AI-POWERED EMPATHY: SENTIMENT ANALYSIS IN PERSONAL CARE USING RoBERTa AND XLNet

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ABSTRACT

Since they reveal vital information about consumer preferences and satisfaction, personal care products in the current digital era depend especially on user reviews. The intricacy and diversity of natural language make large-scale evaluation of these tests challenging. This study is motivated by the need of the personal care industry to discover how sentiment analysis grounded on Natural Language Processing (NLP) techniques could be useful. We want to use NLP models to quickly and more precisely detect consumer sentiment, so guiding classification. From this, companies can choose a lot of knowledge on consumer attitude and product performance. Covered include how to select appropriate models, compile sentiment analysis review data, and how sentiment classification influences marketing and product strategy. In the increasingly competitive personal care industry, natural language processing (NLP) can help to streamline user input thereby facilitating data-driven decisions and greater consumer satisfaction. People are realizing the full possibilities of Advanced Technology, which marks a period of perpetual and never-ending advancement. In the field of shopping and virtually purchasing goods using technology dubious issues of product quality surface. Reviews give us direct answers and allow us to sort through our questions. People are asked to post reviews, in which they provide honest and forthright comments, following purchases of goods. Our objective is to use Sentimental Analysis with NLP to classify the past reviews of the product as either favourable or negative with accuracy of 94%. Customers as well as the product company will benefit from this in order to make appropriate judgments and apply correct modifications.

Keywords: *Natural Language Processing (NLP), Sentiment Analysis, Customer Reviews, Personal Care Products, Opinion Mining, Text Classification, Emotion Detection, Product Feedback Analysis, Consumer Insights*

1. INTRODUCTION

All In the digital era as much as for consumers, customer reviews have become a vital information source for businesses. From hair to skincare, personal care products—range—are not exception. People depend more and more on online reviews as e-commerce sites and social media explode to help them make decisions on what they purchase. However, the sheer volume of evaluations can be draining and makes it difficult for businesses to grow from them. Often labour-intensive and unproductive, traditional methods of analysing consumer feedback reduce their value. Natural language processing (NLP) offers one transformational solution for this challenge. Through its NLP, artificial intelligence enables machines to understand, analyze, and evaluate human language, hence unleashing more insights from unstructured data including text reviews. By means of NLP, sentiment analysis techniques classify consumer comments as positive, negative, or neutral, therefore providing organizations with improved awareness of customer opinions. Sentiment research can help companies in the context of personal care products find trends, evaluate customer happiness, and change marketing plans or product combinations or formulations. This method provides a more comprehensive picture of consumer experiences by looking at the emotions and concepts shown in reviews, therefore transcending simple keyword searches. This work investigates how NLP-based sentiment analysis may greatly increase the knowledge of user reviews for personal care goods, therefore helping businesses to upgrade their products and more precisely satisfy consumer needs. Here we can give the overview, importance, challenging and objectives of the sentiment analysis. Overview of the Personal Care Industry: Covering the personal care industry are items and services aimed to raise general quality of living, beauty, and health. Products consumers everywhere mostly depend on in this sector: skincare, haircare, cosmetics, perfumes, toiletries. Advances in packaging, marketing strategies, and product formulations drive this quickly growing industry forward.

1.1. *Pattern of Market Development*

In wellness as well as a tendency for organic, sustainable, and cruelty-free goods. The industry is unique in that it provides a diverse and competitive environment where newly launched independent businesses fight for market share against established worldwide companies. Thanks to digital channels and e-commerce, customers nowadays may quickly access an incredible range of personal care product reviews and customer comments. Published on review websites, e-commerce platforms, social media, and review tools, these evaluations have become quite important for consumers' choice-process. Knowledge and interpretation of these reviews has become increasingly more important for businesses aiming to simplify product offers and boost customer happiness. Sentiment analysis anchored on natural language processing (NLP) Applied in Personal Maintenance Natural language processing (NLP) driven sentiment analysis has developed into a useful method for examining consumer thoughts and emotions voiced in textual data. NLP helps businesses to automatically identify and classify attitudes—positive, negative, neutral—expressed in customer reviews by use of machine learning algorithms and language approaches. Deep insights into consumer subjective ratings made available by this technology enable companies to monitor customer happiness, pinpoint areas needing work, and observe developing trends.

In the domain of personal care products, NLP-based sentiment analysis offers **very several benefits:** Knowing how consumers view particular product characteristics—such as texture, efficacy, packaging, scent—helps companies to customize their products to fit consumer wants. Constant study of sentiment helps businesses to identify early on bad comments, thereby allowing them to act before damage of reputation results. By showing how customer satisfaction ranks a product against its rivals, sentiment research guides businesses in choosing their marketing or positioning

1.2. *Importance of Customer Reviews:*

Client evaluations are especially important in Natural Language Processing (NLP)-based sentiment analysis for personal care products since they enable to enhance consumer experience and preferences knowledge. Here's how:

- **Instantaneous view:** Customer comments give real-time understanding of impressions on personal care goods. Quick examination of consumer contentment and discontent made possible by sentiment analysis helps businesses to make appropriate changes to products, marketing plans, or customer service.
- **Awareness of Emotional Tone:** Natural language processing can examine not just what but also how a review mentions something. Products like skincare, cosmetics, or hair care define client

contentment dependent on underlying emotions—positive, negative, or neutral—which our emotional tone analysis may expose.

