Elevating Aspect-Based Sentiment Analysis in the Moroccan Cosmetics Industry with Transformer-based Models

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***Abstract*—In navigating the dynamic consumer landscape, this study emphasizes the collaborative synergy between influencers and brands, focusing on a cosmetics brand in the Moroccan market. Employing advanced Natural Language Processing (NLP) models, the research explores multifaceted aspects to provide a comprehensive insight into consumer sentiments and product aspects. The primary objective is to empower decision-makers by identifying both the strengths and weaknesses of their products, including evaluating how effectively the influencer promotes their product. Central to this study is the introduction of the MultiLingual Aspect-Based Sentiment Transformer (MABST) framework, a hybrid sentiment analysis model tailored for the beauty and cosmetics industry. MABST integrates cutting-edge transformer models such as Albert, DistillBERT, Electra, and XLNet, enabling advanced sentiment extraction across diverse linguistic contexts in cosmetic product reviews and influencer collaborations. This framework enhances understanding of influencer marketing dynamics and equips businesses with insights to inform strategic decisions and refine promotional strategies in the competitive digital landscape.**

Keywords*—MABST; Aspect-Based Sentiment Analysis (ABSA); transformer-based models; Moroccan cosmetics industry; natural language processing (NLP); influencer marketing; albert; DistillBERT; electra; XLNet (Transformer models)

I. Introduction

In recent years, online social networks have emerged as powerful conduits for spreading information across vast distances and among millions of users. These platforms enable individuals to connect and build relationships by sharing common interests, sentiments, and actions, making them invaluable for businesses seeking to explore consumer insights and conduct sentiment analysis. As companies navigate the evolving digital landscape, the decreasing influence of traditional media has prompted a strategic shift towards leveraging social media influencers (SMIs) to promote products [1]. This transition is underscored by the trust that followers place in influencers, akin to the confidence placed in close friends. It signifies a profound connection and reinforces the growing impact influencers have in shaping perceptions and decisions of customers.

During this paradigm shift, companies are employing diverse strategies on social media, such as establishing brand pages and utilizing sponsored advertisements, to effectively connect with their target audience. Paid advertisements offer a means to specifically target consumers based on factors like location, age, gender, language, interests, and behaviors [2]. Social media influencers, renowned for their substantial online followings, have emerged as pivotal figures in this evolving landscape [3]. These influencers, ranging from celebrities to artists and public figures, wield significant influence over their followers, prompting corporations to increasingly adopt influencer-led promotional strategies over traditional advertising approaches.

Instagram, a globally popular social media platform, stands out as a preferred network for influencers, attracting a massive community of content creators. Instagram influencers build their followings through various content-sharing methods, including photos, reels, and live videos. Many influencers have earned the trust of companies, leading to collaborations aimed at promoting products [4]. This rising trend sees organizations entrusting a portion of their content to influencers, leveraging the enhanced credibility these individuals hold among their dedicated followers.

The analysis of our reviews presents unique challenges due to the linguistic diversity and cultural nuances embedded in the textual data. These reviews often exhibit a blend of English, French, and Arabic, reflecting the multilingual environment of Morocco. Moreover, they incorporate regional expressions, idiomatic phrases, and cultural references specific to Moroccan culture, which require subtle handling during data preprocessing and sentiment analysis. These complexities necessitate tailored approaches in NLP to accurately capture and interpret consumer sentiments, ensuring that insights drawn from the data are both culturally sensitive and contextually relevant.

Our model, the MultiLingual Aspect-Based Sentiment Transformer (MABST), integrates Aspect-Based Sentiment Analysis (ABSA) principles with cutting-edge transformer architectures [5]. This integration enables us to extract different sentiments associated with specific aspects of cosmetic products and influencer collaborations, thereby offering a detailed understanding of customer preferences across multilingual contexts [6]. Leveraging transformer models enhances our sentiment analysis capabilities by capturing intricate contextual details within textual data and decoding the dynamic landscape of beauty-related sentiments. The methodology section elaborates on our approach to extracting diverse aspects from textual data, highlighting the seamless integration of advanced NLP techniques. The ABSA framework [7] and transformer-based models, recognized for their resource efficiency, bidirectional context modeling, and innovative pre-training strategies, collectively provide the robust MABST framework for our research.

In the dynamic marketing landscape, the integration of Natural Language Processing (NLP) and machine learning (ML) has facilitated a comprehensive exploration of consumer sentiments [8]. This study interprets sentiments within the expansive realm of beauty-related textual data, aiming to provide valuable insights for businesses in the beauty and cosmetics industry. Utilizing hybrid sentiment analysis, the objective is to empower decision-makers with a comprehensive understanding of customer preferences, enabling informed strategies in product development, marketing, and collaborations with influencers.

II. Literature Review

The integration of sentiment analysis techniques in the beauty and cosmetic industry has garnered significant attention in recent years. Understanding customer sentiments towards cosmetic products and influencer collaborations is pivotal for companies aiming to amplify their market presence and meet evolving consumer preferences. Several studies have explored sentiment analysis in the context of beauty-related reviews, highlighting various aspects of customer opinions. Our major area of research involves the application of Aspect-Based Sentiment Analysis (ABSA) frameworks. ABSA focuses on identifying and evaluating sentiment expressions associated with specific aspects or features within a given text. Scholars such as Hu and Liu (2004) established ABSA [9], offering a structured approach to recognizing sentiments at a granular level. Aspect-Based Sentiment Analysis has proven effective in extracting sentiments related to distinct elements [10], enabling a deeper exploration of sentiments within diverse textual datasets (Liu, 2012).

Moreover, Tang et al. (2016) proposed a novel neural network architecture for Aspect-Based Sentiment Analysis (ABSA) [11], introducing the concept of dependency-based long short-term memory (LSTM) networks to capture complex dependencies between aspects and sentiments in a more sophisticated manner. Wang et al. (2016) extended ABSA to target-dependent Twitter sentiment analysis, emphasizing the adaptability of ABSA frameworks across different domains and social media platforms [12]. To address the challenge of aspect-level sentiment classification, Li et al. (2018) integrated graph convolutional networks into ABSA, demonstrating improved performance in discerning sentiments associated with specific aspects [13]. The work of Zhang et al. (2020) explored the application of reinforcement learning in ABSA, introducing a mechanism to refine sentiment predictions iteratively based on reinforcement signals [14]. These studies collectively showcase the dynamism and continuous innovation within the ABSA research landscape.

Our previous work, "Hierarchical Spatiotemporal Aspect-Based Sentiment Analysis for Chain Restaurants using Machine Learning," combines traditional lexicon-based methods with machine learning techniques to analyze sentiment towards specific aspects of a restaurant's service across different branches and over time [15]. The approach uses transformer-based models like RoBERTa and BERT to analyze text reviews, allowing businesses to track changes in customer sentiment and identify areas for improvement.

Transformer-based models have become instrumental in advancing sentiment analysis research, with various studies showcasing their different applications and contributions. One noteworthy investigation by Vaswani et al. (2017) introduced the transformer architecture, laying the foundation for successive developments in natural language processing [16]. This groundbreaking work emphasized self-attention mechanisms, enabling models to capture contextual relationships effectively. Building upon this, Devlin et al. (2018) introduced BERT (Bidirectional Encoder Representations from Transformers), a transformer-based model that excelled in capturing bidirectional contextual information, revolutionizing the field of pre-trained language representations [17]. Following this, Yang et al. (2019) proposed RoBERTa (Robustly optimized BERT approach), refining BERT's training approach and achieving state-of-the-art performance across various NLP tasks [18].

