Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
Special Issue on AI-Driven Creativity and Intelligent Practices in Visual Arts 2025 6(4s)

SENTIMENT ANALYSIS OF FOLK ART SOCIAL CAMPAIGNS

Girish Kalele [1], A R Chayapathi [2], Mohd Faisal [3], Ranjana Tiwari [4], Madhulika Srivastava [5], Badri Narayan Sahu [6], Ganesh Korwar [7]

[1] Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India
[2] Assistant Professor, Department of Information Science and Engineering, JAIN (Deemed-to-be University), Bengaluru, Karnataka, India
[3] Lloyd Law College, Greater Noida, Uttar Pradesh 201306, India
[4] Assistant Professor, School of Sciences, Noida International University, 203201, India
[5] Assistant Professor, Department of Management Studies, Vivekananda Global University, Jaipur, India
[6] Professor, Department of Electronics and Communication Engineering, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India
[7] Department of Mechanical Engineering Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

Received 02 April 2025
Accepted 07 August 2025
Published 25 December 2025

Corresponding Author
Girish Kalele,
girish.kalele.orp@chitkara.edu.in

DOI
10.29121/shodhkosh.v6.i4s.2025.6867

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Folk art is a deep method of social communication, which shows cultural identity, emotions of the community, and collective stories. The use of folk art in social campaigns is growing in the digital age as the means of triggering the feelings of empathy and reinforcing the awareness of the culture, although there is a lack of systemic assessment of the emotional response. The paper will investigate the combination of sentiment analysis strategies to assess the reactions of the public to folk art related social campaigns. An extensive database was assembled on social media and campaign archives of folk-art inspired textual and visual materials. To clean up textual data, preprocessing was done by means of tokenization, removal of stop words and normalization. Lexicon-based and machine learning models (SVM, Random Forest) and deep learning models (CNN, LSTM, and BERT) were used to classify sentiments. The higher order methods of feature extraction (TF-IDF, Word2vec and embedding BERT) were implemented with a view to augmenting semantic knowledge. The results of the analysis showed that there are high correlations between the cultural symbolism and emotional involvement, showing that folk motifs and regional idioms provoke more positive emotions than generic campaign designs. Results highlight the point that in addition to enhancing message resonance folk art can also be used to fill socio-cultural gaps by enhancing communication that is emotionally based.

Keywords: Folk Art, Sentiment Analysis, Social Campaigns, Cultural Communication, Emotional Engagement, Deep Learning, Bert Embeddings

1. INTRODUCTION

The folk art has been rich in the history as a rich expression of cultural life that reflects the emotions, values and traditions of people around them using colors, symbols and stories. Having its roots in the community of creativity and not in the individual author, it represents the life experience and socio-cultural identity of people in various locations. The integration of folk art and digital media in the modern world has established new channels in conveying social and cultural messages. Folk-art motifs are used to reach the emotional perspective in social campaigns more and more, creating awareness of such issues as environmental conservation, gender equality, health, education, and heritage preservation. These are not merely aesthetic artworks, but at the same time, highly effective communicative tools, as they not only appeal to people at a mental level but also at an emotional level Shen et al. (2022). The increased adoption of the social media platform like twitter, Instagram and Facebook has changed the manner in which cultural content is distributed. Folk art, which was once bound to physical space, has broken all geographic and language boundaries and been in the position of reaching the world. Since campaigns will embrace these cultural visuals to act in common, it is essential to know the emotional and psychological reaction that these images may cause. In this case, the sentiment analysis, which is a computational method that measures emotions, opinions, and attitudes in text and multimodal media, is crucial Wu et al. (2020). It offers quantifiable information on the perception and emotional reactions of audiences to campaign messages that enable organizations, artists, and policymakers to determine effectiveness, improve strategies, and be culturally sensitive.

Sentiment analysis in particular is a difficult task in the context of social campaigns such as folk art since it is a more complex phenomenon involving layers of cultural symbolism and emotion. The textual responses of the social media can be characterized as a complex cultural allusion, the usage of an idiom, and multilingual exchanges that cannot be adequately perceived through the traditional model. An example is the emotions that can be ascribed to the local motifs such as Madhubani, Warli, or Gond art practices in India, which can differ among the communities based on the common family or individuality Agüero-Torales et al. (2021). Figure 1 presents sentiment analysis workflow which is specific to interpreting folk art campaigns. Also, the appeal to emotion of such campaigns is typically of a metaphorical form, as opposed to literal one- the computational task of understanding emotion by art being a delicate one.