- **Identifying tendencies and trends:** NLP-based sentiment analysis made possible by high amount of review data helps to spot consumer preferences patterns. It could also imply, for instance, that consumers either appreciate some chemicals or worry about particular harmful effects of a product. This knowledge helps companies to more precisely promote their products.
- **Encouraging Product Development Innovation:** Sentiment analysis reveals consistent patterns in user comments pointing out areas needing improvement for a product. If a scent or texture is seen often, a corporation might change the manufacturing process to more suit consumer preferences.
- **Strongly advised guidance:** Research of personal consumer opinions and judgments made feasible by NLP-driven systems helps businesses to offer customized recommendations. For example, a tailored recommendation engine can provide items in line with moral criteria should a consumer choose organic or cruelty-free products. Natural language processing-based sentiment analysis helps businesses to control even if unpleasant feelings are inevitable. Knowing the particular kind of client complaints helps companies to specifically handle problems, so raising client happiness and reducing the turnover risk. Even if they are unavoidable, NLP-based sentiment analysis enables companies to manage negative emotions. Knowing the specific kind of client complaints enables businesses to fix issues directly, therefore increasing client satisfaction and lowering the turnover risk.
- **Information obtained on social media:** Moreover, NLP approaches enable sentiment research to reach social media platforms. Many people post about personal care items on Twitter, Facebook, or Instagram. Examining these assessments in line with official consumer reviews helps to show the entire picture of the opinion of a product.
- **Excellent All-around Research:** Sentiment analysis rooted on natural language processing can be extended to rival products. Examining opposing points of view helps businesses identify areas where distinctive product appeal or market shortages can be found. Along with cost control, this information guides pricing policies, product positioning, and marketing activities.
- **Mechanisms for Consumer Service Assurance:** Automaton sentiment analysis allows companies swiftly go over customer ratings and comments. Negative sentiment reviews, for example, should be actively watched for more research so businesses might quickly appease unhappy consumers.
- **Raising customer allegiance:** By way of a feedback loop, active review analysis benefits companies by addressing consumer issues, improving product offers, and thus strengthening positive experiences. Customers coming out of this feel appreciated and hence get more dedicated.

Sentiment analysis based on natural language processing allows user comments embedded in personal care items to provide invaluable customer experience data. Through which their products appeal, companies not only enhance their offers but also raise customer pleasure, foster brand loyalty, and maintain competitiveness in a market getting more and more packed. Beyond conventional approaches, NLP improves customer interactions and helps to provide a deeper, more thorough knowledge of consumer input, therefore influencing business decisions.

1.3. Challenges in Interpreting Customer Reviews:

Sentiment analysis based on natural language processing (NLP) for personal care products finds it challenging to interpret consumer reviews due

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of various factors that hamper the acquisition of unambiguous and practical insights. The primary challenges are:

- **Contextual awareness:** Precise reading of consumer remarks depends on context, which sentiment analysis machines can find challenging. For example, a review noting, "I love this moisturizer, but it left my skin greasy" expresses conflicting emotions—positive and negative—which are difficult for automated systems to fairly represent. Advanced NLP models with contextual understanding—such as transformer-based models (e.g., BERT, GPT—can help resolve such uncertainty—by looking at the complete meaning of the sentence rather than focusing simply on individual words.
- **Ambiguity in Sentiment Problem:** Personal care product reviews often expose contradictory or complicated attitude. Review like "It worked well, but it caused some irritation" is both excellent and bad, hence it is challenging to identify sentiment in class. By means of adapting sentiment models for the particular sector (personal care items), the system may more precisely identify the subtleties and grade attitudes on a spectrum than give binary labels.
- **Multilingual Sentiment Analysis Problem:** Examining Views in Various Dialects The multilingual character of customer evaluations presents a possible barrier for companies selling personal care items on a global basis when it comes to undertaking sentiment analysis. Models trained just on English data, for instance, could struggle to comprehend the tone of a Spanish review. Combining translation tools with domain-specific or multilingual sentiment analysis models ensures precise sentiment capture across languages.
- **Product-Specific Sentiment Drift Problem:** New reviews can affect our perceptions of a product, hence our fourth point—product-specific sentiment drift—comes from here. Even if a product was once well-liked, changes in formulation or packaging could affect consumers' impressions. Time-sensitive sentiment analysis or temporal sentiment analysis models let companies monitor consumer mood fluctuations and get alarms when they occur.
- **Bias in Sentiment Classification:** The Mechanism of Sentiment Classification and Bias Including prejudices into the data used to develop sentiment analysis models could cause oversimplification or incorrect interpretation of consumer opinion. One possible result is that a sentiment analysis system taught on an oversupply of positive reviews would mistakenly mark all of those reviews as positive. Adversarial training, diversity your dataset for frequent model training, and update and diversify your dataset for model training will help to make sentiment analysis more accurate.

There are several reasons for developing and putting into practice an Advanced NLP for Sentiment Analysis: Implementing RoBERTa and XLNet in Personal Care Reviews.

R1: For personal care reviews, how accurate, contextual aware, and sentiment classification performing RoBERTa and XLNet compare?

R2: By use of domain-specific personal care datasets, can fine-tuning RoBERTa and XLNet enhance their capacity to identify subtle emotions, including sarcasm and mixed emotions?

R3: How may sentiment analysis driven by artificial intelligence utilizing RoBERTa and XLNet improve consumer involvement in the personal care sector and product recommendations?

1.4. Objectives

Mostly aiming on enhancing the comprehension of user feedback for personal care items, a Natural Language Processing (NLP)-Based Sentiment Analysis study.

Ob1: Improve accuracy of sentiment classification. Sort consumer comments into good, negative, and neutral categories using a consistent approach. With methods including neural networks, transformer-based models (e.g., BERT, GPT), or supervised learning, increase recall and classification accuracy.

Ob2: Statements Designed for a particular domain: Natural language processing models create assessments of personal care products (including skincare, haircare, and cosmetics) by **means of** domain-specific vocabulary, slang, and jargon modifications. Reviewers should stress notable brands, product features, and consumer comments.

Ob3: Also derived from elements are emotional profiles. Using aspect-based sentiment analysis, you might separate assessments of the effectiveness, scent, packaging, pricing, and quality of a product into their component elements. Including the emotional condition of the client with every element helps you depict their experience more fully.

Ob4: Reduce Noise and Improve Data Quality: Establish plans to filter low-quality or meaningless reviews—such as spam or off-target ones. Use NLP techniques to handle typically found in reviews sarcasm, misspellings, and clever sentence building.

Ob5: Track and fix consumer grievances: Early discovery of negative reviews and consumer issues determines faster response or product changes. Sort your degree of dissatisfaction to concentrate on issues that call for attention (e.g., little irritations against more urgent safety concerns).

