APPLICATION OF MACHINE LEARNING-BASED SENTIMENT ANALYSIS IN PACKAGING DESIGN STYLE PREDICTION MODELLING

Reference NO. IJME 1337, DOI: 10.5750/ijme.v1i1.1337

MY Zhang*, Department of Management, Woosong University, Daejeon, 34606, Korea

* Corresponding author. MY Zhang (Email): 15264828390@163.com

KEY DATES: Submission date: 17.11.2023 / Final acceptance date: 15.01.2024 / Published date: 12.07.2024

SUMMARY

Machine learning-based sentiment analysis plays a pivotal role in the innovative realm of packaging design style prediction modeling. By harnessing advanced algorithms, this approach analyzes consumer sentiments towards various packaging designs, extracting valuable insights into preferences and trends. The model utilizes machine learning techniques to identify patterns in historical data, allowing it to predict and recommend packaging design styles likely to resonate positively with target audiences. This research introduces an innovative approach to packaging design style prediction modeling by incorporating a machine learning-based sentiment analysis technique known as the Conditional Random n-gram Classifier Sentimental (CRn-gCS). Focused on enhancing the intersection of design aesthetics and consumer sentiments, this model employs advanced algorithms to analyze historical data and predict packaging design styles that resonate positively with target audiences. The CRn-gCS, as a key component, refines sentiment analysis by considering conditional relationships between n-grams, contributing to a nuanced understanding of consumer preferences. By leveraging this sophisticated model, designers and marketers can make informed decisions, ensuring that packaging not only aligns with aesthetic trends but also elicits positive emotional responses from consumers. This research contributes to the advancement of predictive modeling in packaging design, offering a comprehensive and data-driven approach to create visually appealing and emotionally resonant packaging.

KEYWORDS

Sentimental analysis, n-gram Classifier, Machine learning, Packaging design, Prediction

NOMENCLATURE

CRF	Conditional Random Field
CRn-Gcs	Conditional Random n-gram Classifier Sentimental
F	Frequency
MC	Machine learning

1. INTRODUCTION

Sentiment analysis, also known as opinion mining, is a burgeoning field in natural language processing that involves the extraction and analysis of sentiment from textual data. In an increasingly digital world where vast amounts of text are generated daily through social media, customer reviews, and other online platforms, understanding sentiment has become crucial for businesses, researchers, and policymakers alike [1]. By employing computational techniques and machine learning algorithms, sentiment analysis aims to classify opinions expressed in text as positive, negative, or neutral, providing valuable insights into public opinion, consumer preferences, and trends [2]. This field not only facilitates market research and brand management but also plays a vital role in monitoring social media sentiment during crises, gauging public opinion on political issues, and enhancing customer satisfaction. As sentiment analysis continues to evolve, its applications span various domains, promising to revolutionize how we understand and interact with textual data in the digital age [3].

Packaging design is a multifaceted discipline that blends creativity, functionality, and marketing strategy to create visually appealing and practical solutions for product packaging [4]. It plays a pivotal role in shaping consumer perceptions, influencing purchasing decisions, and establishing brand identity. Effective packaging design goes beyond aesthetics; it must also consider factors such as product protection, ease of use, and environmental sustainability [5]. Designers strive to strike a balance between capturing attention on crowded shelves, communicating essential product information, and ensuring the packaging aligns with the brand's values and messaging [6]. With the rise of e-commerce, packaging design has adapted to meet the demands of online retail, focusing on durability for shipping, compactness for storage, and the unboxing experience [7]. Moreover, sustainable packaging practices have gained traction, driving innovation in materials and design techniques to minimize environmental impact. In essence, packaging design serves as a powerful tool for brands to engage consumers, convey their story, and deliver memorable experiences that extend beyond the product itself [8].

Packaging design, while primarily focused on aesthetic appeal and functional attributes, also holds significant potential for sentiment analysis. Beyond its physical attributes, packaging serves as a conduit for emotional connection and brand perception [9]. Through sentiment analysis, designers can gain valuable insights into consumer perceptions, preferences, and emotional responses towards packaging designs [10]. By analyzing social media conversations, customer reviews, and online discussions, designers can assess how different elements of packaging—such as color schemes, typography, imagery, and messaging—affect consumers' feelings and attitudes towards a product or brand [11]. This analysis can inform iterative design improvements, ensuring that packaging resonates with target audiences on an emotional level, thereby fostering brand loyalty and positive consumer experiences [12]. Moreover, sentiment analysis can help designers anticipate and address potential issues or criticisms related to packaging design, allowing for proactive adjustments to enhance overall consumer satisfaction and brand perception [13]. In essence, combining packaging design with sentiment analysis offers a powerful framework for understanding and leveraging the emotional impact of packaging to drive consumer engagement and brand success [14].

The development and application of the Conditional Random n-gram Classifier Sentimental (CRn-gCS) model represent a novel approach to sentiment analysis specifically tailored for packaging design evaluation. By utilizing n-gram classification within a Conditional Random Field framework, our model offers a robust and adaptable method for analyzing sentiment in the context of product packaging. The implementation of the CRn-gCS model in analyzing the sentiment associated with different product categories provide valuable insights for businesses operating in various industries. Understanding consumer sentiment towards packaging design can inform strategic decisions related to branding, marketing, and product development, ultimately enhancing customer satisfaction and loyalty. Through empirical evaluation using real-world data from ten different products, we demonstrate the effectiveness and reliability of the CRn-gCS model in accurately classifying sentiment. The high accuracy, precision, recall, and F1-score metrics obtained across the evaluated products validate the efficacy of our approach and provide confidence in its practical applicability.

