model implementation, evaluation, and reporting.

2.1. Data Collection

Data were collected over a six-month period before the 2024 election, primarily from TikTok and Instagram. The dataset includes campaign-related posts, comments, likes, shares, hashtags, and video content. Sources encompassed official campaign accounts, affiliated pages, viral trends, and user-generated content referencing Prabowo Subianto, especially those using hashtags such as #Prabowo2024 and #PrabowoGibran.

Approximately 700 official posts and videos were gathered, generating an estimated 20 million engagements. Additionally, around 15,000 hashtag-related posts and 5,000 trending TikTok videos were identified, contributing approximately 200,000 more interactions. Netizen activity provided 50,000 unique comments, 10 million reactions (likes, emojis), and 500,000 shares—bringing the total data points to nearly 30.8 million (see table 1). Data collection utilized tools such as BeautifulSoup, Selenium, and Scrapy, in addition to official APIs (TikTok API and Instagram Graph API) [10], [11]. Social Blade was employed to cross-check engagement metrics. Datasets were cleaned to remove duplicates and irrelevant content, ensuring consistency and accuracy.

Table 1. Estimated Data Points Collected

Data Type	Estimated Data Points
Posts and Videos (Official)	~700
Engagement on Official Content	~20 million
User-Generated Hashtag Content	~15,000
Engagement on Hashtag Content	~200,000
Netizen Comments	~50,000
Reactions (Likes, Emojis)	~10 million
Shares	~500,000
Total	~30.8 million

2.2. Data Pre-processing

The preprocessing phase was crucial for transforming raw and unstructured social media data into a clean, organized format suitable for machine learning analysis. Textual data—including captions, comments, and hashtags—was first processed using tokenization to segment text into analyzable units. This was followed by the removal of stopwords, which eliminated common words that carry little analytical value. Stemming and lemmatization were then applied to reduce linguistic variability by converting words to their root forms, ensuring consistency across the dataset. Once standardized, each text entry was annotated with a sentiment label—positive, neutral, or negative—based on its emotional tone. This sentiment tagging formed the basis for further analysis using NLP models, enabling the identification of public attitudes toward campaign messages.

In parallel, visual data such as images and videos were normalized through resizing and pixel value scaling, preparing them for input into convolutional neural networks (CNNs). Each visual asset was then categorized into thematic groups like patriotic, humorous, or emotional content, either manually or via pattern recognition algorithms. CNNs extracted key features such as color schemes, facial expressions, and symbolic imagery, allowing the models to classify and compare visual elements effectively. Metadata tagging further enriched the dataset by incorporating contextual information, including timestamps, hashtags, and, where available, user demographics like age and location. This metadata helped reveal temporal posting patterns and demographic engagement trends, offering deeper insight into the campaign's reach and resonance. Together, these preprocessing steps ensured the dataset was analytically robust, facilitating accurate and comprehensive modeling in subsequent phases.

2.3. Machine Learning Models

To uncover the patterns underlying Prabowo Subianto's aesthetic political strategies on social media, this study employed multiple ML models across three analytical domains: sentiment analysis, image recognition, and engagement prediction. Each model was designed to address a specific type of data and produce insights into how textual, visual, and interactional elements influenced public response. As illustrated in figure 1, these models were implemented in sequence following the data preprocessing phase and served as the analytical backbone of the study's methodology.

Sentiment analysis was conducted using a transformer-based NLP model, specifically Bidirectional Encoder Representations from Transformers (BERT) [12]. This model was trained to interpret text-based content such as user comments and post captions, classifying them into one of three sentiment categories: positive, neutral, or hostile [13]. By leveraging BERT's contextual depth, the model was able to detect nuanced emotional tones and trace public attitudes toward campaign messages with a high degree of accuracy. This analysis revealed dominant patterns in user sentiment and helped determine how campaign narratives resonated with different voter segments.