2. LITERATURE SURVEY

Sentiment Analysis Techniques: Explore existing methods and techniques used in sentiment analysis, such as supervised learning, unsupervised learning, and deep learning models.
NLP in Consumer Sentiment Analysis: Review studies that applied NLP in understanding consumer sentiments for various industries, with a focus on personal care or beauty products.
Challenges in NLP for Sentiment Analysis: Discuss challenges like sarcasm, ambiguous language, and domain-specific terms that can affect sentiment classification.
Zixu Liu; Huchang Liao; Maolin Li; Qian Yang; Fanlin Meng[1]: A useful method for expressing emotion intensities in unstructured text reviews and supporting multicriteria online product rating is the probabilities linguistic term set (PLTS). Ranking results are impacted by the low prediction accuracy of traditional machine learning techniques for creating PLTSs. To solve this, we provide a sentiment analysis method based on deep learning for creating PLTSs from internet reviews. Our approach uses state-of-the-art deep learning models to classify sentiment after extracting product attributes and review texts using natural language processing. By associating emotion trends with suitable language phrases, an experimental matching mechanism increases classification accuracy. Through a real-world case study, the results support the usefulness of our technique in online product decision-making and show competitive accuracy in sentiment intensity prediction.
Ming-Chuan Chiu, Cheng-Zhou Tsai, Yu-Chen Huang[2]: Product Service System (PSS) combines products and services to better meet customer needs, and Smart PSS (SPSS) enhances this model using AI. However, prior studies often rely on single models, limiting multitasking capabilities and personalization. To address these gaps, this study proposes a multi-model SPSS approach involving three steps: data collection and object detection model construction, development of SPSS solutions, and optimization using NLP-based feedback for personalized services. A case study on attraction recommendations verifies the method, showing timely optimization and improved personalization. This research uniquely integrates text and image data to capture customer characteristics and preferences effectively.
Jahanzeb Jabbar; Iqra Urooj; Wu JunSheng; Naqash Azeem [3]: One of the most crucial aspects of natural language processing, sometimes referred to as sentiment analysis, is opinion mining, which is used to find out what people think about a company's goods and services on social media platforms. An efficient technique for forecasting the emotion polarity should be employed in order to enhance marketing efforts utilizing product reviews. In this study, a model is designed using a machine learning approach known as Support Vector Machine (SVM), and it is then used to an e-commerce application. The online product reviews that were gathered from Amazon.com served as the study's data source. Sentiment analysis tests are conducted at the review and sentence levels of classification. This paper's primary goal is to improve the customer

experience by presenting an emotive analysis of e-commerce product reviews in real time.

Sheshadri Chatterjee; Ranjan Chaudhuri; Patrick Mikalef [4]: Big Data Analytics (BDA) and Natural Language Processing (NLP) are transformative technologies that analyze diverse, large-scale data sets and enhance human-computer interactions. While many firms have adopted these applications, limited research exists on their multidimensional impacts on organizational performance. This article identifies key factors driving BDA and NLP usage in business, leveraging dynamic capability theory and prior literature. A theoretical model was developed and validated through structural equation modeling using data from 1287 samples across 23 firms in Asia and Europe. The findings reveal that BDA and NLP significantly enhance operational efficiency, ultimately boosting overall firm performance.

Mouna Kaouni; Fatima Lakrami; Ouidad Labouidya [5]: Online learning systems like Moodle, Canvas, and Open edX have become more popular as a result of the quick digitization of education. These platforms improve learning efficiency and flexibility. However, because of their static architecture, these platforms frequently fail to meet the various demands of educators and students. Promising options for customizing display, navigation, and content are provided by developments in artificial intelligence (AI) and natural language processing (NLP). Educational platforms can undergo a transformation thanks to methods like text analysis, content translation, sentiment analysis, voice recognition, and recommendation algorithms. In order to better address the changing demands of both educators and students, this study emphasizes the benefits and difficulties of incorporating AI and NLP into the classroom.

Satyesh Das; Divyesh Das[6]: This study explores the role of Natural Language Processing (NLP) in enhancing Human-Computer Interaction (HCI). Recent advancements in Artificial Intelligence (AI) and deep learning, coupled with large datasets, have enabled machines to understand and produce human language with remarkable accuracy. These developments facilitate the use of advanced dialect models and computations. The study employs secondary data collection and thematic analysis to evaluate NLP's impact on HCI. Findings reveal that NLP techniques support computerized opinion analysis, empowering organizations to make data-driven decisions and improve customer loyalty, highlighting its transformative potential in modern interactions.

Vaishali Vaibhav Hirlekar; Arun Kumar [7]: Online social media plays a critical role during real-world events like natural disasters, elections, and social movements. However, the rise of social media usage has also led to an increase in fake news, which often spreads misinformation by modifying true news or creating false content. This poses significant threats, especially from a national security perspective, making fake news detection vital for ensuring the trustworthiness of information on social networks. This paper reviews various methodologies, tools, browser extensions, and techniques for fake news detection. It also explores the general approach to fake news identification and the taxonomy of feature extraction, highlighting the role of Machine Learning and Natural Language Processing algorithms in achieving high accuracy.

Abdul B. Maqsood; Angelica Maag; Indra Seher; Md Sayfullah[8]: A subfield of artificial intelligence called natural language processing (NLP) is utilized to improve data interaction and decision-making with high accuracy and dependability. Additionally, it makes greater computer-human interaction possible for better comprehension and results. This study examines NLP-based data extraction methods for streamlining user and business analysis procedures. A literature study examines techniques such as K-nearest neighbor and data analytics, emphasizing approaches that improve data extraction and interpretation. The accuracy and precision of algorithms like soft computing, FCMA, and factorization are evaluated. Additionally covered are tools for behavior analysis, customer identification, decision-making, and visualization. For more accurate analysis, PRM and embedding matrix techniques are also taken into account. The study emphasizes elements such as consumer behavior, NLP-based data extraction, and e-commerce company evaluation, and it shows how data extraction, feature analysis, and machine learning models may be integrated to improve user experience and mistake estimation.

Samira Zad; Maryam Heidari; James H Jones; Ozlem Uzuner[9]: One subfield of data mining is text mining, which is the computational process of discovering previously undiscovered patterns and relationships across information. The multidisciplinary area of data mining creates new methods for finding patterns in datasets by combining database systems, artificial intelligence, and statistics. Similar to this, we must employ a variety of techniques from several fields of computer science (such as linguistics) and statistics when working with textual data. This paper examines the preprocessing, aspect extraction, feature selection, and classification methods that have been employed recently by researchers in the text-based sentiment analysis pipeline. Additionally, it examines several uses of semantic analysis in marketing, social media, and product evaluations.