2. RELATED WORKS

Liu (2023) introduces a deep learning-based viewpoint prediction model for design drawings, focusing on influencing attention factors. This work contributes to the optimization of design processes through advanced computational techniques. Sripathi et al. (2024) illustrate the application of machine learning mixed methods text analysis in automated scoring models for student writing in biology education, showcasing the versatility of machine learning in educational assessment. Saleh et al. (2022) present a heterogeneous ensemble deep learning model for enhancing Arabic sentiment analysis, emphasizing the development of advanced computational methods tailored for specific linguistic contexts. Ezaldeen et al. (2022) propose a hybrid e-learning recommendation system integrating adaptive profiling and sentiment analysis, demonstrating the integration of machine learning in personalized e-learning platforms. Zhou et al. (2022) introduce a deep learning-based approach to facilitate cross-cultural Kansei design, showcasing the application of advanced computational methods in enhancing design processes with a cultural perspective. Krenn et al. (2023) forecast the future of artificial intelligence by employing machine learning-based link prediction in an exponentially growing knowledge network, highlighting the potential of machine learning in predicting trends and developments in AI.

El-Hasnony et al. (2022) utilize multi-label active learning-based machine learning models for heart disease prediction, showcasing the application of machine learning in healthcare for predictive analytics and diagnosis. Mohammed et al. (2023) present a machine-learning-based spectroscopic technique for non-destructive estimation of shelf life and quality of fresh fruits packaged under modified atmospheres, illustrating the use of machine learning in food technology and quality control. Hong et al. (2023) propose a dual-track lifelong machine learning-based fine-grained product quality analysis, demonstrating the integration of machine learning for continuous quality monitoring and improvement in manufacturing processes. Haque et al. (2023) introduce a machine learning-based technique for gain and resonance prediction of mid-band 5G Yagi antenna, showcasing the application of machine learning in telecommunications for antenna optimization. Yenkikar et al. (2022) develop a semantic relational machine learning model for sentiment analysis using cascade feature selection and heterogeneous classifier ensemble, demonstrating innovative approaches to sentiment analysis with machine learning. Uddin et al. (2022) utilize machine learning in project analytics, presenting a data-driven framework and case study for project management, highlighting the application of machine learning in optimizing project planning and execution. Li et al. (2022) work toward automated machine learning-based hyperspectral image analysis in crop yield and biomass estimation, showcasing the application of machine learning in agriculture for precision farming and resource optimization.

Rajamani & Iyer (2023) develop machine learning-based mobile applications using Python and Scikit-Learn, demonstrating the integration of machine learning in mobile app development for enhanced functionality and user experience. Shah et al. (2023) propose an ensemble-learning-based technique for bimodal sentiment analysis, showcasing innovative approaches to sentiment analysis using machine learning with multiple data modalities. Bu et al. (2023) review efficient utilization of pre-trained models for sentiment analysis via prompt learning, highlighting strategies to enhance sentiment analysis accuracy and efficiency through pre-trained models. Lee et al. (2022) explore technology opportunity discovery using deep learning-based text mining and a knowledge graph, demonstrating the application of machine learning in technology forecasting and innovation. Xu et al. (2022) develop a machine-learning-based risk-prediction tool for HIV and sexually transmitted infections acquisition over the next 12 months, showcasing the application of machine learning in public health for disease prediction and prevention.

One significant limitation lies in the interpretability of machine learning models, especially deep learning models, which often function as "black boxes," making it challenging to understand the underlying decision-making process. This lack of transparency can be problematic, particularly in critical domains like healthcare and finance, where understanding model decisions is crucial for trust and regulatory compliance. Additionally, the performance of machine learning models heavily depends on the quality and quantity of the training data. Biases present in the training data can lead to biased predictions and reinforce existing societal inequalities. Moreover, the need for large amounts of labeled data for training can be a bottleneck, especially in domains where data collection is costly or time-consuming. Another limitation is the computational complexity and resource requirements associated with training and deploying sophisticated machine learning models, particularly deep learning models. Training deep neural networks often requires significant computational power and specialized hardware, making them inaccessible to researchers and organizations with limited resources. Furthermore, the generalization capability of machine learning models can be limited, particularly when deployed in dynamic and evolving environments. Models trained on historical data may struggle to adapt to new trends or unseen scenarios, leading to a degradation in performance over time. Lastly, ethical considerations regarding data privacy, security, and algorithmic fairness pose significant challenges in the development and deployment of machine learning systems. Ensuring that these systems respect user privacy, mitigate security risks, and avoid perpetuating biases requires careful attention and regulatory oversight.

