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Transfer Learning-Based Framework for Sentiment Classification of Cosmetics Products Reviews

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Abstract- **The exponential growth in online reviews and recommendations availability drives sentiment classification, an interesting topic in industrial research. There is a vital requirement for organizations to explore client behaviour to assess the competitive business environment. This study aspires to examine and predict customer reviews using Transfer learning (TL) approaches. Reviews can span so many domains that it is challenging to gather annotated training data for all of them. Hence, this paper proposed an annotation algorithm to label a large unlabeled dataset. These reviews must be pulled and examined to predict the sentiment polarity, whether the review is positive, neutral, or negative. We propose a deep learning-based approach that learns to extract a meaningful representation for each review in an unsupervised fashion. Sentiment classifiers trained with this high-level feature representation outperform state-of-the-art methods on a benchmark of reviews of cosmetics brands on Amazon or other platforms. Using the BERT for sentiment analysis, we achieved the highest accuracy of 93.21% compared to previous studies.**

Index Terms-- **Cosmetic purchase behaviour, Text mining, Sentiment analysis.**

I. INTRODUCTION

In this competitive era of business, earning a high profit is a big deal. The primary duty of the brand's manager is to know how a company can boost its profit ratio. The profit ratio is directly related to customer satisfaction regarding high-quality products. When a company introduces a new product, high quality and customer satisfaction are the primary concern of the brand's manager. Nowadays, everyone is conscious about their skin, hair, and complexion to try a product for the first time. To improve product quality or introduce a new product, a brand's manager always wants to get their customer's reviews so they can analyze customer satisfaction and their product quality to give the best service to their customer and introduce better or improved quality.

In this advanced era of technology, people depend on the internet, mobile, social media, and online shopping (e-commerce). According to a report by DMC media (digital marketing and advertising company) in South Korea in 2016, about 51.5% of people shared their experiences of online consumption [1].

The trend of online shopping has influenced the decision-making process of customers. When people want to buy a new product, they first want to know about customer reviews. As shown by the evidence of [2] and [3], the retail sale of a product is highly affected by customers' online reviews, consumer decision processes, and product quality. So the brand manager seeking high sales must analyze customers' requirements and evaluate their needs and satisfaction regarding high quality and trends.

According to [4], to explore customers' preferences regarding delicate products, brand managers face different opinions for the same product because the same product has different effects on different skin characteristics of individuals. For such reasons, cosmetics are considered a high-risk category product, and customers' opinion directly influences the company's sale. By keeping the marketing firm theory in mind, the research explores the possibility of improving the bilateral contingent relationship between customers and marketing firms within the cosmetic domain. When a customer wants to buy cosmetics online, they first want to know about other consumers' reviews for such cosmetics, so they can predict what kind of cosmetic will suit their sensitivity problem or needs. As for cosmetics characteristics in comparison to available products such as home appliances or food, they are highly dependent on customer reviews [5], [6]. When a company devotes a large amount of its budget to developing high-quality products to gain selling advantages. This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium provided the original work is properly cited. Online reviews are assets to improve their products and distinguish their product from other competitors by meeting the requirements of customers [7].

An online shopping mall in South Korea named CJ Mall announced that products with a favourable opinion have an improvement in their sale, averaging 2.5 to 5 more than other products. Online review effects are considerably throwing light on sales. The rise of interest in cosmetic videos positively affected cosmetic purchase behaviour as the respondents were young and more educated [8]. Timon conducted a survey and high-lights the factor that product awareness through online reviews ranked second, at 18%, among the factors considered when purchasing cosmetics. On the other hand, product awareness through traditional TV commercials ranked seventh at 3%, which shows a low impact as a purchase-decision factor.

A practical examination of textual data sentiment categorization utilizing the BERT and Zero-shot transfer learning algorithms was proposed in this paper. For our study, we have extracted unstructured data on cosmetics product reviews from social media and Amazon. The three procedures used in this study are feature extraction, sentiment categorization, and data preprocessing. In the first stage, we preprocessed unstructured reviews, and in the second step, we categorized all of the reviews by computing the sentiment score with a rule-based classifier. In the third step, we carried out classification using BERT and Zero-Shot algorithms. The labelled dataset consists of three classes: "positive," "Neutral," and "Negative." The performance of the suggested strategy is then evaluated empirically using K-fold cross-validation to gauge the system's precision.