Jim Elliot Christopher James; Mahima Saravanan; Deepa Beeta Thiyam; Prasath Alias Surendhar S; Mohammed Yashik Basheer Sahib; Manju Varrshaa Ganapathi[10]:Background: Many individuals lack the medical expertise to understand the severity of their symptoms or conditions. Natural Language Processing (NLP) plays a critical role in healthcare by enabling chatbots to collect patient health data and provide relevant insights and recommendations. Purposes: AI-powered healthcare chatbots assist patients by guiding them to appropriate assistance and facilitating online symptom searches for better health understanding.

Methods: This study developed a health assistant system using Dialog flow API, a Google NLP-powered algorithm, deployed on platforms like Google Assistant, Telegram, Slack, Facebook Messenger, websites, and mobile apps. Users can submit health queries via text and receive relevant health suggestions or recommendations.

Results: The chatbot functions as an informative, conversational tool, providing medical knowledge about symptoms and treatments. It stores patient data in a database for analysis and delivers real-time suggestions from doctors. Conclusion: AI-powered chatbots have revolutionized healthcare, especially during the COVID-19 crisis, by reducing office visits, saving time, money, and energy. They empower patients to access medical knowledge and assistance conveniently from their own locations.

Ashima Yadav & Dinesh Kumar Vishwakarma [11]: social media serves as a powerful platform for individuals to share sentiments, generating vast amounts of unstructured data. Businesses leverage this information to gain insights, requiring sentiment analysis tools. While traditional machine learning and NLP techniques have been widely used, deep learning methods have gained popularity for their superior performance. This paper surveys prominent deep learning models applied to sentiment analysis, presenting a taxonomy of the field and exploring the implications of key architectures. It highlights researchers' contributions, key sentiment analysis tasks, and the languages analyzed. The survey also reviews popular datasets, their features, applied deep learning models, achieved accuracies, and model comparisons. The primary aim is to emphasize the effectiveness of deep learning in addressing sentiment analysis challenges.

Mohamed Boukhlif; Mohamed Hanine; Nassim Kharmoum; Atenea Ruigómez Noriega; David García Obeso; Imran Ashraf[12]: The use of Natural Language Processing (NLP) technologies is one potential strategy for software testing, which is necessary as software applications get more sophisticated. The increasing use of natural language processing (NLP) in IT, especially in software engineering, has improved the ability to extract information from textual input. 24 publications from the Web of Science and Scopus databases are used to examine current research on NLP-based software testing in this systematic literature review (SLR). According to the evaluation, the creation of test cases and requirements analysis are important areas of study. Additionally, it examines different NLP approaches, software testing methodologies, machine/deep learning algorithms, and the tools and frameworks that are employed. The study draws attention to unresolved issues such the ambiguity in natural language requirements and the generalization of NLP algorithms across languages and topics. The results provide researchers and software testing professionals with insightful information on the advantages and difficulties of using natural language processing (NLP) in software testing.

Beigi, G., Hu, X., Maciejewski, R., Liu, H[13]: Sentiment analysis is the process of identifying and characterizing subjective information, like opinions, in text using computational and natural language processing techniques. Its main objective is to categorize a writer's perspective toward subjects as neutral, negative, or positive. The proliferation of user-generated data brought about by the growth of social networking sites, microblogs, wikis, and online apps has created a wealth of potential for sentiment mining. In this chapter, we examine how sentiment analysis might enhance situational awareness and crisis management in social media during emergencies and natural disasters. We investigate how sentiment mining may help with disaster management, damage assessment, and identifying individuals in immediate need by revealing local

population emotions during calamities. The chapter explores the difficulties of assessing online media streams, defines sentiment analysis in social media, and looks at both conventional and contemporary methods. With a focus on sentiment analysis, we also examine how social media might be used for situational awareness and disaster aid. We also emphasize the use of visual analytics for geo-distributed, real-time data processing, and we wrap up by talking about the research difficulties in this area.
M Ramya Sree; Mettu Siddhartha; Poli Vamsi Vardhan Reddy; Meena Belwal[14]: The rise of social media has provided individuals with a global platform for approval and feedback, which was previously limited to local communities. This work presents a detailed analysis of the automated analysis of user-generated content on social media, specifically focusing on sentiment analysis of comments on posts. Given the vast number of conversations occurring in the digital age, manual analysis is impractical. To address this challenge, we propose using models like Linear SVC, Logistic Regression, Gradient Boosting Classifier, Ada Boost Classifier, and HistGradient Boosting Classifier, coupled with lexical analysis. Among these, the HistGradient Boosting Classifier achieves the highest performance, with an accuracy mean of 0.9357 and ROC AUC mean of 0.9057, demonstrating its superior classification accuracy and class distinction. This method proves effective in analyzing live social media activity, offering insights into user emotions and engagement, which can be used to optimize content and enhance audience engagement strategies.
R Prasanna Kumar; Bharathi Mohan G; Elakkiya R; Charan Kumar M; Rithani M[15]: Sentiment analysis plays a vital role in understanding opinions expressed in online reviews, especially on e-commerce platforms like Amazon. This study presents an automated sentiment classification model utilizing Bidirectional Encoder Representations from Transformers (BERT), Long Short-Term Memory (LSTM), and Bidirectional LSTM models. The model effectively extracts sentiment polarity from a dataset of 50,000 Amazon product reviews, categorized as positive, negative, or neutral. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to assess the model's performance. The BERT model achieved 91% accuracy, LSTM 88%, and Bidirectional LSTM 90.7%, with the latter outperforming the others. This research offers valuable insights into consumer sentiments, improving decision-making and enhancing the online shopping experience. Here we can show in **TABLE 1** some existing research work comparative analysis

Table 1: Drawbacks and Future Research Directions of existing sentimental analysis work

S.No	Methodology	AI Model Employed	Important Learnings	Limitations	Future Research Directions
[16]	Review of systematic literature.	Various machine learning models	found how well machine learning performs in sentiment analysis.	concentrated on a particular field	Extend investigation into other spheres, including personal hygiene.
[17]	Sentiment analysis for forecasts of useful reviews.	Support Vector Machine (SVM)	Fore stood 97.95% accuracy in estimating review helpfulness.	limited to particular product lines	Use approach on more diverse variety of items
[18]	Deep learning-based sentiment analysis	Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN)	improved performance in sentiment categorization	Challenges with contextual understanding	Incorporate contextual embeddings to handle sarcasm and nuances
[19]	Hybrid machine learning based on rules	Support Vector Machine (SVM), Naïve Bayes	Improved accuracy in spotting complicated emotions.	Restricted adaptation to fresh slang or phrases	Combining deep learning models will improve slang adaption.