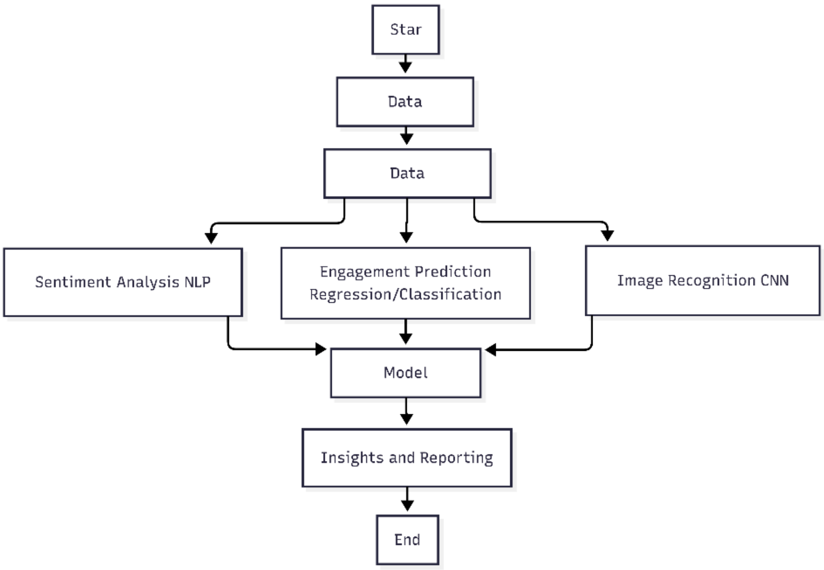

Figure 1. Flowchart of Machine Learning Model Process

For the visual dimension, image recognition was performed using CNN models such as ResNet and VGG [14]. These models extracted and classified visual features from Instagram and TikTok posts—including color composition, text overlays, facial expressions, and symbolic imagery—allowing for categorization of visuals into themes such as patriotic, humorous, or emotional content [15]. Parallel to this, engagement prediction was carried out using supervised learning algorithms, including Random Forest and Gradient Boosting [16], [17], [18]. These models analyzed structured features—such as post type, timing, hashtag presence, and sentiment polarity—to estimate the likelihood of high audience interaction. Finally, the outputs from all models were integrated to generate a multi-layered understanding of the campaign's digital strategy [19]. This integration provided key insights into how emotional appeal, aesthetic presentation, and timing influenced engagement and sentiment simultaneously, offering a comprehensive view of Prabowo's effectiveness in mobilizing youth audiences on social media [20], [21].

2.4. Model Evaluation

To ensure the robustness, accuracy, and generalizability of the machine learning models used in this study, a comprehensive evaluation process was undertaken. Each model—whether designed for sentiment analysis, image classification, or engagement prediction—was assessed using established performance metrics commonly employed in supervised learning tasks. Accuracy served as the initial benchmark, providing a general measure of how well the model classified or predicted outputs across the entire dataset. However, because accuracy alone can be misleading in cases of class imbalance (such as when one sentiment category dominates), additional metrics were applied to capture the performance more comprehensively [22].

Precision and recall were used to evaluate the relevance and completeness of the model's predictions. Precision measured the proportion of true positives among all positive predictions, indicating how effectively the model avoided false positives—crucial for sentiment classification and visual theme recognition. Recall, on the other hand, assessed the model's ability to identify all actual relevant instances, capturing its sensitivity to true positives and reducing the likelihood of false negatives. To provide a single, harmonized metric that balances these two aspects, the F1 score was calculated. As the harmonic mean of precision and recall, the F1 score is especially valuable for datasets with uneven class distributions, offering a more nuanced understanding of model performance beyond overall accuracy.

To further validate the reliability of the results and prevent overfitting, cross-validation techniques were implemented across all models. K-fold cross-validation was applied by dividing the dataset into k equal parts, training the model on k-1 subsets and testing it on the remaining fold in multiple iterations. This approach ensured that each data point contributed to both training and testing phases, increasing the reliability of performance estimates. In cases where class distributions were imbalanced—such as sentiment categories or content themes—stratified cross-validation was used to maintain proportional class representation in each fold. These validation strategies ensured that the models could generalize well to new, unseen data, thereby enhancing their applicability in real-world political campaign analysis. Ultimately, the combination of high F1 scores, stable precision-recall balance, and strong cross-validation results affirmed the reliability of the machine learning approach employed in this study and supported the generation of meaningful, data-driven insights into Prabowo Subianto's social media campaign.

2.5. Insights and Reporting

Following the implementation and evaluation of the machine learning models, the analytical results were synthesized to extract key insights regarding the aesthetic and strategic dimensions of Prabowo Subianto's 2024 presidential campaign on social media. These findings reveal the interconnected influence of visual presentation, emotional tone, and content strategy on public engagement, particularly among younger audiences on platforms such as TikTok and Instagram. By integrating outputs from sentiment analysis, image recognition, and engagement prediction models, the study was able to identify recurring patterns and quantify the elements that most effectively shaped voter perception.