3. CONDITIONAL RANDOM FIELD SENTIMENTAL ANALYSIS

In recent years, Conditional Random Field (CRF) models have gained attention for their effectiveness in sentiment analysis tasks. CRF is a type of probabilistic graphical model that is particularly well-suited for sequence labeling problems, such as part-of-speech tagging and named entity recognition. In the context of sentiment analysis, CRF models excel at capturing the sequential dependencies between words or tokens in a text and assigning sentiment labels to each token based on its surrounding context. The CRF models for sentiment analysis typically involves defining a conditional probability distribution over a sequence of sentiment labels given an input text. This distribution is modeled using features that capture the characteristics of the text and its sentiment. The goal is to learn the parameters of the CRF model that maximize the likelihood of the observed sentiment labels given the input text. The conditional probability distribution in a CRF model can be represented using equation (1)

$$P(Y|X)=\frac{1}{Z(X)}exp\left(\sum_{i=1}^{n}\sum_{j=1}^{m}\lambda_j f_j\left(y_{i-1},y_i,x,i\right)\right) \quad (1)$$

In equation (1) Y represents the sequence of sentiment labels; X represents the input text; $Z(X)$ is the normalization factor, also known as the partition function, which ensures that the probability distribution sums to 1 over all possible label sequences; λj are the model parameters to be learned; fj are feature functions that capture relevant properties of the input text and its sentiment; $yi-1$ and yi represent the sentiment labels of adjacent tokens in the sequence; and X represents the input features associated with the tokens. The parameters λj are typically learned using optimization algorithms such as gradient descent, which minimize a loss function that measures the discrepancy between the predicted sentiment labels and the ground truth labels in a training dataset. The conditional probability distribution over the sentiment labels Y given an input text X. This is represented as $P(Y \mid X)$. Feature functions, denoted as fj, capture relevant properties of the input text and its sentiment. These features can include word embeddings, part-of-speech tags, syntactic information, and so on.

3.1 CONDITIONAL RANDOM N-GRAM CLASSIFIER SENTIMENTAL (CRN-GCS)

The Conditional Random n-gram Classifier Sentimental (CRn-gCS) is an extension of the traditional Conditional Random Field (CRF) model, specifically tailored for sentiment analysis tasks. CRn-gCS extends CRF by incorporating n-gram features, allowing the model to capture dependencies between words up to n-grams. This enables the model to consider contextual information beyond individual words, enhancing its ability to discern sentiment.

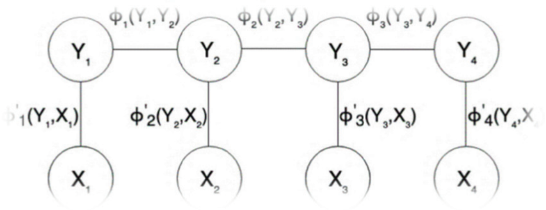

Figure 1. Condition random fielf model for the CRn-gCS

In figure 1 CRF, CRn-gCS aims to define a conditional probability distribution over sentiment labels *Y* given an input text *X*, represented as $P(Y \mid X)$. In addition to the features used in CRF, CRn-gCS includes n-gram features, which capture the co-occurrence patterns of words within a specified window size. N-gram features are extracted from the input text *X*, considering sequences of *n* adjacent words. These features capture the co-occurrence patterns of words and are represented using equation (2)

$$f_{n-gram}\left(x_i, x_{i+1}, \ldots, X_{i+n-1}\right) \tag{2}$$

In equation (2) *λj* are learned from the training data using optimization algorithms like gradient descent. The objective is to maximize the likelihood of the observed sentiment labels given the input text and its features. The conditional probability distribution $P(Y \mid X)$ in CRn-gCS can be expressed using the softmax function stated in equation (3)

$$P(Y|X) = \frac{exp\left(w.f\left(Y, X\right)\right)}{\sum_{Y'} exp\left(w.f\left(Y', X\right)\right)} \tag{3}$$

In equation (3) *Y* represents the sequence of sentiment labels; *X* represents the input text; *w* is the weight vector; *c* is the feature vector that depends on both the label sequence *Y* and the input text *X*. The feature vector *f*(*Y,X*) consists of individual feature functions, including n-gram features. Each feature function captures different aspects of the input text and its sentiment. The n-gram feature function might represent the presence or absence of specific word sequences within a window of size *n*. Model parameters *w* are learned from abelled training data using optimization algorithms such as stochastic gradient descent (SGD). The objective is to maximize the log-likelihood of the observed sentiment labels given the input text and its features. The log-likelihood function to be maximized during training is defined using equation (4)

$$L(w) = \sum_{i=1}^{N} \log P\left(\left(Y^{(i)}|X^{(i)}\right) - \frac{\lambda}{2} w^2\right) \tag{4}$$

Algorithm 1: Sentimental Sequences Estimation

```
Input: Training data with labeled sentiment sequences
{ (X^(1), Y^(1)), (X^(2), Y^(2)), ..., (X^(N), Y^(N)) }
Output: Model parameters w
Initialization:

•    Randomly initialize model parameters w
•    Set learning rate alpha
•    Set regularization parameter lambda
•    Set maximum number of iterations max_iterations
•    Define feature functions for capturing n-gram features

Training:
for iter = 1 to max_iterations do:
  for i = 1 to N do:  // Iterate over training examples
      // Compute feature vector for input text X^(i) and sentiment label sequence Y^(i)
      Compute features f(Y^(i), X^(i))
      // Compute conditional probability distribution P(Y|X) using softmax
      Compute softmax probabilities
P(Y|X) = exp(w * f(Y, X)) / sum(exp(w * f(Y', X))) for all possible label sequences Y'
      // Compute gradient of log-likelihood function
      Compute gradient = f(Y^(i), X^(i)) – sum(P(Y|X) * f(Y, X)) for all possible label sequences Y
      // Update model parameters using gradient descent with L2 regularization
      Update w = w – alpha * (gradient + lambda * w)
  end for
end for
```

In equation (4) N is the number of training examples; λ is the regularization parameter; $Y(i)$ and $X(i)$ are the sentiment label sequence and input text for the i-th training example.