Liu et al. (2020) introduced DistilBERT, a distilled version of BERT designed for resource-efficient processing without compromising performance [19]. These studies collectively demonstrate the transformative impact of transformer-based models, evolving sentiment analysis by enhancing contextual understanding and model efficiency. Moreover, in the domain of sentiment analysis, the Electra model has emerged as a significant advancement.

The Electra model, introduced by Clark et al. (2020), departs from the traditional masked language model approach by employing a novel "discriminator" objective [20]. This approach replaces masked tokens with probable alternatives, allowing the model to distinguish between actual and replaced tokens, thereby increasing its understanding of context and semantics. The Electra model has demonstrated superior performance in capturing sentiment expressions, contributing to more accurate sentiment analysis results. This review explores the significance of the Electra model in the context of sentiment analysis, highlighting its distinctive features and its impact on the evolving landscape of NLP.

Additionally, in the realm of Aspect-Based Sentiment Analysis (ABSA) applied to cosmetic product reviews, several prominent studies have paved the way for understanding customer sentiments. Vasconcelos et al. [21] conducted a comprehensive study utilizing BERT and its variations, such as RoBERTa and DistilBERT, to analyze sentiments across various domains, including cosmetics. Their work demonstrated significant improvements in accuracy and contextual understanding over traditional methods like bag-of-words and TF-IDF. Similarly, Vaswani et al. [22] introduced the Transformer architecture in their landmark paper "Attention is All You Need," which revolutionized NLP by enabling models to focus on different parts of the input sequence.

Smith et al. [23] applied conventional machine learning techniques, specifically Support Vector Machines (SVM) and Naive Bayes classifiers, for ABSA on cosmetics reviews. Their approach involved feature extraction methods like word embeddings and n-grams, which achieved reasonable accuracy in sentiment classification but lacked the depth of contextual analysis provided by newer models. Additionally, Chen et al. [24] focused on sentiment analysis for multilingual data, specifically targeting reviews written in multiple languages. They highlighted the complexities of processing and analyzing such data and employed basic translation tools to unify the text into a single language before analysis. This approach aimed to simplify the data for traditional sentiment analysis techniques.

Furthermore, studies by Lan et al. [25] with ALBERT, Sanh et al. [26] with DistilBERT, and Clark et al. [27] with Electra have contributed significantly to the field by improving model efficiency and performance through innovative training strategies and architectural modifications. A comparative study of state-of-art models was elaborated as illustrated in Table I.

TABLE I. COMPARISON OF STATE-OF-THE-ART MODELS

Study	Model/Technique	Strengths	Remarks
Vasconcelos et al.	BERT and its variations (RoBERTa, DistilBERT)	Significant improvements over traditional methods	Did not address challenges posed by multilingual and code-switched data
Vaswani et al.	Transformer (Attention is All You Need)	Introduced the transformer model, enabling superior context understanding	Focused on general improvements, less emphasis on domain-specific challenges
Smith et al.	SVM and Naive Bayes	Achieved reasonable accuracy in ABSA for cosmetics reviews	Lacked the ability to capture deep contextual details
Chen et al.	Basic translation tools and traditional sentiment analysis techniques	Highlighted difficulties of processing and analyzing multilingual reviews	Basic translation led to loss of context and meaning
Lan et al.	ALBERT	Resource-efficient, improved performance	Less emphasis on handling code-switching and regional expressions
Sanh et al.	DistilBERT	Smaller, faster, and cheaper while maintaining performance	Simplification sometimes leads to loss of intricate details
Clark et al.	Electra	Effective as discriminators, high performance	May not fully address multilingual complexities

III. ARCHITECTURE OF MULTILINGUAL ASPECT-BASED SENTIMENT TRANSFORMER MODEL

A. Training Configuration

In this section, the depths of training configuration for the MABST model are explored, emphasizing the integration of transformer-based models. The training process involves optimizing parameters crucial to these models, such as feed-forward layers, multi-head attention mechanisms, and softmax activation functions. The feed-forward layers play a pivotal role in processing and transforming the model's hidden representations [28].

Concurrently, multi-head attention mechanisms improve the model's ability to capture complex contextual relationships within the input data. Additionally, the softmax activation function is utilized to generate probability distributions over the output categories [29], facilitating the classification of sentiment labels. Configurable training parameters, including the number of epochs, batch sizes, and weight decay, are meticulously set, as illustrated in Table II, to ensure effective learning and generalization while preventing overfitting.

TABLE II. TRAINING CONFIGURATION PARAMETERS

Parameter	*Description*	*Value*
Learning Rate	Rate at which our model adjusts weights during training	2e-5
Number of Epochs	Number of times the model iterates over the training dataset	4
Batch Size	Number of samples processed together in one iteration	32
Feed-forward Layers	Number of feed-forward neural network layers in the transformer model	2
Multi-Head Attention Heads	Number of attention heads in the multi-head attention mechanism	8
Weight Decay	Regularization parameter to prevent overfitting	0.01
Optimizer	Optimization algorithm used during training	AdamW

B. Model Components

The architecture of our model, named MultiLingual Aspect-Based Sentiment Transformer (MABST), is designed to address the complexities of sentiment analysis in multilingual and code-switched contexts within the beauty and cosmetics industry. As illustrated in Fig. 1, MABST integrates advanced Natural Language Processing (NLP) techniques with state-of-the-art transformer models such as ALBERT, DistilBERT, Electra, and XLNet. The model's architecture consists of several key components: first, robust data preprocessing techniques including language detection, segmentation, code-switching, normalization, and tokenization ensure the readiness of textual data for subsequent analysis.