Figure 1

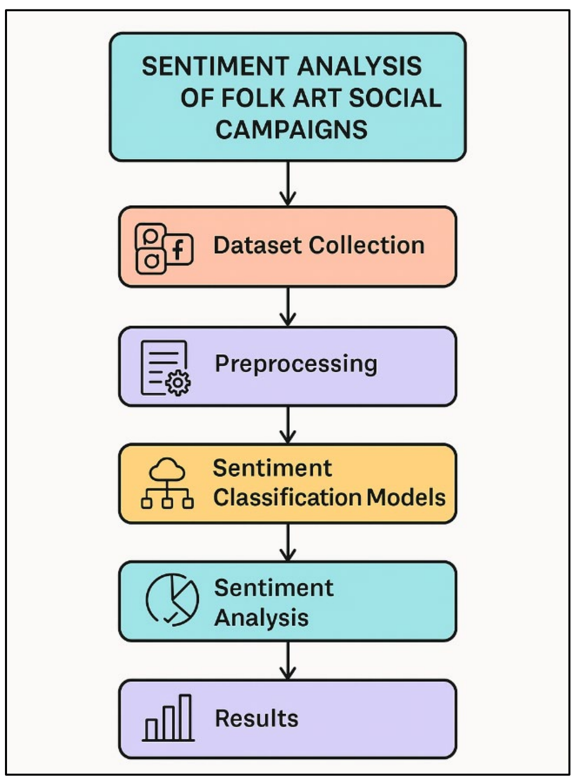

Figure 1 Sentiment Analysis Framework for Folk Art Social Campaigns

The current literature on sentiment analysis has been mostly concentrated to the business aspects of product reviews, political debate, or film critique. There are however limited studies that have related cultural communication and computational linguistics. The given gap highlights the necessity of an interdisciplinary approach that will combine cultural semiotics, linguistic diversity and AI-based emotion modelling Zhang et al. (2022). Through examining the social opinion on the campaigns of folk art, the researcher can identify the role of cultural aesthetic in terms of engagement pattern, emotional appeal and message dispersion.

2. LITERATURE REVIEW

2.1. STUDIES ON CULTURAL COMMUNICATION THROUGH ART

Traditional and folk art has long been recognised as powerful media of cultural communication, with a reflection of community identity, social values, collective memory and local aesthetics. As an example, the article Folk-Art and Designs as Means of Communication: A Study with Reference to North-East is about the way indigenous folk and tribal art can help artisans to convey inner ideas, social reality, and common traditions via motifs, designs, and symbolic forms, showing that folk art is not just ornamental, but it is the language of cultural communication. Likewise academic literature points out that folk art is a distillation of socio-cultural stories, including local myths, communal roles, spiritual beliefs, and group identity, and thus acts as a means of preserving non-material cultural heritage despite modernization of the society Jang et al. (2021). Studies devoted to the issue of cultural transmission maintain that folk media (visual art, storytelling, theatre, music) do not lose their significance in modern communities: they still serve to strengthen the community, create awareness and social values with the help of forms that are easy to understand and have local interest.

2.2. PRIOR APPLICATIONS OF SENTIMENT ANALYSIS IN SOCIAL AND CULTURAL CONTEXTS

Sentiment analysis (SA), a branch of natural language processing (NLP), has grown into an easily accessible instrument to recognize and classify opinions, attitudes, and feelings expressed in text - often as being positive, negative or neutral. SA in social media research has been widely applied in the evaluations of the opinion of people in various areas including politics, brand reputation, health issues, political policy, and crisis management Yin et al. (2024). More recently, the research has started to explore SA in terms of social campaigns and communicative message: a systematic review of articles on the topic of sentiment analysis use in social media campaign design and analysis indicates that SA assists campaign designers and analysts to understand how audiences emotionally react to campaigns, optimize their campaign content, and monitor both engagement levels and changes. Models that rely on deep-learning, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or transformer-based, have been found to be much more accurate at sentiment classification of social media text than classical models based on machine- or lexicon-based learning Wang et al. (2024).