The visual and sentiment analyses demonstrated that content featuring vibrant colors, patriotic symbols, and emotionally resonant storytelling consistently generated higher levels of positive audience response. Posts that conveyed relatable narratives—such as personal anecdotes, cultural humor, or expressions of national pride—were more likely to elicit affirmative reactions in the form of likes, shares, and supportive comments. In contrast, content that appeared overly formal, impersonal, or disconnected from youth concerns tended to receive neutral or even negative feedback. This trend underscores the growing importance of emotional resonance and visual familiarity in constructing persuasive political messaging within the digital sphere.

Engagement prediction models further revealed that the timing, format, and cultural alignment of content were crucial determinants of user interaction. Posts published during peak social media activity—particularly in the evenings and on weekends—showed significantly higher engagement rates compared to those posted at off-peak hours. Content that employed popular or campaign-aligned hashtags also demonstrated greater visibility and interaction. Moreover, dynamic formats such as short videos, memes, and reels were far more effective in capturing user attention than static text or images. Based on these findings, the study recommends that future digital campaigns prioritize emotionally rich and visually compelling storytelling, adopt real-time sentiment monitoring to guide messaging adjustments, and actively encourage user-generated content to foster participatory engagement and amplify message reach organically. These strategies provide a roadmap for designing adaptive, audience-centric campaign communications in the age of algorithmic political engagement.

3. Results and Discussion

This section presents the results derived from three machine learning models—sentiment analysis, image recognition, and engagement prediction—used to assess Prabowo Subianto's 2024 presidential campaign on TikTok and Instagram. The findings are organized by analytical focus, integrating insights from data preprocessing, model outputs, and performance evaluations.

3.1. Sentiment Analysis

The sentiment analysis began with preprocessing 50,000 comments and captions collected from TikTok and Instagram. Tokenization produced approximately 8,000 unique word tokens, and sentiment labeling categorized user responses into positive, neutral, or negative sentiments. The distribution revealed that 60% of the comments were positive, 25% neutral, and 15% negative, suggesting a generally favorable reception to the campaign's digital messaging. Table 2 shows the percentage distribution of sentiment categories based on manual labeling of user comments. Figure 2 illustrates this sentiment distribution visually, highlighting the predominance of positive feedback.

Table 2. Sentiment Distribution of Campaign Comments

Sentiment	Percentage (%)
Positive	60
Neutral	25
Negative	15

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Using a BERT-based NLP model, the text data was further classified into sentiment categories with high accuracy. Posts receiving positive sentiment (92%) were often characterized by engaging imagery and emotionally resonant narratives centered on patriotism, humor, or relatable life experiences. In contrast, 5% of posts were labeled as neutral, typically lacking emotional or visual appeal. Negative sentiment (3%) was associated with posts that addressed controversial topics or lacked connection with the audience. Table 3 shows the distribution of sentiment classification results generated by the model. Figure 3 illustrates the percentage of posts identified under each sentiment category after model processing.