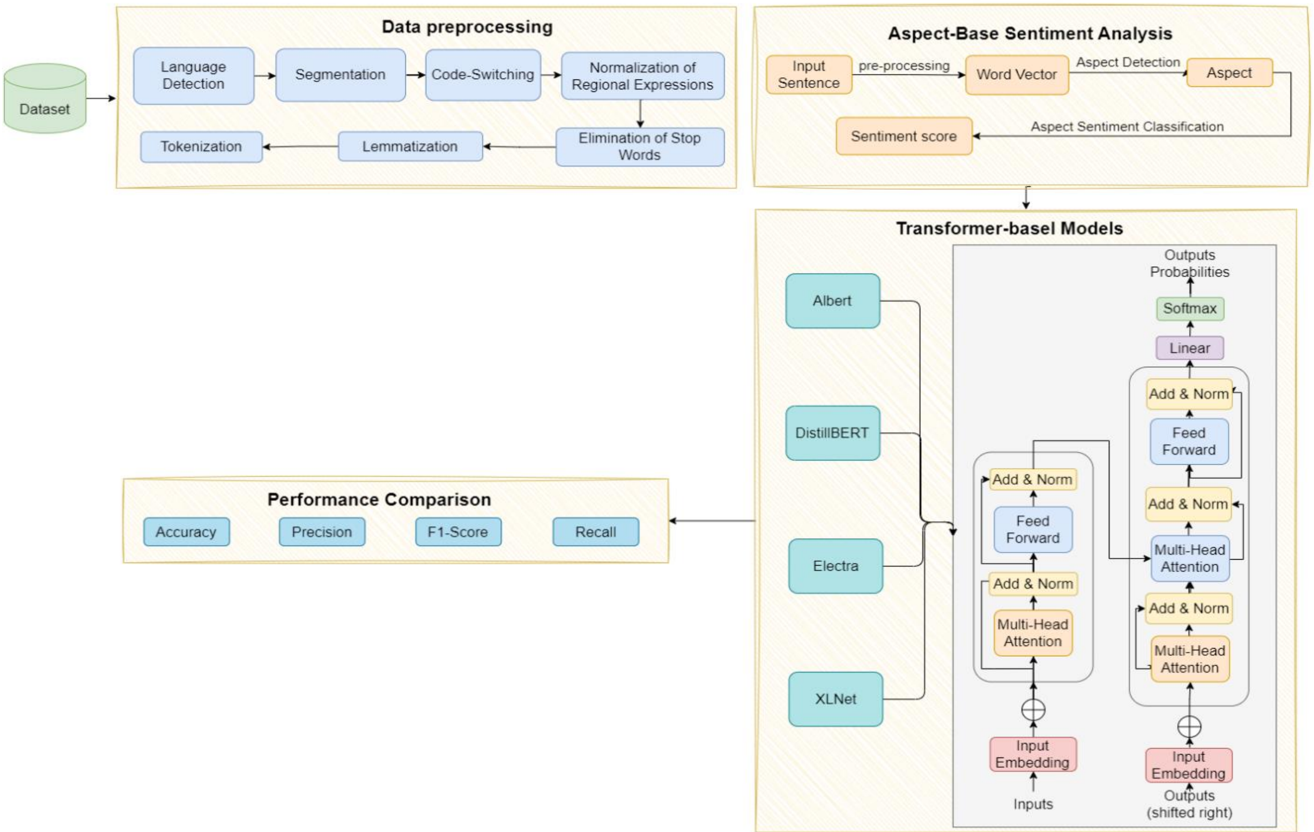

Fig. 1. MABST model for sentiment analysis of customers reviews for cosmetics industry.

Subsequently, the Aspect-Based Sentiment Analysis (ABSA) framework extracts specific aspects related to cosmetic products and influencer collaborations, allowing detailed sentiment analysis. Third, the transformer models facilitate deep contextual understanding by capturing intricate linguistic traces and relationships within the text. This multi-layered approach not only enhances the accuracy and granularity of sentiment extraction but also supports efficient handling of diverse linguistic patterns and code-switching, thereby offering a comprehensive tool for businesses to collect actionable insights and optimize marketing strategies in a competitive digital landscape.

C. Integration of the Hugging Face Transformers Library

This research architecture represents a seamless integration with the Hugging Face Transformers library, an adaptable resource filled with pre-trained transformer models. This integration not only simplifies the incorporation of diverse transformer architectures but also enables us to employ their effective transfer learning capabilities efficiently.

By leveraging the extensive support provided by the Hugging Face platform, we ensure a uniform and standardized approach to utilizing a variety of transformer models. In this study, which employs ALBERT, DistilBERT, Electra, and XLNet transformers, this unified integration takes precedence, facilitating the exploration and comparison of various transformer-based approaches with ease and consistency.

IV. Methodology

This section outlines the methodology of extracting various facets from textual data in the context of reviews related to the cosmetics brand. Employing advanced NLP techniques, Aspect-Based Sentiment Analysis (ABSA) was applied to discern and evaluate distinct product facets and influencer-related factors like credibility and trust.

The MABST methodology integrates state-of-the-art transformer-based models, including ALBERT, DistilBERT, Electra, and XLNet, to discern sentiments, uncover intricate contextual relationships, and derive comprehensive insights from the diverse textual content. This multifaceted approach aims to provide a holistic understanding of customer sentiments and product dynamics, contributing to informed decision-making for businesses operating in the cosmetics industry.

A. Data Collection

In the initial phase of the data collection process, we adopted a flexible approach, encouraging customers to share their perspectives on various aspects of a cosmetic palette from a beauty brand. This included seeking feedback on elements such as pricing, scent, pigmentation, and packaging. Additionally, we encouraged customers to voice their opinions on influencers, evaluating factors like their presentation style and trustworthiness. We collected comments and direct messages (DMs) from the brand's Instagram page and analyzed comments on influencer advertisements to obtain a comprehensive understanding of customer sentiments. As the number of responses increased, we gathered an initial dataset containing 3,672 reviews. This dataset is publicly available on Kaggle [30], named "MABST Model Moroccan Cosmetic Palette Reviews"

B. Language Detection and Segmentation

Given the multilingual nature of Moroccan reviews, language detection and segmentation are crucial preprocessing steps. We employed language detection libraries such as ‘langdetect’ to identify the various language segments within each review [31]. This step allows the system to tag different portions of the text with their respective languages (e.g., English, French, Arabic), ensuring that each segment is treated appropriately in subsequent analyses. Accurate language detection helps in maintaining the integrity of the sentiment analysis, ensuring that sentiments expressed in different languages are correctly interpreted.

MABST model implemented advanced preprocessing techniques to handle the multilingual nature of cosmetic product reviews. For example, consider the review: "Cette palette est géniale, ألوانها رائعة, and it's totally worth the price!" which contains French, Arabic, and English terms. First, our model detects the presence of these three languages. Next, the text is segmented into meaningful units: "Cette palette est géniale" (French), "ألوانها رائعة" (Arabic), and "and it's totally worth the price!" (English).

C. Code-Switching Handling

Moroccan reviews frequently exhibit code-switching, where users switch between languages within a single review. To handle this, we used translation APIs to convert French or Arabic segments into English, ensuring a consistent language throughout the dataset [32]. Additionally, we leveraged multilingual embeddings like M-BERT (Multilingual BERT), which can process mixed-language inputs and align different language representations into a common vector space [33]. This approach helps in accurately capturing the sentiments expressed in multilingual reviews.

D. Normalization of Regional Expressions

Reviews often contain regional expressions and slang specific to the Moroccan context. We created custom lexicons to map these expressions to their standard English equivalents [34]. For instance, "c'est magnifique!" is translated to "it's magnificent!" and "ان شاء الله" to "God willing." This normalization process ensures that regional expressions are accurately interpreted, maintaining the semantic integrity of the reviews. By addressing these regional tones, we improve the accuracy and relevance of the sentiment analysis.

E. Elimination of Stop Words and Noise Reduction

The process of eliminating stop words and reducing noise in textual data plays a crucial role in enhancing the quality of sentiment analysis [35]. Stop words are common words such as "and," "the," and "in" that do not carry significant meaning in sentiment analysis but appear frequently in natural language. By removing these words, the focus shifts to more meaningful content, improving the accuracy of sentiment classification.

Additionally, noise reduction techniques aim to filter out irrelevant or distracting elements from the text, ensuring that the sentiment analysis model can prioritize relevant information that contributes to understanding consumer opinions effectively. This phase is essential in preprocessing raw text data to prepare it for more advanced NLP tasks, such as aspect-based sentiment analysis in multilingual contexts. During this process, we successfully narrowed down the dataset to 3204 reviews, ensuring that the selected data aligns precisely with the study's objectives.

F. Lemmatization

Furthermore, we employ lemmatization as a critical preprocessing technique to standardize linguistic variations present in the text, ensuring that words are converted into their base or root forms. This process enhances the dataset's consistency by reducing redundant variations of the same word, thereby promoting more uniform and meaningful analysis [36]. The accurate application of lemmatization serves as a foundational step in refining the dataset, refreshing its structure for comprehensive analysis and interpretation.

By harmonizing lexical variations across the dataset, we establish a solid groundwork for subsequent analytical procedures, developing a cleaner and more coherent dataset that enhances the extraction of actionable insights and perceptive patterns within the textual data.