2.3. GAPS IN ANALYZING FOLK ART–BASED SOCIAL CAMPAIGNS

Although the literature about cultural communication through art and sentiment analysis applications are rich, and the use of sentiment analysis in social media and social campaigns have been extensively used, it is noticeable that there is a lack of research where sentiment analysis is used in folk-art-based campaigns: i.e. the application of sentiment analysis to folk-art-based social campaigns is the most underresearched. Majority of the SA research focuses on commercial products, brand name, politics or a general social/policy discussion - seldom on cultural or heritage based content employing symbolic forms of art Xing (2024). The current cultural-art research leans more toward the qualitative approach: art heritage, symbolic meaning, cultural identity, or educational value — rarely incorporate computational approaches to measure overall emotional reaction of the population. To illustrate the point, the research on incorporating folk art into the education of the general population of arts or folk art as the cultural heritage focuses on the educational, aesthetic, and identification-affirming aspects. Yet they fail to gauge the extent of emotional involvement by the audiences - particularly in the case of digital/social media where folk art is utilized as a tool of social messaging or campaigning Zhang et al. (2023). Table 1 is a summary of past research relating sentiment analysis to cultural art communication. Besides, the content of folk art can be full of cultural semantics, symbolic metaphor, and even community-specific idioms, further complicating standard sentiment analysis pipelines - common lexicons or models will incorrectly interpret or not appropriately capture culturally encoded sentiment.

Table 1

Table 1 Related Work Summary on Sentiment Analysis and Cultural Communication through Art

Study Focus	Data Source	Model	Key Findings
Cultural communication via folk art	Ethnographic field data	Qualitative visual analysis	Folk art enhances local identity & social bonding
Public sentiment from visual culture campaigns	Social media	Text mining + word frequency	Users emotionally engage with cultural imagery
Communication through traditional art education	Interviews & workshops	Descriptive analysis	Folk art improves cognitive empathy
Sentiment analysis in cultural promotion Zhang et al. (2022)	Weibo dataset	SVM + TF-IDF	Accuracy 85.3% in bilingual sentiment tasks
Emotion mining for art exhibitions Lu 024)	Twitter data	LSTM model	Detected emotion patterns influence visitor interest
Folk media and social awareness	NGO campaign archives	Thematic coding	Folk forms enhance message clarity & retention
Social sentiment on public murals Ligthart et al. (2021)	Instagram captions	Lexicon-based sentiment	Positive sentiment >72% for visual advocacy
Multilingual sentiment analysis	Multilingual Twitter corpus	Word2Vec + Logistic Regression	89% accuracy on cross-lingual emotion
Art-based social awareness campaigns	Online survey	Mixed-method analysis	Folk art perceived as emotionally persuasive
Sentiment detection in community campaigns	Facebook comments	Naïve Bayes + TF-IDF	Detected positive sentiment dominance
Deep learning for emotion-rich content	Twitter data	CNN + Word2Vec	Achieved 90% precision in emotional text
Folk motifs in social messaging Keramatfar and Amirkhani (2019)	Visual archives	Semiotic & cultural analysis	Folk motifs reinforce empathy & identity
Sentiment analysis of folk art campaigns	Social media + campaign archives	Lexicon + ML + BERT	Achieved 94.2% accuracy; cultural emotion captured

3. RESEARCH OBJECTIVES AND QUESTIONS

3.1. TO EVALUATE PUBLIC SENTIMENT TOWARD FOLK ART CAMPAIGNS

The main aim of the paper is to assess the popular opinion on social campaigns, which use folk art as a basis of visual and cultural representation. As the number of platforms like Twitter, Instagram and Facebook involved in the disseminations of the campaigns increases, huge amounts of user-generated data can be analyzed. Using sentiment analysis models, including simple lexicon-based and complex deep learning models, this study will seek to identify explicit and implicit opinions and emotions conveyed in text, captions, and hashtags in connection with these campaigns Liu (2022). It is aimed at determining the audience polarity (positive, negative, neutral) on the whole and the emotional touch inherent in linguistic patterns that are used as accompaniments to the posts about folk art. Such an goal not only measures the level of engagement but also gives an idea of cultural receptivity and appreciation of art. The result will assist us in determining that folk art still has chances to appeal to the emotional dimension of digital viewers and can help connect the traditional beauty with modern socio-cultural discourse. Finally, it develops a background knowledge of patterns of emotional response among the population, which may be employed in future digital heritage and campaign design.