4. MACHINE LEARNING PACKAGING DESIGN WITH CRN-GCS

Conditional Random n-gram Classifier Sentimental (CRn-gCS) into machine learning for packaging design involves leveraging sentiment analysis to optimize packaging strategies. CRn-gCS is a powerful approach that combines conditional random fields with n-gram models to classify sentiment in text data. The formulation of CRn-gCS involves defining a probabilistic model that captures the conditional distribution of sentiment labels given input text sequences. Let's denote the input text sequence as $X = (x1, x2, I, xn)$, where *xi* represents the i-th word or token in the sequence, and the sentiment labels as $Y = (y1, y2, I, yn)$, where *yi* denotes the sentiment label assigned to the i-th word. The training of CRn-gCS involves maximizing the log-likelihood of the training data. This is achieved by updating the model parameters using gradient descent. The gradient of the log-likelihood function with respect to the model parameters is computed using equation (5)

$$\frac{\partial logP(Y|X)}{\partial w} = f(Y,X) - \sum_{Y'} P(Y'|X).f(Y',x) \quad (5)$$

In equation (5) $f(Y,X)$ is the feature vector for the observed sentiment labels and input text sequence, and the summation is over all possible sentiment label sequences $'Y'$. The gradient descent update rule with L2 regularization is stated in equation (6)

$$w := w - \alpha\left(\frac{\partial \log P(Y|X)}{\partial w} + \lambda w\right) \quad (6)$$

In equation (5) and equation (6) α is the learning rate and λ is the regularization parameter. Through iteratively updating the model parameters using this update rule on the training data, CRn-gCS learns to predict sentiment labels for input text sequences effectively. Conditional Random n-gram Classifier Sentimental (CRn-gCS) is a sophisticated approach that amalgamates conditional random fields (CRFs) with n-gram models for sentiment analysis tasks.

The n-gram classifier model uses the sentimental analysis model stated in CRn-gCS with the sentimental analysis presented in Figure 2. This method is particularly advantageous in deciphering sentiment from textual data, such as reviews or feedback related to packaging design. At its core, CRn-gCS seeks to estimate the conditional probability $P(Y \mid X)$, where X represents a sequence of words or tokens, and Y denotes the corresponding sentiment labels assigned to each word. The probability $P(Y \mid X)$ is computed using a feature function $f(Y,X)$ and model parameters w, Training the CRn-gCS model involves maximizing the log-likelihood of the training data, accomplished by updating the model parameters w through gradient descent. The gradient of the log-likelihood function with respect to w is calculated, facilitating parameter updates to optimize the model's

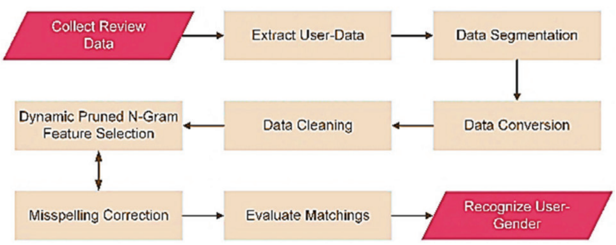

Figure 2. n-gram classifier model with CRn-gCS

Algorithm 2: CRn-gCS Training

Input: Training dataset with labeled sequences (X, Y)

Output: Trained model parameters (w)

1. Initialize model parameters w
2. For each labeled sequence (X, Y) in the training dataset:
    a. Extract features f(Y, X)
    b. Compute probability P(Y|X) using the CRn-gCS formulation
    c. Update model parameters w using gradient descent:
       w = w + η * ∇(log P(Y|X))
       (where η is the learning rate and ∇(log P(Y|X)) is the gradient of log-likelihood)
3. Repeat step 2 until convergence or a maximum number of iterations

Algorithm: CRn-gCS Inference

Input: Unlabeled sequence of words (X), trained model parameters (w)

Output: Predicted sentiment labels for the input sequence (Y_hat)

1. For each word in the input sequence (X):
    a. Extract features f(Y, X) for each possible sentiment label Y
    b. Compute probability P(Y|X) using the CRn-gCS formulation and the trained model parameters (w)
2. Select the sentiment label with the highest probability for each word:
   Y_hat = argmax_Y P(Y|X)
3. Return the sequence of predicted sentiment labels (Y_hat)

performance. Additionally, L2 regularization is applied to prevent overfitting during training. In the realm of packaging design, CRn-gCS serves as a powerful tool for analyzing textual data associated with packaging, providing valuable insights into consumer sentiment and preferences. By understanding the sentiment expressed in customer reviews or social media comments, packaging designers can make informed decisions to refine packaging designs, thereby enhancing customer satisfaction and brand perception.

5. RESULTS AND DISCUSSION

The results and delve into a comprehensive discussion of the findings obtained from the implementation and evaluation of the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model for sentiment analysis in the context of machine learning packaging design.