The parameters of recall precision and F1 score for each model are also evaluated. The best accuracy is obtained using the suggested transfer learning BERT approach, surpassing all previous classifiers for the cosmetic and beauty products dataset. The following are the study's contributions.

1. An algorithm is suggested and put into practice to perform annotation on a dataset of unlabeled product reviews.
2. A feature vector generation technique is suggested for categorizing sentiment polarity.
3. Based on the sentence and review levels, two sentiment polarity categorization studies are carried out.
4. Based on their experimental findings, BERT and Zero-Shot transfer learning models for sentiment categorization are assessed and contrasted.

II. LITERATURE REVIEW

The concept of "sentiment analysis" has undergone much evolution and engagement in recent years. This method's main objective is to understand human emotions expressed as sentiments on social media or other platforms. It reenacts an influential position in various organizations about health, education, the financial market, and numerous goods and services. This section discusses the research that has been done in this direction. Word-of-Mouth is defined as sharing information in the form of thoughts and sentiments; in contrast, online evaluations of a company's product or service posted on the company's website are regarded as online (WOM) [9]. Compared to traditional word-of-mouth, online reviews have a more significant impact on purchasing decisions [10]. Online reviews are more objective, truthful, and thorough than information made public by merchants [11] [12]. Online reviews significantly influence a company's sales and purchases. Because of this, research on online reviews and e-commerce has grown considerably. [13] Asserts that emotional and subjective reviews strongly influence sales and product purchases.

In summary, there are several automated methods and algorithms for extracting internet reviews; most of them have concentrated on text data analysis, but some have also looked at relative customer satisfaction ratings and causes of consumer happiness. Sentiment analysis automatically extracts opinions, such as people's feelings and emotions about particular entities, and locating those opinions [9]. The three categories into which sentiment analysis can be divided are the machine learning technique, the lexicon-based approach, and the hybrid strategy that combines the previous two approaches [10]. Nowadays, computational technologies are being used in various domains of life, including healthcare [14], security [15] [21] [25] and also in safety purposes [16], disaster [17], and situational awareness [19] [26] [27] in the educational domain [18] as well. Sentiment analysis is a prominent research topic in demand under the category of NLP [20]. Another method has been used to forecast human emotions reflected in product reviews taken from Amazon [2]. Review text characteristics, such as subjectivity degree, were investigated to reevaluate the effect of reviews on sales and purchases. It is possible to accurately predict how reviews affect sales using a Random Forest-based classifier [3]. Textual data was less emphasized in earlier studies than numerical and categorical data. Some earlier research in opinion mining only counted favourable and negative evaluations. A suggestion for an automatic summarising method based on analyzing the internal topic structure of review articles to compile customer complaints was made to progress it. Peer techniques were employed, including opinion mining and clustering summarization [9].

Real-time deep learning models were also integrated with the IoT- based screening system for classification and detection purposes, such as face mask detection. VGG-16, MobileNetV2, Inception v3, ResNet-50, and CNN employing a transfer learning technique are used for classification [9]. Emergency monitoring systems developed using deep learning models to perform pedestrian counting in practical contexts have generated interest. Based on piezoelectric sensors and footstep-induced structural vibration signals, an indoor pedestrian counting method has been proposed. This method calculates the number of pedestrians by analyzing the space differential features from the vibration signals brought on by their footsteps. The Deep learning model (CNN) was used in [9] to achieve this. Moreover, we also reported the advantages and disadvantages of previous research work in text analytics and sentiment analysis, as shown in Table I.