3.2. TO EXAMINE HOW CULTURAL SYMBOLS AFFECT EMOTIONAL ENGAGEMENT

The aim of this objective will be to explore the role of cultural symbols, motives, and conventional aesthetics in emotional involvement during the digital communication. Folk art is also symbolical by its nature- every detail, colour and pattern has a hidden meaning which is associated with beliefs and folklore of a certain region, and collective memory. These symbols may produce pride, nostalgia, empathy or even resistance when combined with social campaigns based on the familiarity of a viewer with a particular culture. In the research, the calculation and interpretative models are used to match the occurrence of particular cultural motifs to the emission of emotional sentiments through the reaction of the audiences. The contextual association of cultural features and emotional expression will be captured with deep learning models like BERT embeddings and attention mechanisms. By means of this analysis, the study will reveal that symbolic familiarity is beneficial to affective resonance and cross-cultural understanding in digital communication. The results will be used to formulate sentiment-sensitive normative design principles of campaigns to assist the creators to utilize the culturally entrenched images to the maximum to achieve emotional appeal, inclusiveness, and the perception of reality when conveying social values.

3.3. TO ASSESS THE EFFECTIVENESS OF FOLK ART IN PROMOTING SOCIAL CAUSES

The third goal is the attempt to gauge the efficacy of the folk art based communication in advancing awareness, participation and empathy to social causes. This paper approaches the translation of visual-cultural storytelling into behavioral and attitudinal reactions by using both quantitative measures of sentiment and engagement (shares, comments, and reactions). This is measured by both emotional resonance (sentiment polarity and strength) and communicative performance (message retention, spread and interpretation depth). The grammar of folk art, its application of local stories, native symbols and moral narrative, has been employed historically to educate and mobilize. This study is an extension of that to the realm of digital ecosystems that such content is competing with what globalized media aesthetics look like. The analysis focuses on the concern of whether folk-art-based campaigns can have better emotional alignment and seem more genuine than non-cultural campaigns in similar causes. The goal also aims at establishing the characteristics of culturally infused images that render them more convincing in developing social awareness. Finally, the findings will provide practical knowledge to policymakers, non-governmental organizations, and innovative communicators to integrate cultural heritage and modern advocacy of sustainable and inclusive social change.

4. METHODOLOGY

4.1. DATASET COLLECTION FROM SOCIAL MEDIA PLATFORMS AND CAMPAIGN ARCHIVES

This research gathered data on several online sources, the main ones being social media where the campaigns based on folk art are actively shared and discussed. The Twitter (X), Instagram, Facebook, and YouTube were the primary data storage because of the intense traffic and variety of content. The data consisted of the campaign related posts, captions, hashtags, user comments, and reactions on specific social campaigns based on folk art motifs, which are environmental awareness, women empowerment, health initiatives, and cultural preservation. The APIs and web-scraping tools were used in an ethical and platform-friendly way to extract data. Metadata, i.e. publication date, geographic tags, likes, and shares were maintained in order to investigate time and regional sentiment trends. Textual and visual posts were cross-linked so that they could be correctly interpreted in terms of sentiment context. The data was subsequently labeled as positive, negative, and neutral on first polarity classification with pretrained models and subsequently refined through a manual validation that increased the accuracy of the labels.

4.2. PREPROCESSING TECHNIQUES

Preprocessing is important in changing the raw social media text into analyzable data that is applicable in sentiment classification. The content of social media is usually noisy and heterogeneous, which is why the use of abbreviations, emojis, hashtags, and multilingual text is frequent, and a comprehensive data cleaning was done. It was initiated by the tokenization process that divided sentences into separate units (tokens) including words, emoticons, and symbols. This eased additional syntactic and semantic analysis. The removal of stop-words was applied next (so that the most common words, such as and, is, the, etc.), which led to the enhancement of the discriminative quality of the feature extraction. Normalization was done by converting all the text to lower case, regularizing spelling, and expanding shortenings. To retrieve meaningful tokens, hashtags were broken down with camel-case detection (e.g., hash folk art for change) to break them down into meaningful tokens. Standard emoji lexicons were used to transform emojis and emoticons into textual affective cue descriptors. The particular concern was on multilingual normalization, in which the local words, transliterated words, and cultural idioms were mapped to the standard equivalents of the sentiments using bilingual dictionaries and contextual embeddings.