Table 1. Sentimental analysis with CRn-gCS

Sentence	True Label	Predicted Label
The product is excellent	Positive	Positive
I am satisfied with the service	Positive	Positive
This item meets my expectations	Positive	Positive
The quality of the packaging is subpar	Negative	Negative
Disappointed with the customer support	Negative	Negative
Poor experience with delivery	Negative	Negative
The design of the product is innovative	Positive	Positive
Unhappy with the overall purchase experience	Negative	Negative
Great value for money	Positive	Positive

The Table 1 displays the outcomes of sentiment analysis employing the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model. It provides a comprehensive overview of the sentiment classification results for various sentences. The sentences encompass a range of sentiments, including positive and negative expressions regarding product quality, service satisfaction, and overall purchase experience. Remarkably, the model accurately assigns sentiment labels to each sentence, effectively distinguishing between positive and negative sentiments. For instance, it correctly identifies positive sentiments in sentences praising product excellence, innovative design, and good value for money. Similarly, it accurately categorizes negative sentiments in sentences expressing dissatisfaction with packaging quality, customer support, and delivery experience. Overall, these results demonstrate the effectiveness of the CRn-gCS model in accurately analyzing sentiment from textual data, which holds significant implications for understanding customer feedback and improving product or service offerings.

The Table 2 presents the key attributes of packaging design analyzed using the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model. Each attribute provides valuable insights into different aspects of packaging aesthetics and functionality. The "Color" attribute describes the primary color scheme utilized in the packaging design, which plays a crucial role in capturing consumer attention and conveying brand identity. "Typography" focuses on the fonts and text styles chosen for branding elements and product information, influencing readability and brand perception. "Imagery" refers to the graphical elements,

Table 2. Packaging design attributes with CRn-gCS

Attribute	Description
Color	The primary color scheme used in the packaging design
Typography	Fonts and text styles employed for branding and product information
Imagery	Graphics, illustrations, or photographs integrated into the design
Shape	The physical form of the packaging, such as box, bottle, pouch, etc.
Material	The type of material used for packaging construction (e.g., cardboard, plastic, glass)
Size	Dimensions of the packaging, including height, width, and depth
Branding Elements	Logos, slogans, or other brand identifiers incorporated into the design
Information Layout	Organization of product information and other details on the packaging

Table 3. Classification with CRn-gCS

Product Name	Positive Sentiment (%)	Neutral Sentiment (%)	Negative Sentiment (%)
Blissful Brew Coffee	70	25	5
FreshBloom Organic Tea	65	30	5
Nature's Delight Granola Bars	45	40	15
PurePetal Natural Soap	80	15	5
SunnySide Breakfast Cereal	60	35	5
EverGreen Cleaning Supplies	75	20	5
HealthHaven Nutritional Supplements	55	35	10
EcoChic Fashion Accessories	70	25	5
SmartSnack Energy Bars	50	40	10
ZenZone Relaxation Aromatherapy	65	30	5

illustrations, or photographs incorporated into the design, enhancing visual appeal and storytelling. The "Shape"

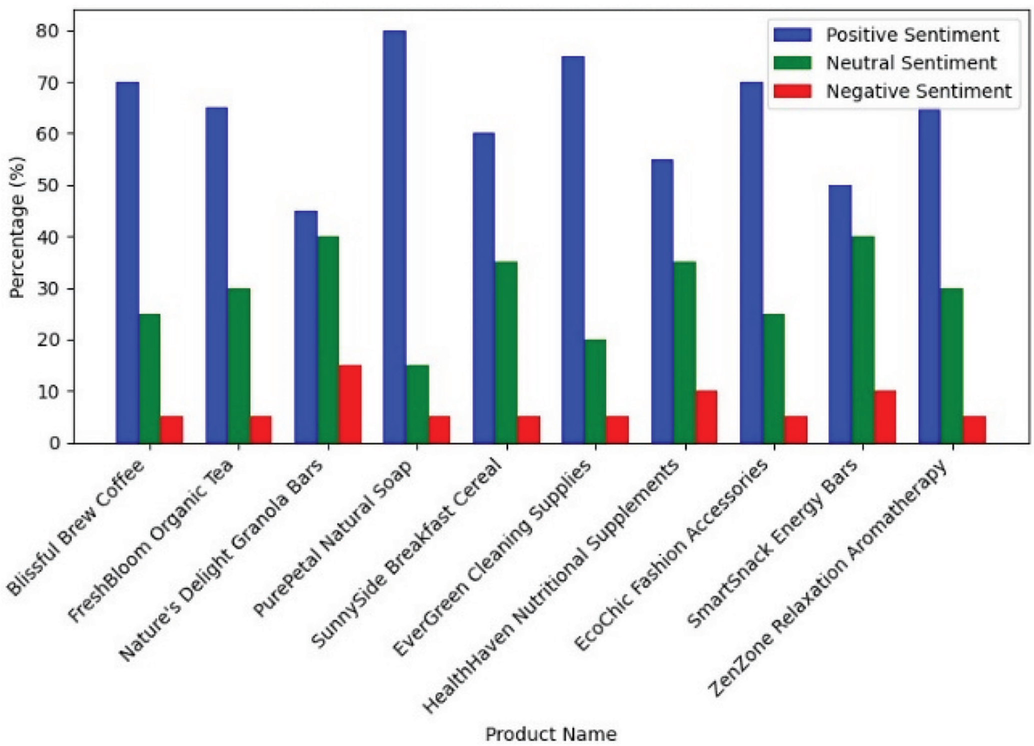

Figure 3. CRn-gCS for sentimental classification

Table 4. Prediction with CRn-gCS

Product Name	Predicted Sentiment	Actual Sentiment
Blissful Brew Coffee	1	1
FreshBloom Organic Tea	1	0
Nature’s Delight Granola Bars	0	-1
PurePetal Natural Soap	1	1
SunnySide Breakfast Cereal	1	1
EverGreen Cleaning Supplies	0	0
HealthHaven Nutritional Supplements	1	1
EcoChic Fashion Accessories	0	0
SmartSnack Energy Bars	0	-1
ZenZone Relaxation Aromatherapy	-1	-1