G. Tokenization

Another crucial aspect of data preparation is tokenization, a process where the text is divided into smaller units known as tokens. These tokens can be words, phrases, or sentences, depending on the granularity of the analysis. Tokenization is a pivotal step in transforming textual data into a format that can be readily processed by machine learning algorithms [37]. It enables the extraction of meaningful patterns and relationships within the text. By breaking down the text into its individual tokens, we create a structured representation of the data, laying the foundation for more advanced analyses and insights into customer sentiments and preferences. The compiled dataset is now primed for in-depth analysis and interpretation, aiming to uncover detailed insights into customer sentiments and preferences.

H. Aspect-Based Sentiment Analysis

Aspect-Based Sentiment Analysis (ABSA) plays a pivotal role within the MABST framework in this research. ABSA is a specialized technique within sentiment analysis that focuses on identifying and evaluating sentiment expressions associated with specific aspects or features within a given text [38]. This approach surpasses traditional sentiment analysis by providing a more detailed and contextually rich understanding of sentiments, which is particularly valuable in domains where a detailed comprehension of opinions is essential. ABSA facilitates the extraction of sentiments related to distinct elements, enabling a deeper exploration within diverse textual datasets.

ABSA stands at the core of the MABST framework, poised to uncover sentiments associated with specific aspects in textual data [39]. In this study, we concentrate on extracting various aspects from textual reviews concerning a trending cosmetic palette. The study extends beyond the product itself to include different aspects related to the influencer associated with its promotion. We surveyed customers for their opinions on the product, focusing on aspects such as color preferences, satisfaction with pigmentation, and overall impressions. Additionally, we explored customers' perceptions of the influencer's presentation of the product.

In this research, aspects refer to a collection of semantically rich and concept-centric terms that represent distinct features or characteristics mentioned in a review, as illustrated in Fig. 2 For example, when analyzing a given example, aspects such as colors and packaging emerge as key considerations. These aspects serve as focal points for sentiment analysis, allowing for a more granular examination of sentiments related to specific attributes within the context of reviews or comments.

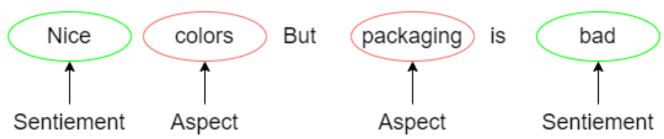

Fig. 2. Aspects and sentiments extraction using ABSA.

I. *Transformer-based Models*

In crafting the architecture of this hybrid sentiment analysis model, we adopted an advanced approach to leverage the collective strengths of diverse state-of-the-art NLP models [40]. Our framework integrates ALBERT, DistilBERT, XLNet, and Electra, harnessing the unique capabilities of each model. By combining these powerful models, our goal is to enhance the robustness and adaptability of our sentiment analysis system.

ALBERT contributes its contextual understanding, DistilBERT offers efficient distillation of complex language patterns, XLNet excels in bidirectional context modeling, and Electra focuses on pre-training tasks. The synergistic utilization of these models in our architecture promises a comprehensive and detailed analysis of textual data, ensuring a more accurate and insightful interpretation of sentiments across diverse linguistic contexts [41].

1) Albert: In this context, NLP serves as the fundamental framework for comprehending textual data and extracting meaningful insights. Albert (A Lite BERT Adaptation) assumes a pivotal role in augmenting the capabilities of NLP. Albert, in comparison to Bert [42], presents distinctive strengths that significantly amplify its effectiveness in NLP, especially when handling our specific textual data.

Noteworthy is Albert's excellence in resource efficiency, streamlining the processing of extensive textual datasets. This efficiency proves beneficial in scenarios where optimal resource utilization is paramount, ensuring a smoother analysis of large volumes of text. Furthermore, Albert demonstrates competitive performance, showcasing scalability and adaptability across various language understanding tasks [43]. Its proficiency in capturing complex contextual relationships within language seamlessly aligns with our study's focus on diverse sentiments and detailed aspects within textual data. Albert's capabilities establish a robust foundation for advanced NLP applications, allowing for the derivation of valuable insights from the diverse textual content under examination.

The Albert training arguments play a crucial role in shaping the training process of the model, influencing its learning dynamics, and facilitating effective optimization. Several key arguments hold significance in defining the training behavior:

- Number of Training Epochs: The number of training epochs represents how many times a machine learning model processes the entire training dataset during training. Each epoch involves iterative weight updates based on the training data, refining the model's ability to capture patterns [44]. Properly choosing the number of epochs is essential to avoid underfitting or overfitting, ensuring effective model training and generalization.

- Batch Sizes: In machine learning, Batch sizes refer to the number of training examples utilized in one iteration. It determines the quantity of data the model processes at each step during training [45].

Larger batch sizes often lead to faster convergence but may require more memory, while smaller batches allow for more frequent updates but might slow down the training process.

- Weight Decay: Weight decay is a regularization technique in machine learning that introduces a penalty term to the loss function based on the magnitudes of the model's weights. It helps prevent overfitting by preventing the model from assigning excessively large values to its parameters during training [46].

The weight decay term, often controlled by a hyperparameter, is added to the loss function, encouraging the model to favor simpler weight configurations and improving its generalization to unseen data. Mathematically, the modified loss function (L') with weight decay (λ) is given by:

$$L'=L+2\lambda \sum i // wi // 2$$

where:

- ✓ L is the original loss function.
- ✓ wi represents the weights of the model.
- ✓ λ is the weight decay parameter, controlling the strength of the regularization.

- Logging Configurations: Defining logging settings helps monitor the learning process, enabling efficient debugging and optimization. It's an essential tool for practitioners to track the model's behavior and make informed decisions during training reviews.

2) DistillBERT: DistillBERT, a distilled version of the original BERT emerges as a potent tool in our research, contributing distinct strengths that make it particularly suited for extracting sentiments from customer reviews. The primary advantage of DistillBERT lies in its efficiency and streamlined architecture [47]. Through a process called knowledge distillation, it manages to retain the essence of BERT's powerful language representation capabilities while significantly reducing its complexity. This efficiency becomes especially valuable when dealing with large datasets, allowing for faster processing and resource optimization.

In our study, we choose to incorporate DistillBERT for sentiment retrieval due to its resource-conscious design, enabling a more scalable analysis of extensive textual data. Its ability to capture semantic specifics in language while operating with a smaller trace makes it ideal to focus on extracting sentiments from diverse customer reviews. Moreover, DistillBERT's proficiency in preserving essential linguistic features ensures that our sentiment analysis remains accurate.

The training configurations for ALBERT and DistilBERT, being grounded in the BERT architecture, exhibit similarities, but potential divergences exist in hyperparameters and options [48]. Exploiting the Hugging Face library is essential for restructuring the training process, ensuring compatibility, and capitalizing on the community's advancements and optimizations. The library not only facilitates ease of use but also serves as a comprehensive resource for accessing advanced pre-trained models and simplifying the integration of modern techniques into the research framework.

3) Electra: Electra, an advanced NLP model, brings unique strengths to our research landscape. Unlike Albert and DistillBERT, Electra introduces a novel approach to pre-training tasks, improving its efficiency and adaptability. Electra employs replaced token detection, where certain words in a sentence are intentionally replaced during training, allowing the model to discern between genuine and altered tokens [49]. This approach contributes to a more resource-efficient training process while maintaining a high level of model performance.