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[20]	Sentiment analysis based on aspects	XLNet, RoBERTa	Offer greater context-aware sentiment detection.	calls for big sets for optimal tweaking.	Use pretraining tailored for your domain to raise performance on lesser datasets.
[21]	Analyzes multimodal sentiment	BERT + Vision Transformer	Enhanced precision by including image sentiment signals	Higher model complexity	Investigate light-weight multimodal models for instantaneous analysis.

3. METHODOLOGY

3.1 Data Collection:

The primary objective of the data collection phase is to gather an extensive dataset of consumer reviews of personal care items from multiple internet sources. These resources include well-known e-commerce sites, review websites, and social media sites where consumers post frequent reviews. The dataset consists of a wide variety of user opinions from Amazon and Flipkart sales, mostly reviews of skincare, haircare, and hygiene products. We ensured the reliability and representativeness of the dataset by using available APIs and online scraping methods. This methodology helped us to effectively automate the extraction of substantial amounts of review data. The review text, a user generated rating commonly 1 -5, date of the review and metadata details which include; the name, brand and category of a given product typically comprise each of these reviews. Much of context given by those attributes is essential in the method followed for analysis of sentiment for a review. All identifiable personal data used when collecting it, was obfuscated to fulfil with ethical research conduct and follow any data-protection regulations and standards.

3.2 Preprocessing:

Preprocessing is an essential step in preparing the dataset for sentiment analysis as it ensures the text is standardized, clean, and ready to be fed into machine learning models. The first step in this preparation process is text cleaning, which involves the removal of punctuations, special characters, and numeric values not relevant to the sentiment analysis. Subsequently, the text is converted to lowercase to maintain uniformity and prevent case sensitivity from affecting the functionality of the model. The text is tokenized, meaning it is split into discrete words or tokens, to make data processing easier for the model. Stop words that carry minimal semantic meaning, such as "the," "and," and "is," are removed to highlight the reviews' relevant information. Another technique used for reducing the size of the vocabulary is lemmatization or stemming. The words are reduced to their base or root form, reducing vocabulary size without reducing the context. Raw text is structured and cleaned up for the preparation of data so that it is efficiently analysed in sentiment analysis. The NLP models can identify the underlying sentiments from the customer evaluation more precisely with this transformation.

3.3 Sentiment Analysis with NLP:

Natural language processing (NLP) sentiment analysis uses complex machine learning models to classify textual data, such as customer reviews, into sentiment categories like neutral, negative, and positive. These models are fed the tokenized and pre-processed reviews, which initiates the sentiment analysis process. Every review has a sentiment label attached to it, and this labelled data is used to refine the models. The models adjust their internal parameters over a number of training epochs to minimize the errors in prediction. Using the final output, which is a classification of the sentiment of each review, businesses can gain insight into consumer opinions and levels of satisfaction. Our automatic sentiment analysis method makes the interpretation of huge volumes of client feedback much more accurate and efficient. Shown in **Figure 1**: Dataset Distribution Graph for Sentiment Analysis.

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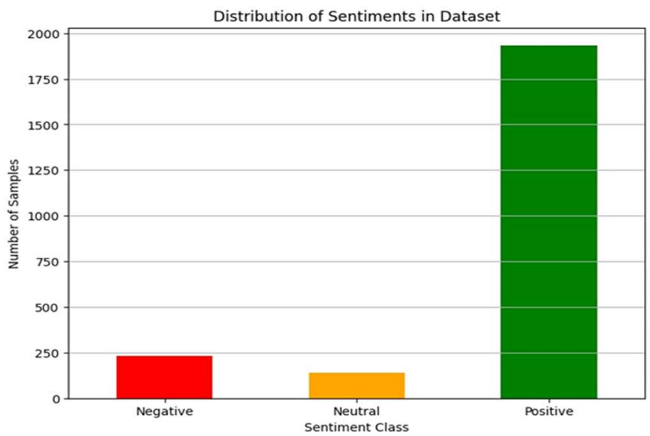

Figure 1: Dataset Distribution Graph for Sentiment Analysis

This study uses two of the most advanced transformer-based models, RoBERTa and XLNet, respectively represented in **FIGURE 2 & FIGURE 3** because of their outstanding understanding of the complexities and nuances of human language and context. These Advanced transformer-based models such as XLNet and RoBERTa (Robustly optimized BERT method) do improve the overall performance of natural language processing (NLP) applications, such as sentiment analysis, by a vast margin. While improving its training procedure, incorporating more data and eliminating the goal of Next Sentence Prediction (NSP), it surpasses the performance of BERT and remains an extremely strong tool for any kind of text-categorization-related problem. RoBERTa achieves better understanding of language semantics and context by training on a larger dataset and over longer iterations. On the other hand, XLNet employs a permutation-based training strategy which keeps track of both past and future context for each token; thus, it captures the advantages seen both from an autoregressive model and also BERT's bidirectional context. This enhances the performance in applications like sentiment analysis by enabling XLNet to predict dependencies in text sequences much more accurately. Both models increase the accuracy of sentiment classification on customer reviews of personal care goods, thus providing more personalized recommendations and a richer knowledge of what customers think.