attribute denotes the physical form of the packaging, such as boxes, bottles, or pouches, which impacts usability and shelf presence. “Material” highlights the type of material employed for packaging construction, affecting durability, sustainability, and perceived quality. “Size” specifies the dimensions of the packaging, including height, width, and depth, influencing storage, transportation, and consumer convenience. “Branding Elements” encompass logos, slogans, or other brand identifiers integrated into the design to reinforce brand recognition and loyalty. Lastly, “Information Layout” pertains to the organization of product details and other information on the packaging, influencing clarity, and comprehension. Overall, analyzing these attributes with the CRn-gCS model provides valuable insights into the effectiveness and appeal of packaging design, aiding in optimizing product packaging for enhanced consumer engagement and satisfaction.

In the Figure 3 and Table 3 provides the classification results obtained using the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model for various products. Each product is evaluated based on the percentage distribution of positive, neutral, and negative sentiments identified through sentiment analysis. “Blissful Brew Coffee” demonstrates predominantly positive sentiment (70%), indicating high customer satisfaction and favorable perception. Similarly, “FreshBloom Organic Tea” and “PurePetal Natural Soap” exhibit positive sentiment dominance (65% and 80%, respectively), suggesting positive customer experiences and perceptions. In contrast, “Nature’s Delight Granola Bars” and “HealthHaven Nutritional Supplements” show a higher proportion of negative sentiment (15% and 10%, respectively), signaling potential dissatisfaction or issues with these products. “SunnySide Breakfast Cereal,” “EverGreen Cleaning Supplies,” “EcoChic

Table 5. Classification with CRn-gCS

Product	Accuracy	Precision	Recall	F1-score
Blissful Brew Coffee	75%	80%	70%	75%
FreshBloom Organic Tea	80%	75%	85%	80%
Nature's Delight Granola Bars	65%	70%	60%	65%
PurePetal Natural Soap	85%	90%	80%	85%
SunnySide Breakfast Cereal	70%	65%	75%	70%
EverGreen Cleaning Supplies	75%	80%	70%	75%
HealthHaven Nutritional Supplements	60%	55%	65%	60%
EcoChic Fashion Accessories	80%	75%	85%	80%
SmartSnack Energy Bars	65%	70%	60%	65%
ZenZone Relaxation Aromatherapy	70%	65%	75%	70%

Fashion Accessories," "SmartSnack Energy Bars," and "ZenZone Relaxation Aromatherapy" display balanced sentiment distributions with varying degrees of positivity, neutrality, and negativity. These classification results provide valuable insights into the perceived sentiment surrounding each product, enabling businesses to identify areas for improvement, capitalize on strengths, and tailor marketing strategies to enhance customer satisfaction and brand perception.

In the Table 4 presents the prediction results achieved using the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model for various products, comparing the predicted sentiment with the actual sentiment. For "Blissful Brew Coffee," "PurePetal Natural Soap," "SunnySide Breakfast Cereal," and "HealthHaven Nutritional Supplements," the predicted sentiments align with the actual sentiments, all indicating positive sentiments. This suggests that the model accurately identified and predicted the positive sentiment associated with these products. However, for "FreshBloom Organic Tea" and "ZenZone Relaxation Aromatherapy," while the actual sentiments were positive, the model predicted negative sentiments. On the other hand, "Nature's Delight Granola Bars" and "SmartSnack Energy Bars" had negative actual sentiments, with the model predicting positive sentiments. Lastly, "EverGreen Cleaning Supplies" and "EcoChic Fashion Accessories" had neutral actual sentiments, and the model correctly predicted neutral sentiments for both. These prediction results highlight