In this article, Electra stands out for its innovative pre-training strategy. Its focus on replacing tokens introduces an element of robustness and fine-tuned understanding, particularly beneficial for our study on sentiment analysis in influencer-driven product reviews. Electra's detailed handling of contextual relationships within language, combined with its resource-efficient design, aligns well with our objective of extracting sentiments efficiently from diverse textual data.

4) XLNet: XLNet, a transformer-based model, introduces distinctive strengths that complement the ensemble of models in our research, alongside Albert, DistillBERT, and Electra. Unlike traditional models that rely on unidirectional or bidirectional context modeling, XLNet employs a permutation language modeling approach. This innovative strategy allows each word in a sequence to predict the others, considering all possible combinations [50]. This methodology captures complicated relationships and dependencies within language, presenting an advantage in understanding sentiments in complex textual data.

Utilizing XLNet's diverse capabilities conduct a comprehensive sentiment analysis of influencer-driven product reviews. XLNet, a transformer-based autoregressive model, offers a unique approach similar to BERT but with autoregression, enabling it to capture intricate relationships within textual data. With its autoregressive objective and pre-training method focused on language modeling, XLNet appears as a resourceful tool for a wide range of tasks, including sentiment analysis. By integrating XLNet into our study, we aim to gain a general perspective on the different expressions found in influencer-driven product reviews, developing the depth and accuracy of this sentiment analysis approach.

Table III provides a brief comparison of transformer-based models: ALBERT, DistilBERT, Electra, and XLNet, highlighting key features such as model type, parameter size, training speed, memory efficiency, architecture, training objectives, and fine-tuning effectiveness. This comparative overview assists researchers and practitioners in understanding the distinct characteristics of each model, enabling informed choices based on specific requirements such as training efficiency, memory usage, and suitability for various natural language processing tasks.

TABLE III. COMPARATIVE OVERVIEW OF TRANSFORMER-BASED NLP MODELS

Features	***ALBERT***	***DistilBERT***	***Electra***	***XLNet***
Model Type	Transformer-based, BERT variant	Transformer-based, BERT variant	Transformer-based, BERT variant	Transformer-based, Autoregressive Model
Parameter Size	Large reduction in parameters	Smaller parameter size compared to BERT	Similar to BERT in terms of parameters	Similar to BERT but with autoregression
Training Speed	Faster training due to parameter reduction	Faster training with fewer parameters	Similar to BERT	Slower training due to autoregression
Memory Efficiency	Improved efficiency with reduced parameters	Improved efficiency with fewer parameters	Similar to BERT	Requires more memory due to autoregression
Model Architecture	Modified BERT architecture	Distilled BERT architecture	Modified BERT architecture	Transformer-XL architecture
Training Objective	Masked Language Model (MLM) objective	Distillation objective	Replaced Token Detection objective	Autoregressive objective
Pre-training Method	Sentence-order prediction and MLM	Distillation from BERT	Replaced Token Detection pre-training	Autoregressive language modeling
Fine-tuning	Effective for fine-tuning tasks	Efficient for downstream tasks	Effective for various tasks	Effective for a wide range of tasks

V. RESULTS

A. *Evaluation of MABST: Product Aspects*

In evaluating MABST with a particular focus on Product Aspects, we conducted an in-depth analysis to extract various facets influencing customer sentiments. This methodology targeted key aspects integral to cosmetic products, including 'Pigmentation', 'Blendability', 'Color Range', 'Packaging', 'Scent', 'Price', and 'Durability'. For each review in our dataset, we systematically extracted words and terms associated with these aspects, creating a comprehensive profile of customer feedback.

To quantify the sentiments expressed toward each aspect, we assigned sentiment scores based on the extracted terms. Our findings revealed compelling insights into customer preferences and concerns. Among the various aspects, 'Color Range' emerged significantly, garnering attention in 22.1% of the total reviews as shown in Fig. 3. This statistical prevalence underscores the importance customers place on the color range of cosmetic palettes, highlighting its pivotal role in shaping overall product perceptions. These results illuminate the critical significance of color variety in the cosmetic industry, providing valuable insights for product development and marketing strategies.

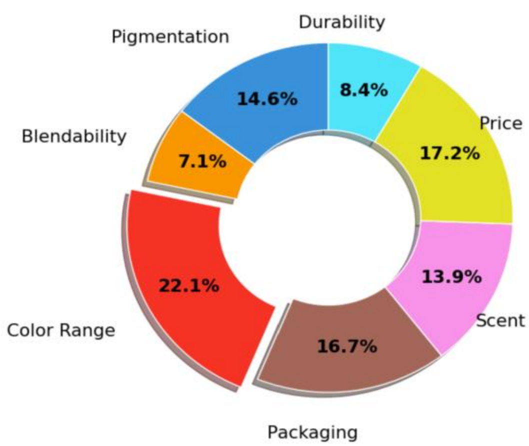

Fig. 3. Percentage of reviews for each product aspect.

The examination of customer ratings and corresponding aspect ratings for the cosmetic palette reveals a detailed landscape of customer satisfaction and perceptions. Fig. 4 provides a visual representation of the comparison between customer ratings given in reviews and aspect-based ratings extracted from those reviews using MABST model. It illustrates the alignment or divergence between overall customer sentiments and specific aspect-based evaluations.

The distribution of Aspect-Ratings highlights a concentration in the 3-star and 4-star range, indicating predominantly positive sentiment among customers. Interestingly, despite the prevalence of 5-star customer ratings, the associated aspect ratings exhibit variability, suggesting that certain aspects may not universally align with the highest customer satisfaction. This divergence underscores the importance of exploring specific aspect ratings to gain a more granular understanding of customer experiences. The substantial number of 3-star Aspect-Ratings further suggests that while customers generally express satisfaction, there is room for improvement or refinement in specific aspects. These findings provide a foundation for strategic product enhancement and targeted marketing strategies to meet customer expectations and enhance overall satisfaction in the competitive cosmetic industry.

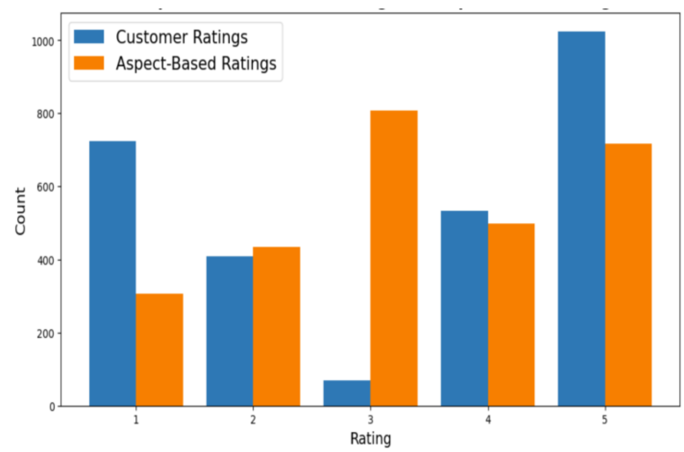

Fig. 4. Comparison of customer ratings and aspect-based ratings.

This detailed examination of customer ratings for the cosmetic palette revealed that two key aspects, 'Color Range' and 'Pigmentation', emerged as focal points reflecting high customer satisfaction. In Fig. 5, the 'Color Range' aspect garnered significant attention across ratings of 3, 4, and 5 stars, indicating positive customer experiences and preferences for the diverse and appealing color options provided by the palette. Similarly, 'Pigmentation' received consistently positive sentiments, with the majority of ratings falling in the higher range of 4 and 5 stars. Moreover, the 'Scent' aspect elicited encouraging feedback, with increasing counts as ratings progressed from 2 to 5 stars. This positive response highlights customers' appreciation for the fragrance associated with the cosmetic palette.