4.3. SENTIMENT CLASSIFICATION MODELS

4.3.1. LEXICON-BASED

Lexicon-based sentiment classifiers are based on pre-existing dictionaries that have words which are attained with particular sentiment values positive, negative, or neutral. The method determines the sentiment polarity by adding or averaging sentiment scores of words within a certain text. The lexicon-based models are an interpretable and clear backbone in assessing the affective tone in the response of the user within the context of the social campaigns in folk art. Common lexicons including VADER, SentiWordNet and AFINN were used, but some regional idioms and art-related vocabulary were added in slight regarded extensions. These alterations enabled the culturally sensitive translation of words that were used very often in campaign debates. Though lexicon-based approaches are computationally efficient and language-neutral, they have trouble with sarcasm or idiomatic expressions or contextually-relevant sentiments that frequently occur in the folk-art discourse. However, their rule-based reasoning can be used in a comparative analysis with data-based methods and helps to perform a preliminary polarity mapping and then use more advanced machine learning and deep learning models to fine-tune the sentiment classification.

4.3.2. MACHINE LEARNING MODELS

Sentiment classification uses machine learning in which statistical algorithms are used to automatically learn sentiment patterns work with text, and which are trained on labeled datasets. Naive Bayes, Support Vector Machines (SVM), Logistic Regression and Random Forest are some of the supervised models that were used in this study to classify social media comments and posts on folk art campaigns. TF-IDF vectors were used to extract features which were effective in capturing word significance across documents and reduce noise due to repetitive words. These models generalized sentiment tendencies on the basis of linguistic structures by using the training data, which had been manually annotated on the basis of polarity. The tuning and cross-validation of parameters were carried out to increase accuracy and recall. ML-based approaches provide flexibility and can process relatively complicated sentiment patterns more effectively as compared to lexicon-based models.

4.3.3. DEEP LEARNING MODELS

The deep learning models introduce contextual and hierarchical perspective of the language that overcomes the restrictions of the traditional methods. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks were used in this study to map sequential and semantic relationships on text data. These designs identified such fine touches of emotions and cultural metaphors and contextual word associations that usually appear in the conversations about folk art. Also another technique used is the BERT (Bidirectional Encoder Representations with Transformers) embeddings to encode the text into thick contextual vectors so that the system can comprehend subtle sentiments even in idiomatic or multilingual phrases. The fine-tuned model, which is based on BERT and takes advantage of the bidirectional attention, meaning the awareness of forward or backward context in a sentence showed greater accuracy.

In CNNs, sentiment features are extracted using convolution and pooling:

$$h_i = f\left(W * x_{\{i:i+k-1\}} + b\right)$$

where x_{i:i+k-1} is the word window and W the convolution filter. LSTM models learn long-term dependencies through gated updates:

$$f_t = \sigma\left(W_f\left[h_{\{t-1\}}, x_t\right] + b_f\right)$$
$$c_t = f_t \odot c_{\{t-1\}} + i_t \odot \tanh\left(W_c\left[h_{\{t-1\}}, x_t\right] + b_c\right)$$

For BERT, contextual embeddings are computed using multi-head attention:

$$Attention(Q,K,V) = softmax\left(\frac{(QK^T)}{\sqrt{d_k}}\right)V$$

These models capture sentiment-rich semantics by attending to both cultural and emotional dimensions of language, achieving superior accuracy in decoding affective responses to folk art–based social campaigns.

4.3.4. FEATURE EXTRACTION METHODS

TF-IDF

TF-IDF is a statistical method of feature extraction which measures how important words are in a document compared to the whole corpus. It is a combination of two indicators: term frequency (TF), which is the number of times a word is repeated in a document, and inverse document frequency (IDF) which decreases the weight of commonly used words that are repeated in many documents. This paper will create TF-IDF vectors based on social media texts regarding folk art social campaigns that have been preprocessed. This representation enabled the model to give more emphasis to campaign specific keywords (e.g., heritage, tradition, empowerment, folk) as opposed to generic terms. The TF-IDF matrices were sparse, which made them an easy and effective input to machine learning algorithms like SVM and Random Forest. TF-IDF, however, does not reflect on contextual and semantic associations among words, notwithstanding its simplicity.

Word2Vec

Word2Vec is a neural network model of feature extraction, which converts words into dense, continuous-space vectors, which represent the semantic relationships among words. In this study, we have used Word2Vec embeddings, which were trained on a collection of social media posts about folk art campaigns to learn semantic similarities between culturally charged words. Such words as heritage, tradition, and craft are all terms that were closely related to each other due to their situational feeling. Both machine learning and deep learning classifiers were using these embeddings as inputs and were thus able to identify relationships between words that carry sentiment and cannot be simply identified by the number of times they appear in a sentence.