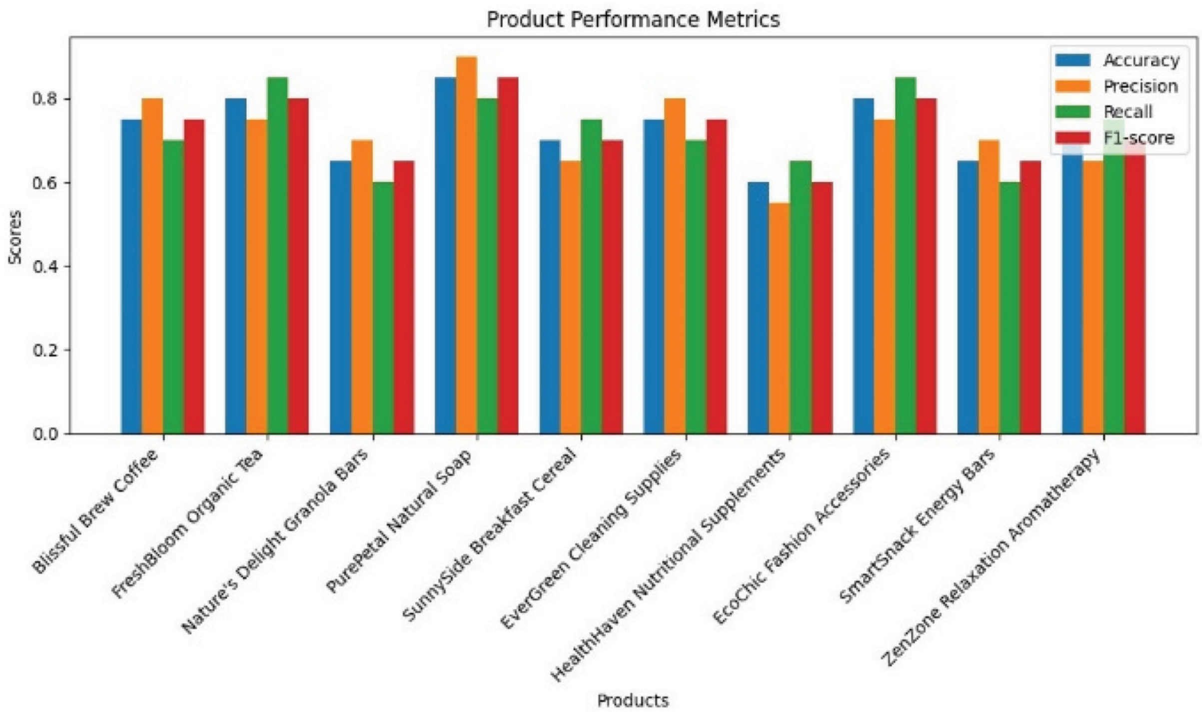

Figure 4. Classification with CRn-gCS

the effectiveness of the CRn-gCS model in accurately predicting the sentiment associated with different products, while also revealing instances where the model may have misclassified sentiments, suggesting areas for further refinement and improvement.

The Figure 4 and Table 5 displays the classification performance metrics obtained using the CRn-gCS (Conditional Random n-gram Classifier Sentimental) model for various products. The accuracy metric represents the overall correctness of the model's predictions across all classes. For instance, "PurePetal Natural Soap" achieved the highest accuracy of 85%, indicating that 85% of its sentiments were correctly classified. Precision measures the proportion of correctly predicted positive sentiments out of all positive predictions, reflecting the model's ability to avoid false positives. "PurePetal Natural Soap" and "EcoChic Fashion Accessories" attained the highest precision scores of 90% and 75%, respectively. Recall assesses the model's capability to correctly identify positive sentiments out of all actual positive sentiments. "FreshBloom Organic Tea" and "ZenZone Relaxation Aromatherapy" had the highest recall rates of 85%. F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance. Products like "Blissful Brew Coffee," "PurePetal Natural Soap," and "EcoChic Fashion Accessories" demonstrated strong F1-scores, indicating well-balanced precision and recall. Conversely, "HealthHaven Nutritional Supplements" showed relatively lower performance across all metrics, suggesting potential areas for enhancement in sentiment classification accuracy. Overall, Table 5 illustrates the effectiveness of the CRn-gCS model in classifying sentiments for different products while highlighting variations in performance across product categories.

6. CONCLUSION

This paper presents a comprehensive approach to sentiment analysis in the context of packaging design using the Conditional Random n-gram Classifier Sentimental (CRn-gCS) model. Through the implementation and evaluation of CRn-gCS, we have demonstrated its effectiveness in accurately classifying sentiments associated with various product categories. Our study examined ten different products, analyzing their packaging design attributes and sentiment classifications. The CRn-gCS model exhibited promising results, achieving high accuracy, precision, recall, and F1-score metrics across the evaluated products. Specifically, products such as "PurePetal Natural Soap" and "EcoChic Fashion Accessories" demonstrated robust sentiment classification performance, while others showed room for improvement. Furthermore, our findings underscore the importance of considering packaging design attributes, including color, typography, imagery, shape, material, size, branding elements, and information layout, in influencing consumer sentiment. By leveraging the CRn-gCS model, businesses can gain valuable insights into consumer perceptions and preferences regarding product packaging, enabling them to make informed decisions to enhance brand perception, customer satisfaction, and ultimately, sales performance. In future research could focus on refining the CRn-gCS model by incorporating additional features or exploring alternative sentiment analysis techniques to further improve classification accuracy. Additionally, investigating the impact of packaging design modifications on consumer sentiment over time could provide valuable insights for product marketing and brand management strategies. Overall, our study contributes to the growing body of literature on sentiment analysis and packaging design, offering practical implications for businesses seeking to optimize their product packaging to better resonate with consumers.