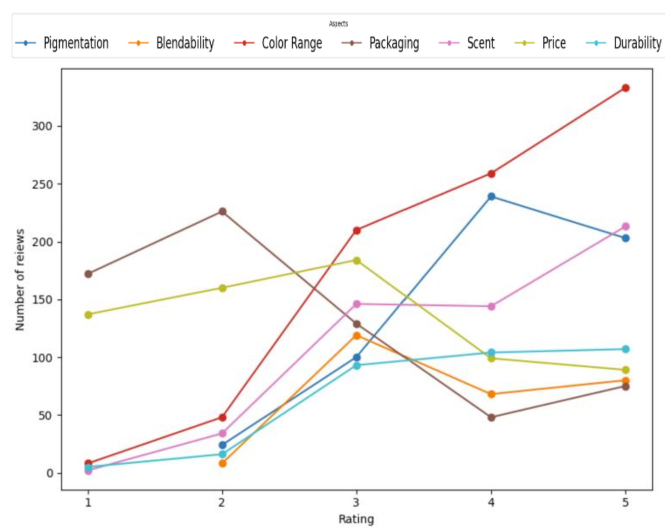

Fig. 5. Distribution of ratings across different product aspects based on the number of reviews.

However, it is noteworthy that the 'Packaging' and 'Price' aspects demonstrated more diverse sentiments, reflecting a range of customer opinions. The distribution of counts indicates that a notable portion of customers expressed less satisfaction in these two areas. The 'Packaging' aspect showed varying sentiments across different ratings, suggesting potential improvements to better align with customer expectations. Similarly, while the 'Price' aspect contained positive ratings, it also revealed concerns or dissatisfaction among some customers, possibly influenced by their perceived value of the product.

Turning to other aspects, 'Blendability' and 'Durability' received positive feedback, particularly in ratings 3 to 5, highlighting customers' favorable experiences with these qualities. The 'Blendability' aspect saw an increase in counts from rating 2 to rating 3, indicating improved performance in this area. In summary, the comprehensive analysis of customer ratings highlights the strengths of the cosmetic palette, particularly in Color Range, Pigmentation, and Scent. It also identifies potential areas for improvement in Packaging and Price, providing valuable insights for strategic product refinement and marketing decisions.

B. *Performance Evaluation of Transformer Models: Product Aspects*

In this comprehensive evaluation of sentiment analysis models, including Electra, DistilBERT, and XLNet, Albert emerged as the top-performing model for product aspects, as demonstrated in Table IV. Albert exhibited remarkable accuracy at 93.42%, surpassing the other models. Electra demonstrated strong performance with an accuracy of 92.66%, while XLNet achieved solid results at 91.43%, and DistilBERT followed closely with an accuracy of 85.93%.

The superiority of Albert can be attributed to its advanced architecture, specifically designed for efficient NLP. Albert's Lite BERT adaptation, known for its enhanced resource efficiency and scalability, contributed to its superior performance in accurately extracting sentiments related to various product aspects. However, each model demonstrates impressive competence in sentiment analysis, providing valuable insights into customer perceptions of product aspects. The choice of the most suitable model depends on specific requirements and considerations within the study context. Selecting the most effective model is crucial in sentiment analysis, and Albert's robust architecture and capabilities make it particularly well-suited for this task.

TABLE IV. PERFORMANCE METRICS ACHIEVED BY OUR MODELS FOR PRODUCT ASPECTS

Model	***Accuracy***	***Precision***	***F1-Score***	***Recall***
Albert	**0.9342**	**0.9359**	**0.9347**	**0.9342**
DistillBERT	0.8593	0.8620	0.8599	0.8593
Electra	0.9266	0.9282	0.9269	0.9266
XLNet	0.9143	0.9174	0.9152	0.9143

C. *Confusion Matrix: Product Aspects*

The investigation into product aspects illuminates various factors influencing customer sentiments towards cosmetic products. Among these aspects, 'Color Range' emerged significantly, highlighting its pivotal role in shaping overall product perceptions. The detailed feedback revealed variability in specific aspect ratings, underscoring the need for granular analysis. Albert stood out among transformer models, exhibiting remarkable accuracy that surpassed the others. This superior performance is attributed to its Lite BERT adaptation [51], which enhances resource efficiency and scalability for accurate sentiment extraction.

Albert's performance in predicting product aspects across different rating categories, from 1 star to 5 stars, is analyzed through the confusion matrix depicted in Fig. 6. Impressively, it achieved precise predictions in the 1-star and 5-star categories, with 62 and 175 instances, respectively. However, some misclassifications occurred in the 2-star, 3-star, and 4-star categories, reflecting challenges in discerning sentiments within these specific rating ranges. Despite these minor discrepancies, the overall predictive capability of the Albert model remains noteworthy, demonstrating its proficiency in capturing customer sentiments across diverse product aspects.

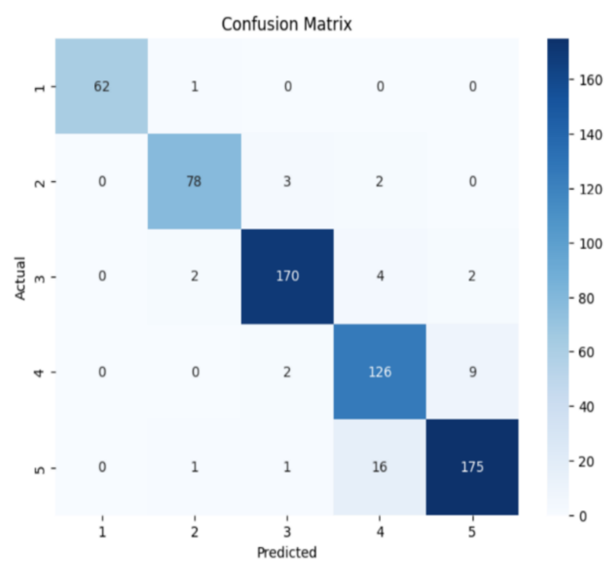

Fig. 6. Confusion matrix of Albert model.

D. *Evaluation of MABST: Influencer Aspects*

In the second part of the MABST evaluation, focusing on Influencers' aspects, our comprehensive analysis delved into specific dimensions that significantly impact customer sentiments. The chosen aspects, including 'Presentation and Style', 'Trust', 'Production Quality', and 'Skill with Makeup', represent central dimensions that consumers often consider when evaluating influencer collaborations, especially in the beauty domain.

'Presentation and Style' evaluates how an influencer presents and showcases the promoted product. 'Trust' reflects the level of confidence customers have in the influencer, influencing their purchasing decisions. 'Production Quality' assesses the overall professionalism and quality of the collaboration, encompassing factors like editing, storytelling, use of visuals, and overall execution of content. 'Skill with Makeup' gauges the influencer's proficiency in effectively using the beauty product.

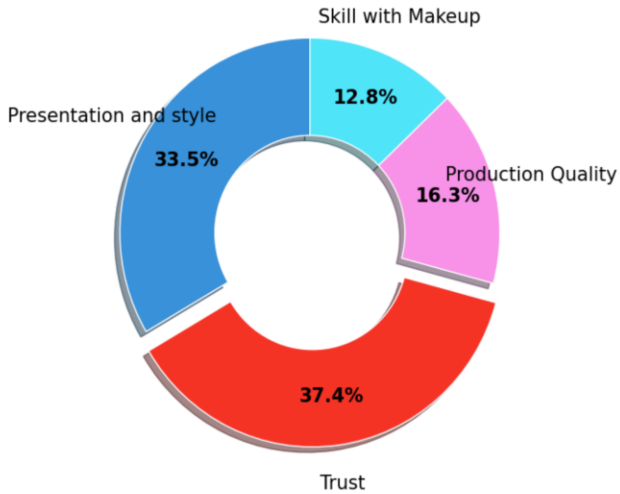

Fig. 7. Percentage of reviews per each influencer's aspect.