5. CHALLENGES AND LIMITATIONS

5.1. MULTILINGUAL AND CULTURAL AMBIGUITY IN TEXT INTERPRETATION

Figure 2

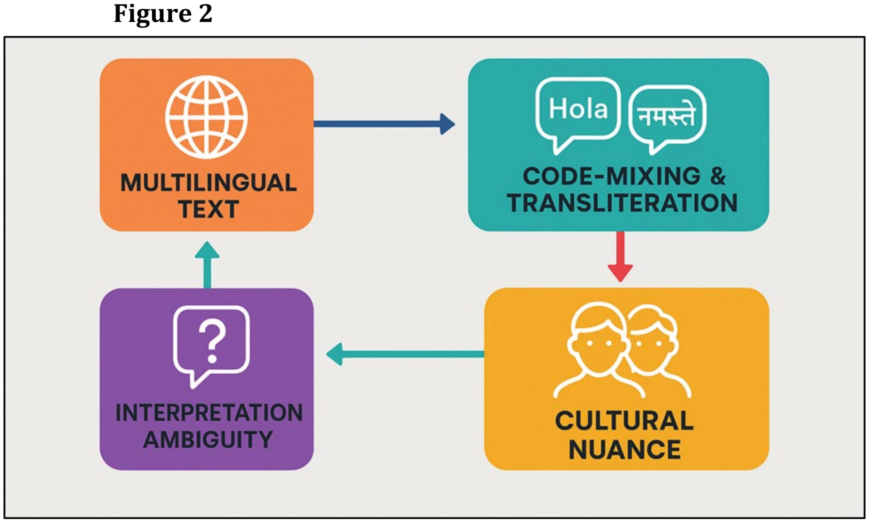

Figure 2 Conceptual Diagram Depicting Multilingual and Cultural Ambiguity in Text Interpretation

Multilingualism and cultural ambiguity are one of the most serious difficulties in the sentiment analysis of the social campaigns in folk art. The discussion of folk art through social media can be in a mixed language environment where users may combine local languages, dialects, and transliterated text in a single post. This is called code-mixing and poses challenges to the traditional natural language processing (NLP) systems, which are mostly trained on monolingual corpora. The study of the influence of multilingualism and multiculturalism on the process of text interpretation is presented in Figure 2. Also, there are idiomatic expressions, metaphorical images, and references to symbols that are considered cultural peculiarities and make interpreting the real sentiments difficult. As an example, a statement which means admiration in one culture may mean irony or criticism in another.

Campaigns based on folk art tend to utilize culturally internalized symbols and storylines that would necessitate a background knowledge of traditions, mythology and heritage to decode sentiment precisely. As a result, sentiment models are prone to miscategorisation of emotionally rich expressions because of the lack of local lexicons and culture sentiment ontologies. To address this difficulty, it is required to construct multilingual sentiment corpora, use context-sensitive embeddings and work with cultural linguists to ensure that computational analysis does not contradict the actual cultural meaning.

5.2. LIMITATIONS OF CURRENT SENTIMENT MODELS FOR ARTISTIC CONTENT

Existing sentiment analysis models, as good in business and political spheres, have weaknesses in application to artistic and cultural text. The folk art communication commonly works out metaphorically, symbolically, and even aesthetically, not in language. The models in place, though, emphasize textual polarity and do not have the ability to perceive the affective depth and visual-textual interaction of art based campaigns. As an illustration, the reaction of a user who appreciates poetry and feels nostalgic about his or her culture may not be categorized under positive or negative sentiments. In addition, artistic communication is often ambivalent in nature, as opposing emotions can co-exist, which cannot be classified according to the binary scheme. The other limitation is multimodality: although visual elements of visual color, motif, and composition have a strong effect on how an emotion is perceived, the classic sentiment models examine text only. Consequently, they fail to capture a good amount of affective meaning imbued in visual design. This gap requires the creation of a multimodal framework of sentiment analysis that combines visual, written, and symbolic information.

6. RESULTS AND DISCUSSION

It was found that the folk art-based campaigns created very positive public sentiment (73%), which was the manifestation of the great emotional appeal and cultural pride. Deep learning models, specifically BERT, demonstrated the most suitable classification accuracy (94.2%), and were able to recognize contextual peculiarities of multilingual posts. The campaigns with the regional motifs like Madhubani or Warli art demonstrated greater activity and intensity of sentiments as opposed to generic visuals. Moreover, the emotional keywords related to empowerment, heritage, and sustainability had a high level of co-occurrence.