Table I: Advantages and disadvantages of previous research work on textual data

Study	Advantages	disadvantages
[9]	Topic2features to handle the data sparsity	Time-consuming and does not attain a significant accuracy
[10]	Sentiment on multimedia data	Pre-build libraries are used for sentiment score
[14]	Enhanced text mining to understand subjective and objective knowledge from text	No methodology to extract sentiments from customer feedback
[15]	Enhanced text mining to understand subjective and objective knowledge from text	No methodology to extract sentiments from customer feedback

For better outcomes in supervised machine learning, classification tasks and feature vector analysis are essential. However, several categorization jobs reportedly failed [9] to provide better results. Public authorities can benefit from situational knowledge disseminated on social media during the COVID-19 pandemic. By thoroughly defining categories and offering data-driven, valuable insights into information, this research study adds to the literature on situational details. Machine learning techniques were employed to examine the propagation scale of situational information, achieving 77 percent accuracy using SVM. User features, content features, and LIWC linguistic features were used. With supervised machine learning techniques (DT, KNN, and SVM) and lexicon-based models (Urdu sentiment analyzer, Urdu sentiment Lexicons), sentiment analysis of Urdu blogs has been carried out. The lexicon-based strategy was superior, according to the results [9]. A hybrid deep-learning strategy has succeeded in forecasting fine-grained sentiments [10].

An aggregation model was created to quantify the hybrid polarity. Additionally, the BoVW was trained using SVM to predict the sentiment of visual content. The recommended ConvNet-SVMBoVW performed better than the traditional models [11]. The LDA (latent Dirichlet allocation) topic modelling methodology has been employed in [12] to give an automated method of labelling the data using the Topic2labels (T2L) framework. Use Bert (the bidirectional encoder representation from the transformer) embeddings to create a feature vector for the classifier to classify the data contextually. In [13], multi-regression, random forest, and CNN techniques from deep learning and machine learning are utilized to speed up the process of creating new varieties of moringa by using fewer resources.

III. PROPOSED METHODOLOGY

In this research work, we have crawled cosmetics brand reviews from different sources like amazon. After collecting the dataset, we performed various preprocessing techniques to normalize the raw dataset. We have used two deep learning approaches for sentiment classification, including Bert and zero-shot learning. The proposed framework of this study is shown in Fig. 1.

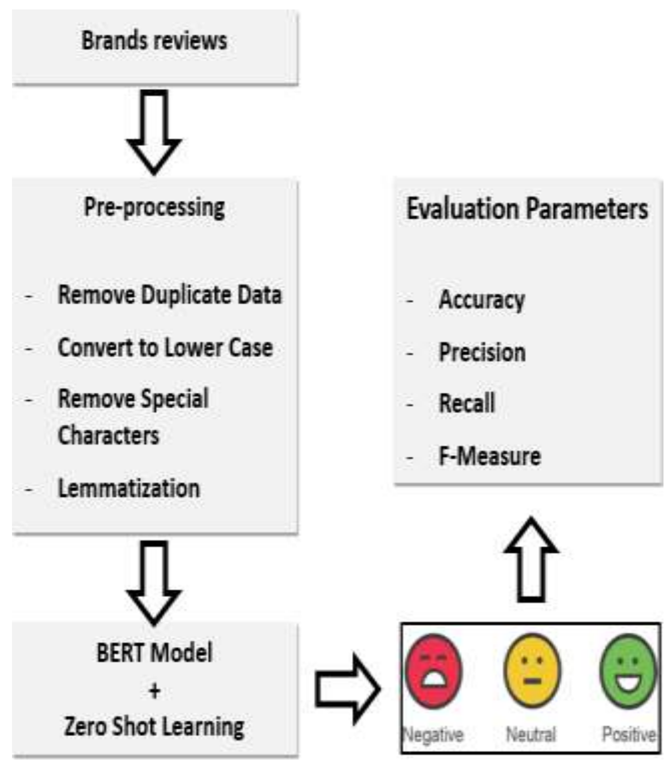

FIGURE 1: The framework of cosmetic brands review analysis

A. DATASETS

We obtained information for the corpus from various sources, including social networking sites and websites on the internet where people post their highly valued opinions. The majority of the data was acquired from comments on Amazon and Facebook. Online stores have moreover developed into a sizable component of digital marketing. As a result, we also obtained information from online product reviews. The Sample dataset is shown in Fig. 2.

	name	brand
95	Midnight Secret Late Night Recovery Treatment	GUERLAIN
171	Water Drop Hydrating Moisturizer	DR. JART+
114	Coconut Melt	KOPARI
109	Black Tea Age-Delay Cream	FRESH
108	Abeille Royale Youth Watery Oil	GUERLAIN

FIGURE 2: The sample dataset

B. DATA PREPROCESSING

To start the sentiment analysis process, firstly, data we collect from different sources, as input data mostly have an unstructured form. To get meaningful information from this raw data, we have to make it structured. Feature representation is motivated by the fact that machine learning tasks such as text classification often require input that is mathematically and computationally convenient to process. Different feature representation techniques convert raw input data into structured form before performing any text classification task by cleaning data. When we talk about unstructured data, it consists of reviews with flaws, such as using informal language on social media. In our proposed work, we have used the following preprocessing techniques.