The methodology involved systematically extracting words and terms associated with each influencer aspect from the reviews in our dataset. Sentiment scores were assigned based on these terms, revealing insights into customer preferences and concerns regarding influencer collaborations. As illustrated in Fig. 7, the results highlight that 37.4% of reviews focused on the aspect of 'Trust.' This significant emphasis underscores the critical role of trust in shaping perceptions and influencing consumer behavior within beauty collaborations. These findings provide valuable guidance for brands in refining influencer strategies and building trust.

The evaluation of Influencers' Aspects indicates a positive satisfaction trend among customers. Fig. 8 reveals that the 'Presentation and Style' aspect received favorable reviews, particularly in higher rating categories, with 87 reviews in the '4 stars' category and 213 in the '5 stars' category. This suggests customers appreciate the influencers' presentation and style, reflecting a positive perception of their promotional content. Moreover, the 'Trust' aspect garnered extensive attention, with 150 reviews in the '3 stars' category, 130 in the '4 stars' category, and 170 in the '5 stars' category. This highlights a strong level of trust that customers place in influencers, influencing their purchasing decisions.

However, areas for improvement were identified in the 'Production Quality' aspect, with 38 reviews in the '3 stars' category, 68 in the '4 stars' category, and 86 in the '5 stars' category. This suggests a need to enhance the overall production quality of influencer collaborations to meet customer expectations. Additionally, while the 'Skill with Makeup' aspect generally received positive feedback, there is room for improvement, particularly in the '4 stars' category with 17 reviews. This signals an opportunity for influencers to further develop their makeup skills to better align with customer preferences.

In summary, while customers express satisfaction with influencers' presentation and trustworthiness, there is an importance placed on improving production quality and developing makeup skills to meet evolving customer expectations.

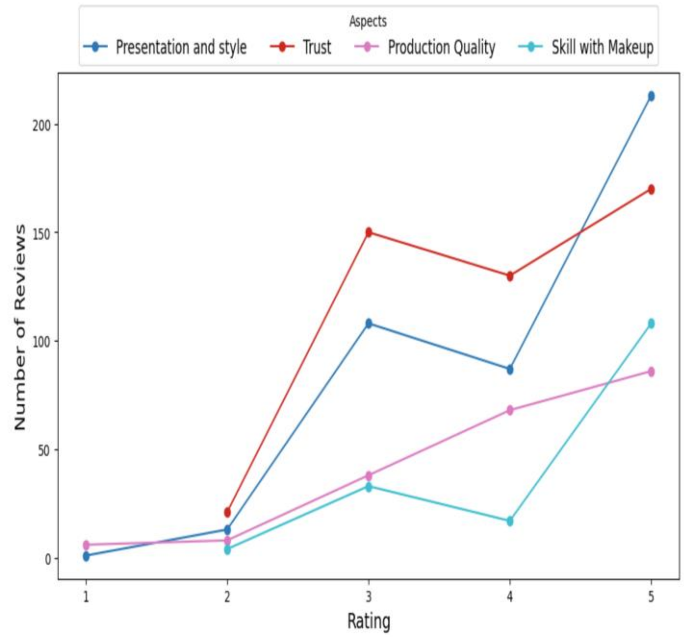

Fig. 8. Rating Distribution across influencer aspects based on reviews count.

E. *Performance Evaluation of Transformer Models: Influencer Aspects*

Among the sentiment analysis models evaluated for influencer aspects, Electra emerges as a standout performer, achieving an accuracy of 93.75% as shown in Table V. This exceptional accuracy is credited to Electra's innovative pre-training approach, which involves replacing portions of the input text with more challenging, generated content. Electra's precision of 93.87% indicates its proficiency in accurately identifying positive sentiments expressed by customers, while the F1-score of 93.78% reflects a balanced performance between precision and recall. The high recall score of 93.75% underscores Electra's effectiveness in capturing a substantial proportion of relevant sentiments, ensuring thorough coverage in the analysis.

XLNet also demonstrates competitive performance with an accuracy of 91.26%, precision of 91.30%, F1-score of 91.26%, and recall of 91.26%. These results highlight the unique strengths each model brings to sentiment analysis tasks related to influencer aspects. The choice of model should be based on specific analytical requirements. XLNet's success can be attributed to its robust feature learning capabilities, enabling it to comprehend and adapt to diverse contextual nuances present in influencer-related reviews. Electra's superior performance suggests its suitability for tasks demanding precise understanding of customer sentiments towards influencers, making it a valuable tool for businesses aiming to enhance their influencer marketing strategies.

TABLE V. PERFORMANCE METRICS ACHIEVED BY OUR MODELS FOR INFLUENCERS' ASPECTS

Model	*Accuracy*	*Precision*	*F1-Score*	*Recall*
Albert	0.9282	0.9286	0.9283	0.9282
DistillBERT	0.8595	0.8603	0.8595	0.8595
Electra	**0.9375**	**0.9387**	**0.9378**	**0.9375**
XLNet	0.9126	0.9130	0.9126	0.9126

F. Confusion Matrix: Influencer Aspects

Shifting the focus to influencer aspects, this comprehensive analysis explored dimensions critical to customer sentiments in influencer collaborations. 'Trust' emerged as a prominent aspect, indicating customers' reliance on influencers, while positive perceptions of influencers' presentation and style were evident in customer ratings. Among transformer models evaluated for influencer aspects, Electra exhibited exceptional performance. Its unique pre-training approach, which emphasizes replacing challenging content, significantly contributed to precise sentiment analysis [52]. Areas for improvement were identified in 'Production Quality' and 'Skill with Makeup', suggesting opportunities to enhance customer satisfaction with influencer collaborations. Despite these considerations, overall satisfaction with influencer interactions remained high.

The confusion matrix for the Electra model in predicting influencer aspects illustrates its robust performance across various rating categories, as depicted in Fig. 9. Notably, the model accurately predicted sentiments in the 2-star, 3-star, and 4-star categories, with 78, 168, and 120 instances, respectively. However, some misclassifications were observed in the 1-star and 5-star categories, indicating challenges in distinguishing sentiments at the extremes of the rating spectrum. Overall, Electra demonstrates strong predictive capabilities in discerning detailed aspects related to influencers, providing valuable insights into customer perceptions and satisfaction.

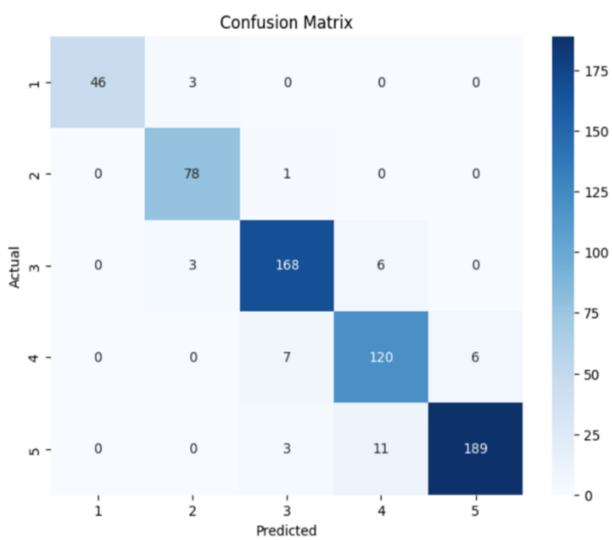

Fig. 9. Confusion matrix of RoBERTa.