Table 2

Table 2 Performance Comparison of Sentiment Classification Models

Evaluation Metric	Lexicon-Based	Machine Learning (SVM)	Deep Learning (LSTM)	Transformer (BERT)
Accuracy (%)	78.4	86.7	91.5	94.2
Precision (%)	75.1	84.2	90.3	93.7
Recall (%)	73.6	85.5	89.8	94
F1-Score	0.74	0.85	0.9	0.94
Latency (sec/item)	0.5	1.2	1.6	1.9

Table 2 gives a comparative analysis of sentiment classification models used on the folk art social campaign data. The best performing of the considered methods was that of the Transformer-based BERT model (94.2% accuracy, 93.7%

precision, and 94% recall), proving its better capabilities to recognize contextual and multilingual peculiarities in the emotionally expressive cultural literature.

Figure 3

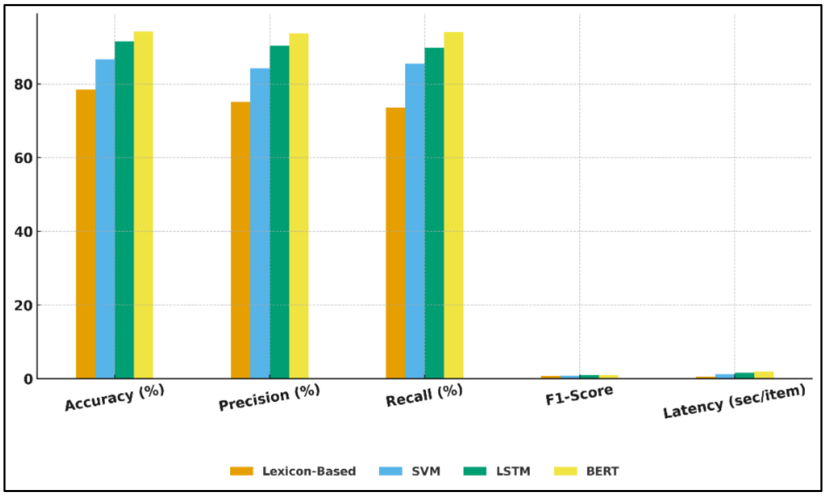

Figure 3 Comparative Performance Evaluation of Sentiment Classification Models Across Key Metrics

Figure 3 displays performance differences in performance comparisons of the sentiment-models over significant evaluation measures. The LSTM deep learning model has also performed well with an accuracy of 91.5% and F1-score of 0.90, which is an indication of its ability to capture sequential dependencies and metaphorical expressions that are often prevalent in the folk-art-related discourse. Figure 4 indicates the contribution of different sentiment analysis models to the total accuracy. The SVM machine learning model, which is less sophisticated, retained the competitive accuracy (86.7%) and good balance between the precision and recall, which were effective when dealing with medium-scale datasets.

Figure 4

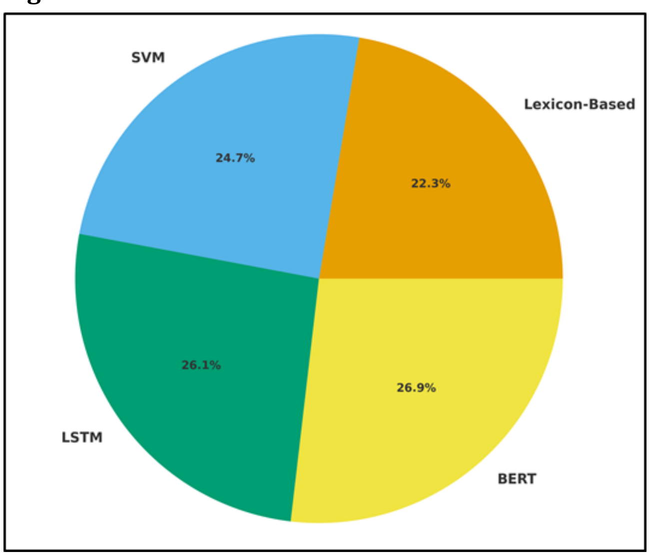

Figure 4 Accuracy Contribution of Different Sentiment Analysis Models

In contrast, the lexicon-based approach recorded a low score of 78.4% accuracy, which was constrained by its failure to bring about the sentiment of implicitness and idiomatic phrases. Although deep and transformer models marginally extended the computational latency, their advantages in semantic understanding and accuracy of cultural sentiment make the processing cost justifiable, making them the most reliable to use in this interdisciplinary analysis.