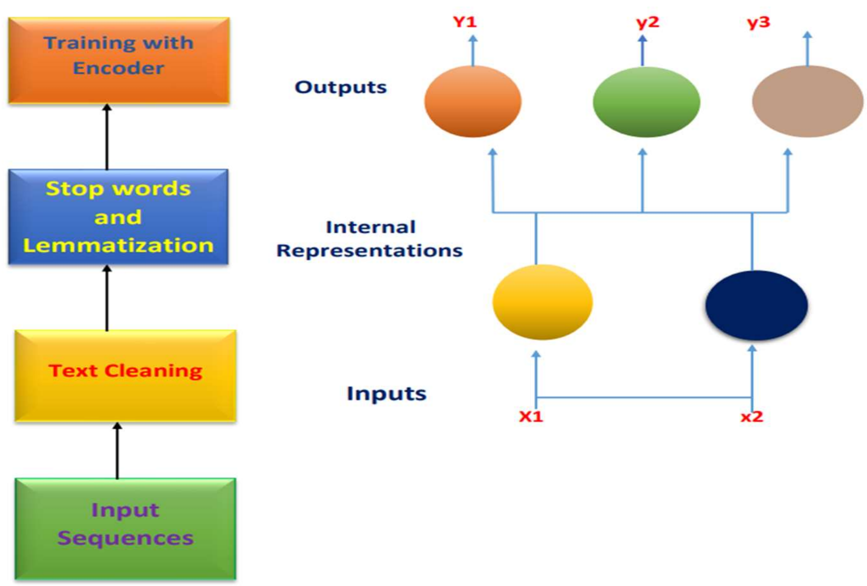

Figure.2: Model Architecture of RoBERTa

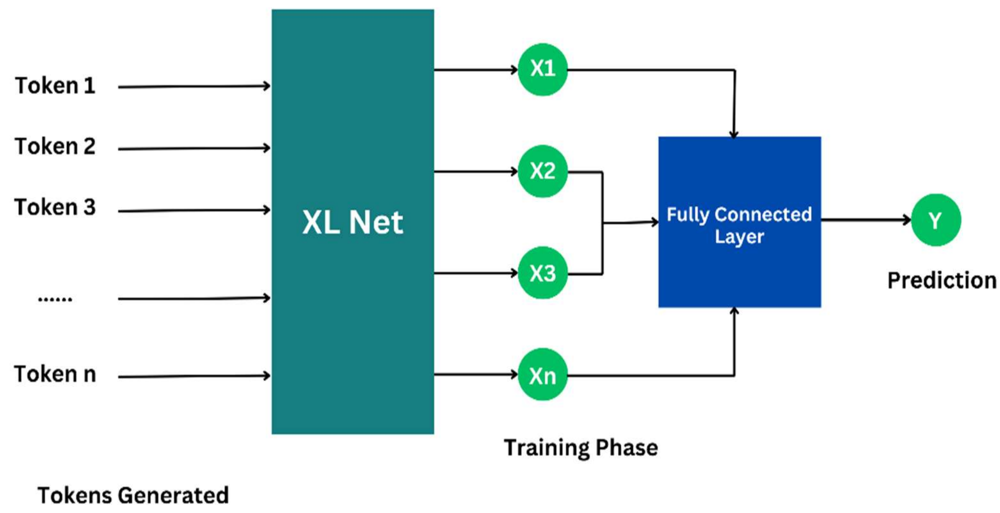

Figure.3: Model Architecture of XLNet

3.4 Evaluation Metrics:

To ensure that sentiment analysis models are reliable and effective in accurately classifying customer reviews, it is important to evaluate their performance. F1-score, recall, accuracy, and precision are some of the most critical evaluation metrics. Accuracy is a simple measure of model performance that measures the total percentage of reviews that are correctly classified shown in Performance Matrix of Models shown in **FIGURE 4**. However, precision alone may not be sufficient, especially when dealing with unbalanced datasets. Understanding the model's ability to avoid false positives relies on precision, which calculates the ratio of actual positive predictions to the total number of predicted positives. Recall, or sensitivity, is the measure of how well the model captures pertinent sentiment by finding the percentage of true positives among all actual positive cases. Because it considers both false positives and false negatives, the F1-score-the harmonic mean of precision and recall-provides a fair evaluation. Confusion matrices are also used to show the distribution of correct and incorrect predictions across sentiment classes, highlighting specific areas that need further development. These indicators together provide a comprehensive evaluation that guides further model improvement and ensures the sentiment analysis system meets the necessary performance requirements for real-world applications.

4. RESULTS AND DISCUSSION

On the review dataset of personal care products, the fine-tuning of the sentiment analysis models RoBERTa and XLNet classified the sentiments into groups of positive and negative. Both performed extremely well; RoBERTa scored at 93%, shown in **FIGURE 5** and **FIGURE 6** while XLNet performed equally as well, nearly close to levels of similar accuracy. Because of their good accuracy rates, which reflect their ability to understand complex language and contextual differences, the models are pretty successful in being able to pick up the correct sentiment of the customer reviews with good accuracy. XLNet was also able to produce strong results, especially given its reputation for permutation-based training methodology and capturing the bidirectional context of reviews. XLNet was similarly accurate and precise and recalled like RoBERTa, although not as accurate. It is therefore a good replacement for sentiment analysis tasks. The performance of the models showcases how well they can decode the comments of clients and provide meaningful information about their thoughts. This level of performance is particularly helpful for businesses in the personal care sector because it enables them to use sentiment analysis to make data-driven decisions that help improve client happiness

4.1 Sentiment Distribution:

The percentage of positive, negative, and neutral sentiments in the dataset is required to analyse the sentiment distribution of customer reviews. This procedure provides a comprehensive understanding of the overall sentiment of consumers about products. Before applying a sentiment classification model, the text data must first be cleaned and standardized