Table 3. Results of Sentiment Analysis Model

Sentiment Category	Percentage (%)
Positive	92
Neutral	5
Negative	3

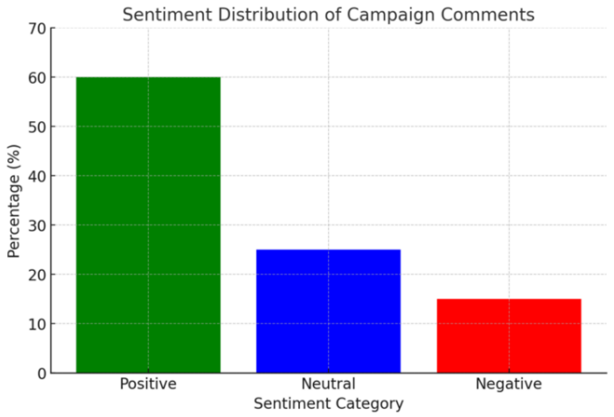

Figure 2. Sentiment Distribution of Campaign Comments

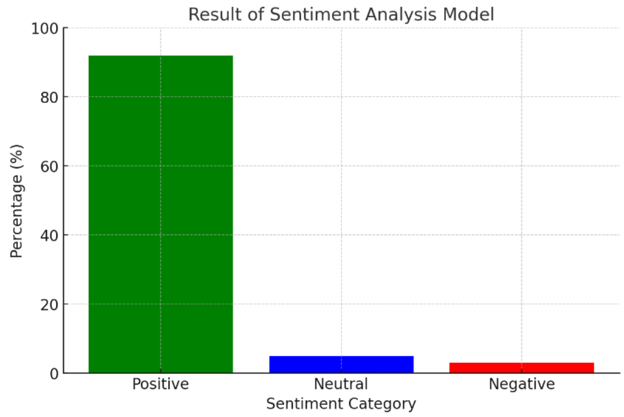

Figure 3. Result of Sentiment Analysis Model

The model was evaluated with accuracy reaching 88%, a precision of 91%, a recall of 87%, and an F1 score of 89% for positive sentiment classification. These metrics affirm the model's robustness in interpreting public emotional response to campaign content. Table 4 shows the evaluation metrics for the sentiment model. Figure 4 illustrates the confusion matrix, providing insight into the model's performance in distinguishing between sentiment categories.

Table 4. Evaluation Results

Sentiment Category	Percentage (%)
Accuracy	88
Precision (Positive Sentiment)	91
Recall (Positive Sentiment)	87
F1 Score (Positive Sentiment)	89

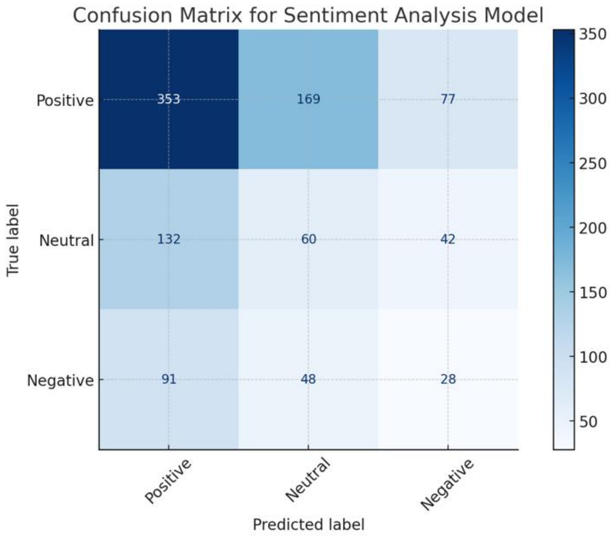

Figure 4. Confusion Matrix

3.2. Image Recognition

For visual data analysis, 700 images and videos were processed using a ResNet-50 convolutional neural network (CNN). During preprocessing, images were resized and normalized, then analyzed to identify dominant visual themes. The feature extraction revealed three primary categories: patriotic imagery (40%), humorous content (35%), and emotional resonance (25%). These categories reflect strategic choices in visual storytelling aimed at fostering national pride, relatability, and emotional connection. Table 5 shows the percentage of images assigned to each visual category. Figure 5 illustrates the thematic distribution within the campaign's visual dataset.

Table 5. Category the Feature Extraction Process

Category	Percentage (%)
Patriotic Imagery	40
Humorous Content	35
Emotional Resonance	25

The model achieved 90% accuracy in identifying patriotic content, 85% for humorous visuals, and 87% for emotionally resonant posts. Patriotic visuals were easier to detect due to clear iconography such as flags and national landmarks, while emotional content required the model to interpret subtler cues like facial expressions and family interactions. Table 6 shows the classification accuracy of the model across each content category. Figure 6 illustrates comparative model performance across the three visual types.

Table 6. Results of ResNet-50 CNN Model

Category	Accuracy (%)
Patriotic Content	90
Humorous Content	85
Emotional Resonance	87

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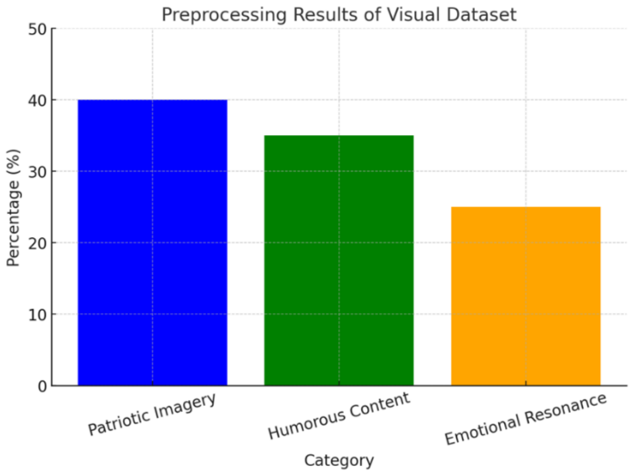