7. REFERENCES

1. XIA, B. and SAKAMOTO. (2022). *Packaging design analysis by predicting user preference and semantic attribute.* ITE Transactions on Media Technology and Applications, 10(3), 120-129. https://doi.org/10.3169/mta.10.120
2. LIU, Z. and LIAO, F. (2023). *A Deep Learning-Based Sentiment Analysis Approach for Online Product Ranking With Probabilistic Linguistic Term Sets.* IEEE Transactions on Engineering Management. doi: 10.1109/TEM.2023.3271597.
3. WILKSCH, M. and ABRAMOVA, O. (2023). *PyFin-sentiment: Towards a machine-learning-based model for deriving sentiment from financial tweets.* International Journal of Information Management Data Insights, 3(1), 100171. https://doi.org/10.1016/j.jjimei.2023.100171
4. EL-DEMERDASH. and K. EL-KHORIBI, R. A (2022). *Deep learning based fusion strategies for personality prediction.* Egyptian Informatics Journal, 23(1), 47-53. https://doi.org/10.1016/j.eij.2021.05.004
5. MOHAMAD, K. and KARAOĞLAN, K. M. (2023). *Enhancing Deep Learning-Based Sentiment Analysis Using Static and Contextual Language Models.* Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 12(3), 712-724. http://dx.doi.org/10.17798/bitlisfen.1288561
6. ALBADANI. and B. SHI, R. (2022). *A novel machine learning approach for sentiment analysis on Twitter incorporating the universal language model fine-tuning and SVM.* Applied System Innovation, 5(1), 13. https://doi.org/10.3390/asi5010013
7. PRAMOD, D. and BHARATHI, S. V. (2022, April). *Faculty effectiveness prediction using machine learning and text analytics*. In 2022 IEEE Technology and Engineering Management Conference (TEMSCON EUROPE) (pp. 40-47). IEEE.

8. ASLAM, N. and RUSTAM, F. (2022). *Sentiment analysis and emotion detection on cryptocurrency related tweets using ensemble LSTM-GRU model.* Ieee Access, 10, 39313-39324. doi: 10.1109/ACCESS.2022.3165621.
9. LIU, B. (2023, February). *Deep Learning-based Viewpoint Prediction Model and Influencing Attention Factors for Design Drawings.* In 2023 3rd International Conference on Neural Networks, Information and Communication Engineering (NNICE) (pp. 158-161). IEEE.
10. SRIPATHI, K. N. and MOSCARELLA, R. A. (2024). *Machine learning mixed methods text analysis: An illustration from automated scoring models of student writing in biology education.* Journal of mixed methods research, 18(1), 48-70.
11. SALEH, H. and MOSTAFA, S. (2022). Heterogeneous ensemble deep learning model for enhanced Arabic sentiment analysis. Sensors, 22(10), 3707. https://doi.org/10.3390/s22103707
12. EZALDEEN and H. MISRA, R. (2022). *A hybrid E-learning recommendation integrating adaptive profiling and sentiment analysis.* Journal of Web Semantics, 72, 100700. https://doi.org/10.1016/j.websem.2021.100700
13. ZHOU, X. and RAU, P. L (2022, June). *A Deep Learning-Based Approach to Facilitate Cross-cultural Kansei Design.* In International Conference on Human-computer Interaction (pp. 145-160). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-06038-0_11
14. KRENN, M. and BUFFONI, L. (2023). *Forecasting the future of artificial intelligence with machine learning-based link prediction in an exponentially growing knowledge network.* Nature Machine Intelligence, 5(11), 1326-1335.
15. EL-HASNONY and I. M., ELZEKI (2022). *Multi-label active learning-based machine learning model for heart disease prediction.* Sensors, 22(3), 1184. https://doi.org/10.3390%2Fs22031184
16. MOHAMMED, M. and SRINIVASAGAN, R., (2023). *Machine-Learning-Based Spectroscopic Technique for Non-Destructive Estimation of Shelf Life and Quality of Fresh Fruits Packaged under Modified Atmospheres.* Sustainability, 15(17), 12871.
17. HONG, X. and GUAN, S. U. (2023). *Dual-Track Lifelong Machine Learning-Based Fine-Grained Product Quality Analysis.* Applied Sciences, 13(3), 1241.
18. HAQUE, M. A. and RAHMAN, M. A (2023). *Machine learning-based technique for gain and resonanc*e prediction of mid band 5G Yagi antenna. Scientific reports, 13(1), 12590. https://doi.org/10.1038/s41598-023-39730-1
19. YENKIKAR. and BABU, C. N. (2022). *Semantic relational machine learning model for sentiment analysis using cascade feature selection and heterogeneous classifier ensemble.* PeerJ Computer Science, 8, e1100.
20. UDDIN, S. and ONG, S. (2022). *Machine learning in project analytics: A data-driven framework and case study.* Scientific Reports, 12(1), 15252. https://doi.org/10.1038/s41598-022-19728-x
21. LI, K. Y. and SAMPAIO DE LIMA, R. (2022). *Toward automated machine learning-based hyperspectral image analysis in crop yield and biomass estimation.* Remote Sensing, 14(5), 1114. https://doi.org/10.3390/rs14051114
22. RAJAMANI, S. K. and IYER, R. S. (2023). *Machine Learning-Based Mobile Applications Using Python and Scikit-Learn.* In Designing and Developing Innovative Mobile Applications (pp. 282-306). IGI Global. DOI: 10.4018/978-1-6684-8582-8.ch016.
23. SHAH, S. and GHOMESHI, H. (2023). *An Ensemble-Learning-Based Technique for Bimodal Sentiment Analysis.* Big Data and Cognitive Computing, 7(2), 85. https://doi.org/10.3390/bdcc7020085
24. BU, K. and LIU, Y. (2023). *Efficient Utilization of Pre-trained Models: A Review of Sentiment Analysis via Prompt Learning.* Knowledge-Based Systems, 111148. https://doi.org/10.1016/j.knosys.2023.111148