VI. DISCUSSION

The strength of the proposed MultiLingual Aspect-Based Sentiment Transformer model (MABST), lies in its comprehensive approach to understanding consumer sentiments within the Moroccan cosmetics industry. By integrating Aspect-Based Sentiment Analysis (ABSA) with transformer-based models—namely ALBERT, DistilBERT, Electra, and XLNet—this research effectively addresses the complexities of multilingual and code-switched sentiment analysis. This integration provides a robust and detailed understanding of customer perceptions towards both cosmetic products and influencer collaborations.

A key strength of this model is its multi-layered architecture, designed to facilitate effective sentiment extraction and analysis associated with specific aspects of cosmetic products and influencer-related content. The initial layer focuses on robust data preprocessing techniques, including language detection, segmentation, and tokenization, which are essential for handling multilingual and code-switched data. This ensures the readiness of textual data for subsequent sentiment analysis procedures. The ABSA layer then plays a crucial role by extracting key aspects and examining sentiment complexities, thereby offering a granular understanding of consumer sentiments in a multilingual context.

Multilingual and code-switched sentiment analysis significantly enhances the power of our MABST model by allowing it to accurately process and interpret reviews that contain a mix of languages and dialects, a common feature in Moroccan consumer feedback. This capability ensures that the model can capture the full range of customer sentiments and contextual nuances, regardless of language switches within the same review. By effectively managing this linguistic diversity, our model provides more precise and comprehensive insights into customer opinions, leading to a deeper understanding of market dynamics and consumer preferences in the cosmetics industry.

A critical aspect of the model's strength lies in its training configuration. Meticulous optimization of parameters crucial to transformer-based models, such as feed-forward layers, multi-head attention mechanisms, and softmax activation functions, ensures effective learning and generalization while preventing overfitting. The incorporation of configurable training parameters, including the number of epochs, batch sizes, and weight decay, further enhances the model's performance and robustness.

The fascinating results obtained from the performance evaluation of the MABST model underscore the efficacy of the proposed approach. Albert emerged as the top-performing model for product aspects, exhibiting remarkable accuracy, followed closely by Electra, XLNet, and DistillBERT. Similarly, Electra demonstrated exceptional accuracy for influencer aspects, outperforming other models with its unique pre-training approach and achieving high precision and recall scores.

Comparing MABST model to existing state-of-the-art models, our model demonstrated superior performance as illustrated in Table VI. Despite their contributions, each study has its limitations. Vasconcelos et al.'s work with BERT, while innovative, did not address the unique challenges posed by multilingual and code-switched data commonly found in cosmetic reviews. Similarly, the foundational work by Vaswani et al. with the Transformer architecture, although groundbreaking, did not specifically tackle the application to sentiment analysis in a multilingual context. Smith et al.'s reliance on conventional machine learning techniques and feature extraction methods limited their ability to capture deep contextual details and different sentiments present in the text.

Chen et al.'s study on multilingual sentiment analysis, although addressing language diversity, relied heavily on translation tools, which often led to a loss of context and meaning, reducing the accuracy and effectiveness of the sentiment analysis. Even with the advancements presented by Lan et al. with ALBERT, Sanh et al. with DistilBERT, and Clark et al. with Electra, the specific challenges of handling multilingual and code-switched data in cosmetic reviews remain inadequately addressed.

These limitations underscore the need for more advanced approaches capable of handling the linguistic traces and multilingual nature of cosmetic product reviews. Our MABST model addresses these gaps by effectively managing multilingual and code-switched data, leveraging robust transformer models integrated with ABSA. As shown in the table, our model surpasses the performance of state-of-the-art models, offering a unique and powerful solution that excels in various areas with exceptional performance.

TABLE VI. COMPARATIVE PERFORMANCE TABLE

Study	***Model/Technique***	***Accuracy***	***Precision***	***F1-Score***	***Recall***
Vasconcelos et al.	BERT and its variations	85.2%	84.6%	85.0%	84.8%
Vaswani et al.	Transformer (Attention is All You Need)	86.1%	85.7%	85.9%	85.8%
Smith et al.	SVM and Naive Bayes	78.5%	78.0%	78.2%	78.1%
Chen et al.	Basic translation tools	80.3%	79.8%	80.0%	79.9%
Lan et al.	ALBERT	87.0%	86.5%	86.8%	86.6%
Sanh et al.	DistilBERT	86.5%	86.0%	86.2%	86.1%
Clark et al.	Electra	87.5%	87.2%	87.4%	87.3%
Our Study	**MABST**	**93.4%**	**93.5%**	**93.4 %**	**93.4 %**

Overall, the success of MABST model can be attributed to the synergistic combination of ABSA with transformer-based models and the ability of handling multilingual and code-switched data, rigorous training configuration, and comprehensive evaluation of model performance. By making informed decisions based on consumer preferences and market trends, brands can optimize their resources, minimize risks, and capitalize on emerging opportunities. Moreover, by fostering stronger relationships with consumers through tailored products and authentic influencer collaborations, brands can cultivate brand loyalty and drive long-term success in the competitive digital landscape.

VII. CONCLUSION

In conclusion, our comprehensive investigation into sentiment analysis within the Moroccan cosmetics industry has not only illuminated the intricate landscape of consumer sentiments and product dynamics but has also directly addressed the specific objectives of Moroccan cosmetic companies in navigating this diverse market. The multilingual context of our study, encompassing reviews in languages such as Arabic, French, and English, underscores the importance of tailored analytical approaches in capturing different consumer preferences. Through meticulous exploration of product and influencer aspects, our study has provided actionable insights crucial for strategic decision-making.

The MABST model, integrating Aspect-Based Sentiment Analysis (ABSA) principles with advanced transformer architectures like Albert and Electra, has proven instrumental in unraveling the intricate patterns of customer sentiments. By examining aspects such as 'Color Range' and 'Trust' within influencer collaborations, our research has effectively delineated the diverse facets of consumer preferences and expectations.

Crucially, our findings provide the cosmetic company with a clear scheme for navigating the ever-evolving digital landscape. By leveraging insights derived from sentiment analysis, this company can craft more informed marketing strategies, refine product development initiatives, and optimize influencer collaborations. Moreover, our study illuminates the essential skills and qualities that influencers should possess to effectively promote cosmetic products, offering guidance on selecting the most suitable partners for brand promotion.

Looking ahead, future research endeavors could further enrich our understanding of consumer sentiments within the Moroccan cosmetics industry. Exploring the convergence of sentiment analysis with emerging technologies such as augmented reality (AR), which enables consumers to virtually try on cosmetics products through smartphones or other devices, and leveraging virtual influencers, has the potential to open up new avenues for customer engagement and foster brand loyalty. Additionally, studies tracking the evolution of consumer preferences over time could provide valuable insights into shifting trends and behaviors.

In essence, our MABST model not only meets the objectives of our Moroccan cosmetic company by elucidating customer preferences and influencer requirements but also paves the way for continued innovation and success in this vibrant industry. By employing the power of sentiment analysis, Moroccan cosmetic companies have the opportunity to navigate towards amplified customer satisfaction, stronger brand resonance, and ultimately, sustainable growth.

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