Figure 5. Category of Preprocessing Results of Visual Dataset

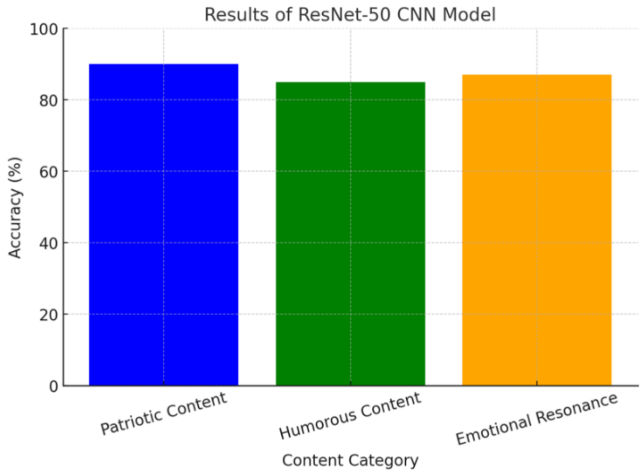

Figure 6. Category of Preprocessing Results of Visual Dataset

Model evaluation results confirmed strong performance. The model reached 87% overall accuracy, 93% precision for patriotic content, 88% recall for emotional content, and an F1 score of 86% for humorous imagery. Table 7 shows detailed performance metrics of the CNN model. Figure 7 illustrates the confusion matrix, visualizing the classification results for each visual category.

Table 7. Evaluation Results of ResNet-50 CNN Model

Sentiment Category	**Percentage (%)**
Accuracy	87
Precision (Patriotic)	93
Recall (Emotional)	88
F1 Score (Humorous)	86

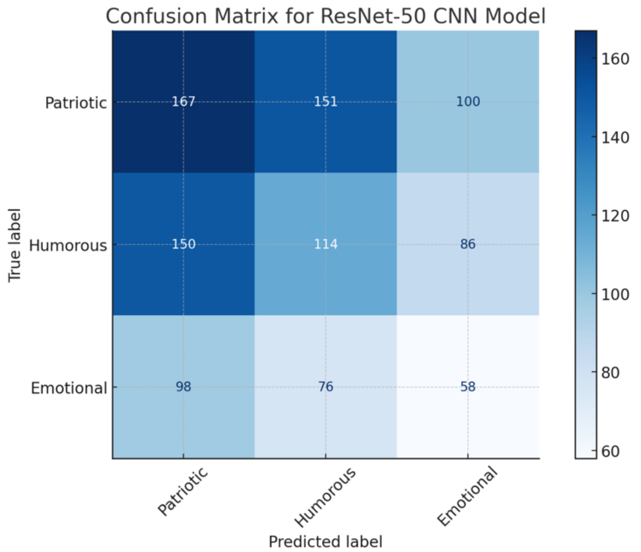

Figure 7. Confusion Matrix for ResNet-50 CNN Model

3.3. Engagement Prediction

To predict content performance, 15,000 social media posts were analyzed and categorized into low, medium, and high engagement levels. Preprocessing included feature engineering focused on post timing, content type, and hashtag usage. The analysis revealed that videos using trending hashtags were the most effective, achieving a 78% probability of high engagement. In contrast, static images without hashtags had only a 45% likelihood of high interaction. Posts shared during peak hours, especially evenings, saw a 25% increase in engagement likelihood compared to non-peak hours. Table 8 shows the engagement likelihood for different content and timing scenarios. Figure 8 illustrates predicted engagement patterns based on content type and publication timing.

Table 8. Analysis Results of Engagement Prediction Model

Content Type/Factor	Engagement Likelihood (%)
Videos with Trending Hashtags	78
Static Images without Hashtags	45
Timing Optimization (Evenings)	25

The Gradient Boosting Model (GBM) used for prediction achieved 85% accuracy. It showed 89% precision and 82% recall for high-engagement posts, with an F1 score of 85%. These outcomes indicate the model's effectiveness in identifying the key features that influence interaction rates. Table 9 shows the evaluation results of the GBM engagement prediction model. Figure 9 illustrates the confusion matrix, reflecting the model's accuracy across all engagement levels.