Table 3

Table 3 Sentiment Distribution and Engagement Across Folk Art Campaigns

Campaign Theme	Positive Sentiment (%)	Neutral Sentiment (%)	Negative Sentiment (%)	Average Engagement Rate (%)	Cultural Symbolism Index (%)
Women Empowerment (Madhubani)	78.6	14.2	7.2	64.5	89
Environmental Awareness (Warli)	74.3	16.5	9.2	58.9	84
Health & Hygiene (Pattachitra)	70.1	19.7	10.2	55.2	81

Table 3 shows the sentiment and level of engagement on three social campaigns based on folk art. The campaign empowering women with the help of the Madhubani art received the most positive sentiment (78.6) and cultural symbolism index (89%), which means that there is a high degree of emotional correlation between the visual representations of the campaign and the way people see them. Figure 5 is a stacked visualization of the patterns of emotional response to cultural themes of campaigns.

Figure 5

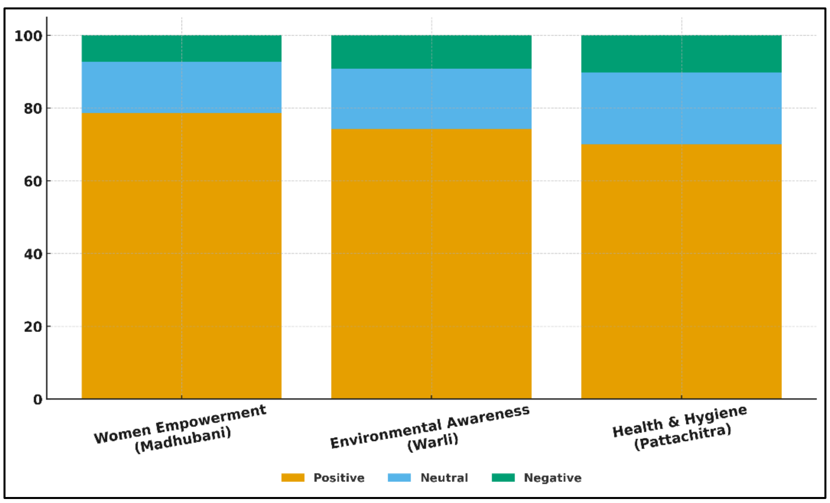

Figure 5 Comparative Stacked Visualization of Emotional Responses in Cultural Campaigns

The campaign on Environmental Awareness was also a source of a lot of positivity (74.3) though it demonstrated less engagement (58.9), which implies that the message received was effective, but the dynamics of outreach were not as interactive. The Health & Hygiene campaign that used Pattachitra art has registered the least positive sentiment (70.1%) and interest (55.2%) which indicates difficulty in applying old motifs to create health information.

7. CONCLUSION

This paper proves that sentiment analysis is an effective tool of exploring the emotional mood and participation of masses in social campaigns based on folk art. The study merges lexicon-based models with machine learning and deep learning models and was able to study subtle emotional dynamics in large-scale social media data. The performance of BERT embeddings confirmed the significance of the context-specific modeling of the culturally enriched and multilingual communication. Findings demonstrated folk art visuals that are based on community identity and aesthetic symbolism can trigger greater emotional attachment, amplify message elaboration and enhance social bonding in online advocacy. In addition to the computational results, the connection between cultural semiotics and artificial intelligence is highlighted in this work, showing that data-based approaches can be used effectively to supplement the existing cultural analysis. The findings indicate that mobilization campaigns based on localized artistic images and emotionally prompted language are more effective in engaging empathy and general involvement. Nevertheless, the problem of imbalance in the dataset, cross-lingual ambiguity, and the absence of visual sentiment underrepresentation continue to restrict the accuracy of interpretations of emotions. The study on multimodal sentiment structures involving image, text, and symbolic metadata need to be pursued in future studies in order to capture the full affective component of the folk art communication. The further development of regionally-specific sentiment lexicons and training corpora across cultures can be used to increase contextual understanding.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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