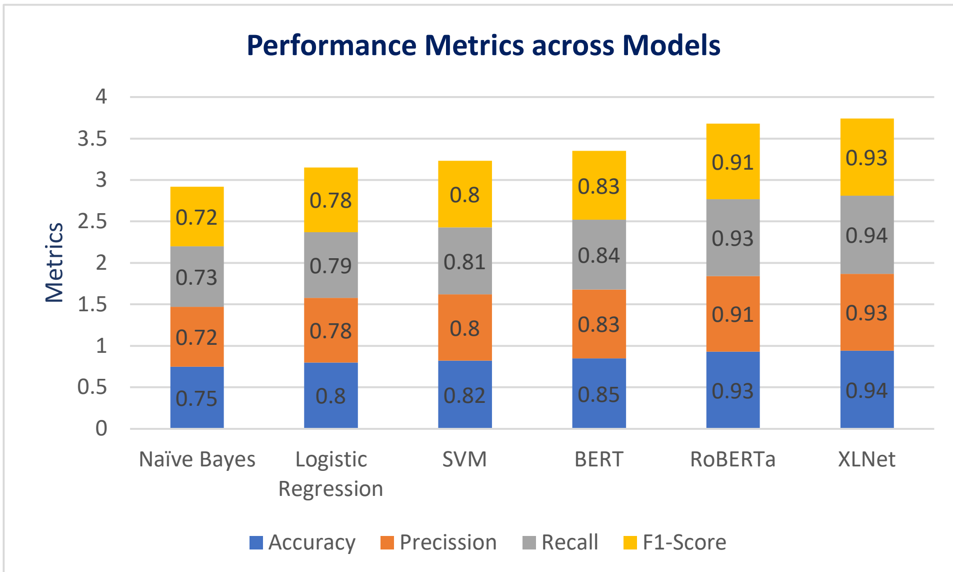

Figure.4: Performance Matrix of Models

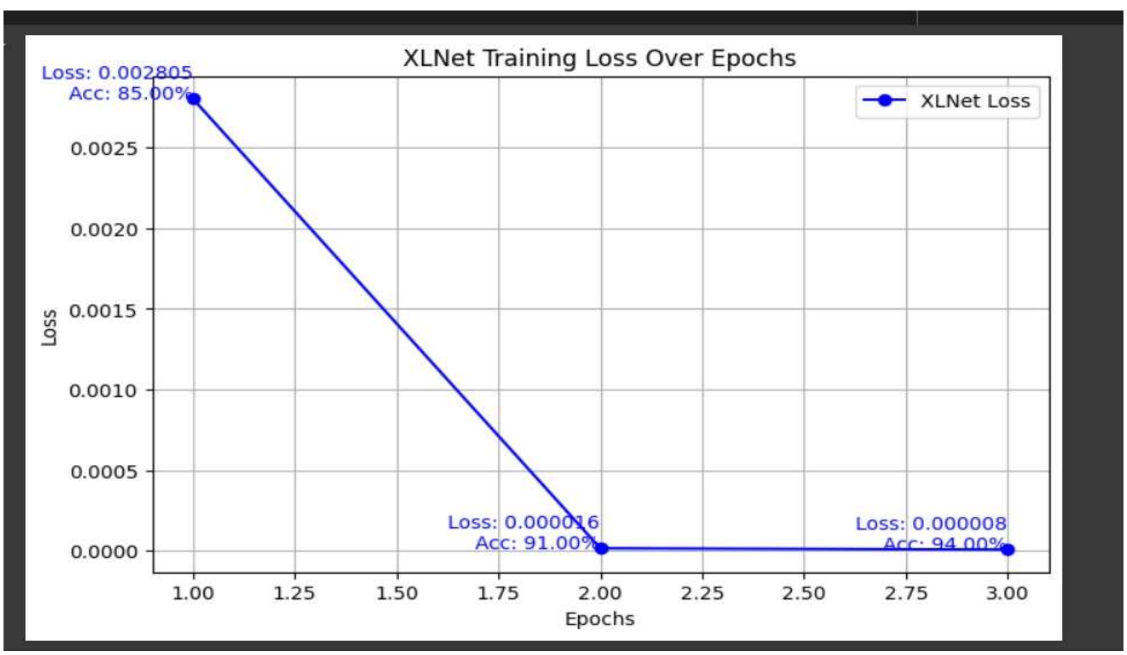

Figure.5: Accuracy of XLNet Model

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through preprocessing. Based on the content of each review, sentiment labels (positive, negative, or neutral) are applied. These can be added up to calculate the percentages or fractions of each of the sentiment types. The general trend of sentiment can be derived by visualizing the results through pie charts, bar graphs, or histograms. For example, if many neutral or negative reviews highlights areas for improvement, then the high percentage of positive reviews indicates that customers are satisfied. Besides helping to understand consumer attitudes, this distribution study helps in making data-driven decisions for improving marketing tactics and product quality.