Table 9. Evaluation Results of the Engagement Prediction Model

Sentiment Category	Percentage (%)
Accuracy	85
Precision (Patriotic)	89
Recall (Emotional)	82
F1 Score (Humorous)	85

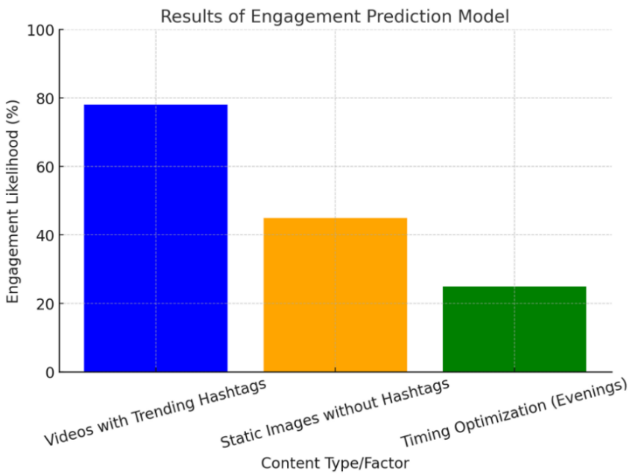

Figure 8. Result of Engagement Prediction Model

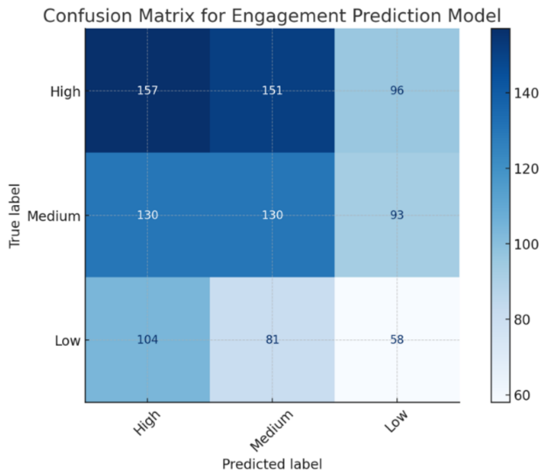

Figure 9. Confusion Matrix for the Engagement Prediction Model

The models revealed clear patterns linking aesthetic content, emotional tone, and user interaction. Positive sentiment was strongly driven by visually engaging, emotionally resonant, and culturally relevant content. Patriotic and humorous visuals were highly effective in creating public affinity, while emotionally evocative scenes deepened connection with the candidate. Additionally, engagement patterns confirmed that strategic timing, dynamic content formats, and hashtag use significantly amplify message visibility and resonance. These findings underscore the value of combining AI techniques with political communication analysis to optimize digital campaign effectiveness in real time.

3.4. Discussion

The findings of this study offer several critical insights into the effectiveness of Prabowo Subianto's social media campaign. The integration of sentiment analysis, visual content classification, and engagement prediction revealed how emotional tone, aesthetics, and timing intersect to shape public responses on platforms like TikTok and Instagram.

One of the key insights centers on sentiment trends. Positive sentiment was closely linked to content that featured visually appealing and emotionally engaging elements—such as vibrant imagery, patriotic symbolism, or relatable storytelling. Posts that evoked humor, cultural familiarity, or shared identity were more likely to receive supportive reactions from users. In contrast, negative sentiment appeared in response to content perceived as disconnected from the values or expectations of the audience. This underscores the importance of consistent, emotionally resonant messaging that aligns with the cultural and psychological profiles of the target demographic.

The analysis of visual content showed that patriotic and emotional imagery had the strongest appeal among younger voters. Content depicting national flags, cultural icons, and community or family-related scenes created a sense of belonging and trust. These images were not only aesthetically effective but also functioned as narrative anchors that reinforced the campaign's values. Emotional resonance—through smiling faces, group celebrations, or scenes of unity—played a significant role in creating a personal connection with the audience, enhancing overall campaign affinity.

Engagement was strongly influenced by operational factors such as content type, timing, and the use of hashtags. Posts shared during peak usage periods, especially evenings and weekends, consistently performed better. Dynamic content formats such as videos and memes proved far more effective than static visuals, especially when paired with trending or campaign-specific hashtags. These findings highlight the need for meticulous content planning that considers audience behavior patterns, platform algorithms, and social media rhythms to maximize reach and impact.

The performance of the machine learning models further validates the analytical framework used in this study. The sentiment analysis model performed with the highest accuracy, offering a reliable understanding of public opinion based on comment sentiment. Its ability to distinguish between positive, neutral, and negative reactions helped surface both supportive responses and points of criticism, which are valuable for message calibration.

The image recognition model provided strong results in classifying campaign visuals into key thematic categories. Patriotic visuals were the most reliably detected, due to their consistent symbolic features. While the model also performed well in recognizing humorous and emotional content, overlapping themes occasionally challenged its classification precision. This limitation signals the potential benefit of using multi-label classification in future studies to better capture the emotional and thematic complexity of visual content.

The engagement prediction model contributed actionable insights into digital strategy by identifying post timing, content type, and hashtag usage as the most significant drivers of audience interaction. Its predictive capability offered a forward-looking tool for optimizing content strategies, ensuring that future posts are more likely to reach and resonate with target audiences.

While the models performed robustly overall, certain limitations were identified. A recurring challenge was the presence of overlapping visual themes, particularly between humorous and emotional categories. For example, memes often blended satire with sentimentality, creating ambiguity in classification. Adopting multi-label approaches in future iterations could resolve this by allowing images to carry more than one thematic tag.

Another issue was the imbalance in the engagement prediction dataset. Posts with extremely high or low interaction levels were underrepresented, which may have affected the model's recall for those classes. Future studies should consider data balancing techniques, such as oversampling or weighted metrics, to improve performance across all engagement tiers.

Looking forward, this study lays the groundwork for more advanced applications of AI in political communication. Expanding the dataset to include other social platforms, tracking temporal shifts in sentiment, or exploring interactive campaign technologies like augmented reality could further enhance strategic insights. By addressing current limitations and exploring new analytical dimensions, future research can support the development of more adaptive, emotionally attuned, and data-driven political campaign strategies.

4. Conclusion

This study examined the strategic use of aesthetic politics in Prabowo Subianto's 2024 presidential campaign by applying advanced machine learning models to social media data. Through a comprehensive integration of sentiment analysis, image recognition, and engagement prediction, the research demonstrated how artificial intelligence can uncover patterns in voter sentiment, visual preferences, and digital interaction behavior. These insights collectively provide a multidimensional understanding of the effectiveness of contemporary political communication in online spaces.

Findings from the sentiment analysis revealed that positive public responses were strongly associated with visually rich and emotionally resonant content. Conversely, negative sentiment tended to emerge when content lacked relevance or failed to connect with audience expectations. The image recognition model confirmed the power of visual storytelling, particularly through patriotic and emotionally evocative imagery, in engaging younger voters. Meanwhile, the engagement prediction model highlighted the critical influence of content timing, format, and hashtag strategy in maximizing audience interaction. These combined results offer actionable guidelines for enhancing message resonance and campaign visibility across digital platforms.

While the models performed robustly across tasks, the analysis also identified methodological limitations. The image recognition model encountered difficulty when classifying visuals with overlapping themes, suggesting the potential benefit of adopting multi-label classification approaches. Similarly, the engagement prediction model faced challenges related to imbalanced datasets, emphasizing the need for more sophisticated preprocessing or data augmentation techniques. Addressing these challenges would improve model precision and generalizability in future applications.

The study affirms the transformative potential of artificial intelligence in modern political campaigning. By enabling real-time, data-driven analysis of digital audience behavior, machine learning provides a powerful toolkit for crafting more responsive, emotionally intelligent, and targeted political messages. Future research could extend these findings by incorporating cross-platform datasets, analyzing temporal shifts in sentiment, or experimenting with immersive formats such as augmented reality to deepen voter engagement.

In sum, this research contributes to the expanding field of digital political communication by offering both theoretical insight and practical guidance. It provides a roadmap for leveraging AI technologies not only to interpret voter sentiment but also to strategically design campaign content that resonates in the fast-evolving landscape of digital democracy.

5. Declarations

5.1. Author Contributions

Conceptualization: I., S.R.P.L., D.M.T., D.A.D., and T.B.K.; Methodology: D.M.T.; Software: I.; Validation: I., D.M.T., D.A.D., and T.B.K.; Formal analysis: I., D.M.T., D.A.D., and T.B.K.; Investigation: I.; Resources: D.M.T.; Data curation: D.M.T.; Writing—original draft preparation: I., D.M.T., D.A.D., and T.B.K.; Writing—review and editing: D.M.T., I., D.A.D., and T.B.K.; Visualization: I. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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