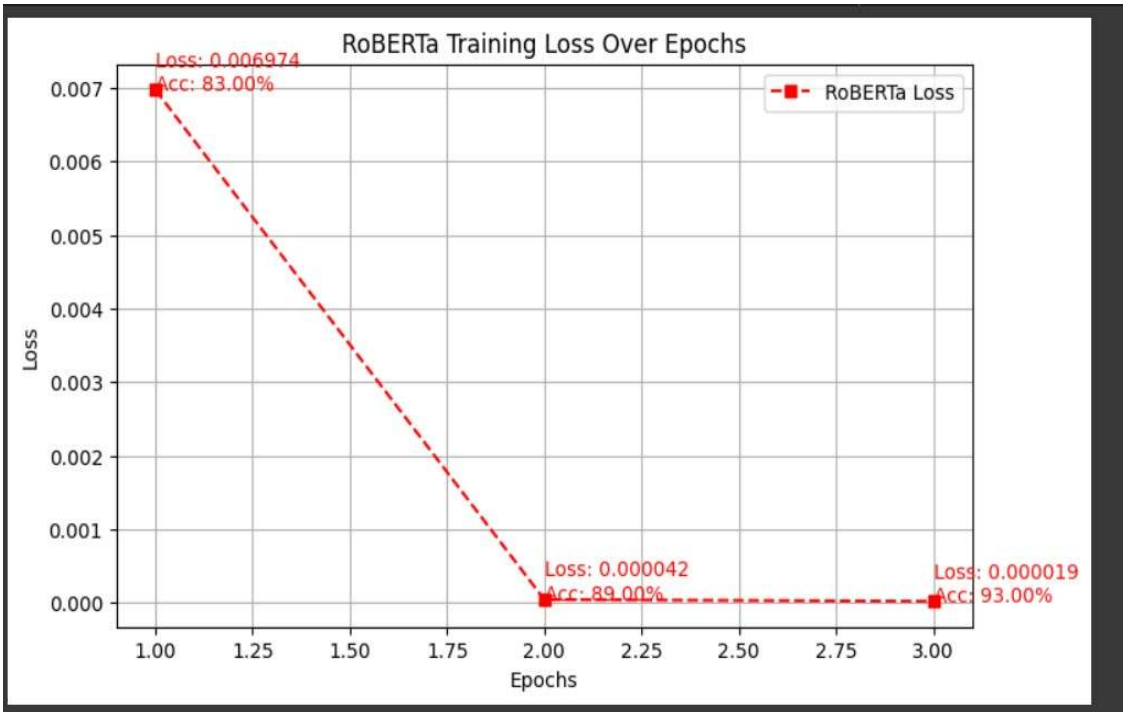

Figure.6: Accuracy of RoBERTa Model

4.2 Insights for Personal Care Brands: Consumer reviews' sentiment analysis helps personal care companies with valuable information regarding client satisfaction and product performance. Companies can fortify their marketing strategy by focusing on product features, such as attractive packaging, fragrances, or good composition, by identifying recurring themes in positive reviews. Conversely, negative reviews often focus on persistent issues, including skin irritation, inefficiency, or sustainability issues, which can guide improvement efforts on the product. Sentiment analysis also allows for the identification of new consumer preferences, such as the desire for eco-friendly or cruelty-free products. This information helps firms make informed decisions, such as redesigning packaging to meet consumer expectations, reformulating products to correct flaws, or shifting marketing emphasis to attributes that appeal to consumers. Brands can also measure the impact of changes and adapt their strategies by tracking patterns of sentiment over time. With the utilization of these findings, personal care companies can retain their competitiveness within a changing market while increasing consumer satisfaction and loyalty.

4.3 Challenges in Sentiment Classification: Sentiment classification is fraught with challenges, especially in cases of user ratings of personal care items. One frequent challenge is that of managing conflicting sentiments in reviews. For instance, if a client compliments the smell of a product but criticizes its efficacy, it is sometimes difficult to find a clear sentiment label. It is only possible to capture such complex thoughts using sophisticated models that can understand the context and reconcile contradictory tones in a single review. Another issue with domain-specific terminology is that the consumers many times use slang or jargon about the product that the general-purpose algorithms of sentiment analysis cannot understand. For example, a "light texture" or "non-comedogenic" cosmetic product might seem to have good sentiment, but the real interpretation requires appropriate training. Sarcasm, irony, and colloquial expressions would also make for a biased estimate of sentiment when used in an inappropriate manner. Another challenge with the data set is the case of data imbalance, which generally leads to bias in the models' predictions because rating datasets are primarily dominated by positive ratings. To address this problem, careful preprocessing, class-imbalanced enhancement, or fine-tuning pre-trained models are required. The contextual embeddings and transfer learning in NLP models like RoBERTa and XLNet help to alleviate these challenges and improve the accuracy of sentiment categorization in complex scenarios.

4.4 Significance of AI-Powered Empathy: The personal care sector employs XLNet and RoBERTa for sentiment analysis, utilizing AI-driven empathy. This enables companies to enhance their comprehension of customers, refine their offerings, and engage with them more effectively. In the realm of recognizing intricate emotions, specialized terminology, and sarcasm, these models surpass conventional sentiment classification techniques. They automate sentiment-driven customer service, customize product recommendations, and conduct real-time analysis of comments with context-aware learning to enhance the user experience. Furthermore, they facilitate the detection of fraudulent reviews, which is advantageous for verifying the legitimacy of customer feedback. They are optimal for addressing delicate personal care matters through empathetic AI-generated insights, owing to their scalability and rapid natural language processing capabilities. They enable firms to observe new patterns across several platforms. The integration of RoBERTa and XLNet in sentiment analysis enables brands to make data-driven, ethical, and customer-centric decisions in the dynamic personal care industry.

5. CONCLUSION & FUTURE RESEARCH DIRECTIONS

Summary of Findings: The study, therefore, presented a clear demonstration that the application of advanced NLP models, most notably RoBERTa and XLNet, would increase the efficiency with which sentiment analysis would be carried on consumer reviews related to personal care items. Consequently, the high accuracy achieved in reaching 94% classification marks would be considered much higher than anything achieved with earlier conventional methods. Even in product reviews that involve intricate and subtle analysis, these models did their job well on interpreting and classifying customer opinion. This only gave a deeper understanding of what consumers want as well as unlocks secrets about its efficacy, quality, and overall satisfaction. The results point out how sentiment analysis is a critical role in personal care products, helping companies improve product offerings, tailor marketing campaigns, and raise customer satisfaction levels, all of which contribute to increased customer loyalty and trust. Implications for Brands: NLP-based sentiment analysis provides brands, which are willing to improve customer satisfaction and develop a better product development strategy, with insightful, useful information. All the knowledge about consumer emotions, preferences, and pain points, which is often difficult to extract using conventional techniques, can be obtained by businesses through the large-scale analysis of customer evaluations. This allows brands to identify both the positive and negative aspects of their products to focus on areas for improvement. For instance, if sentiment research shows that consumers are dissatisfied with the ingredients or packaging of a product, marketers may change these aspects to suit consumer needs better. Along with this, consumer perception over time can be tracked using sentiment trends to provide pre-emptive insights regarding possible problems before they become critical. More importantly, NLP-powered insights enable more personalized consumer interactions due to the ability of firms to adjust their messaging based on opinions of reviews. These results will help brands improve their product offers, develop more focused marketing efforts, and cultivate greater client loyalty, which will ultimately lead to long-term commercial success. **Future Research Directions:** Several interesting avenues for further research can further advance the application and effectiveness of sentiment analysis as it continues to evolve, particularly in consumer reviews for personal care products. Multilingual reviews are an important area of research for sentiment analysis. Since consumer markets are global, developing models that can

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reliably analyse reviews in a variety of languages can help brands gather information from a wider consumer base. This progress would depend on linguistic nuances, cultural variations, and regional expressions, amongst others. An additional direction to explore may involve improving deep learning models in terms of sentiment analysis. Though good results have already been shown for models like RoBERTa and XLNet, further innovation in model architecture may lead to more improved accuracy as well as the domain-specific nature of language, as might be used to describe personal care products in review. In addition, techniques such as domain adaptation or transfer learning may enhance the performance of the model in niche industries or with scarce data. Finally, real-time sentiment tracking offers an exciting opportunity to enhance the customer experience. Brands can respond more effectively to customer concerns, new challenges, and product opportunities by monitoring shifting sentiments and trends through continuous analysis of customer feedback as it is received. Because of these developments, marketing plans could be more elastic, and products could change according to customers' demands more immediately in real time. By bringing all these together, maximizing brands' goods and services with tremendous impacts on consumer engagement can be ensured.

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