- Removing Duplicate Data: With the help of the drop_duplicate function in Python, we have dropped allduplicate rows in our dataset.
- With the help of the to_lower function in Python, we have converted our data into lower cases.
- Furthermore, we used various python methods to remove special characters and stop words.

Tokenization is the following stage of text data preparation. The tokenization method divides the text into smaller components, such as sentences or words. Then, each unit is regarded as a separate token. We will employ the NLTK library to accomplish this. The Natural Language Toolkit library in Python is used for text preprocessing, called NLTK.

C. BERT FOR SENTIMENT CLASSIFICATION

In Natural Language Processing (NLP), sentiment analysis is a crucial activity. It determines whether a person's feelings regarding products, movies, and other such items are positive, negative, or neutral. In 2018, Google Research created the Bidirectional Encoder Representation for Transformer (BERT), an NLP model that has now achieved cutting-edge accuracy on several NLP tasks. Transformer architecture is known as encoder-decoder architecture because it has an encoder stack and a decoder stack, but BERT is only a part of transformer architecture. The architecture complexity of the two variations, BERT-base and BERT-large, varies. The standard model's encoder contains 12 layers, while the large encoder has 24. The complete architecture of BERT is shown in Fig. 3.

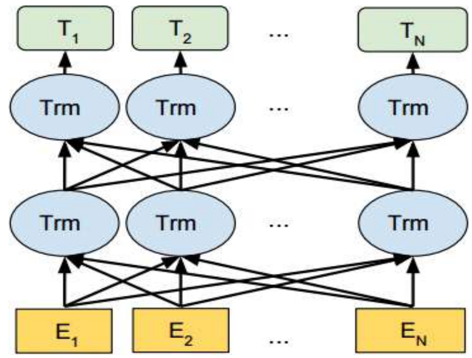

FIGURE 3: The structure of the BERT model

The Transformer encoder reads the entire sequence of words simultaneously, in contrast to directional models, which read the text input sequentially (from right to left or left to right). Although it would be more accurate to describe it as non-directional, it is therefore thought of as bidirectional. This trait enables the model to understand a word's context depending on all of its surroundings (left and right of the word).

D. ZERO-SHOT LEARNING

The goal of zero-shot and few-shot NLP models is to generate predictions for an NLP task without ever having seen a single labelled item for that task (for zero-shot learning) or only a small number of such objects (for few-shot learning). The most well-known example is, without a doubt, OpenAI's GPT-3, a few-shot learner that has excelled in a variety of applications. Even though most developers lack the resources to run GPT-3, there are, fortunately, several more affordable options. The simple structure of zero-shot learning is shown in Fig. 4.

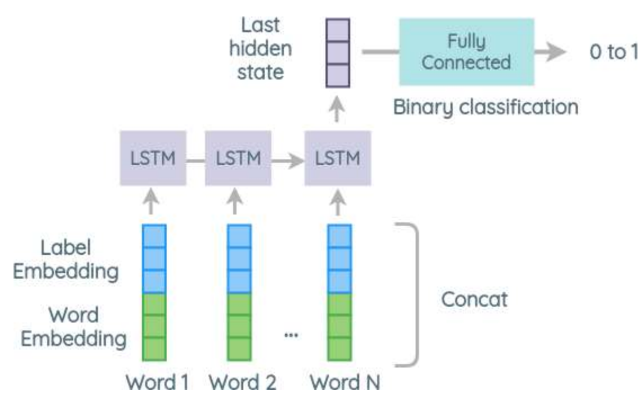

FIGURE 4: The structure of the BERT model

IV. RESULT AND DISCUSSION

A practical examination of textual data sentiment categorization utilizing the BERT and Zero-shot transfer learning algorithms was proposed in this paper. For our study, we have extracted unstructured data on cosmetics product reviews from social media and Amazon. The three procedures used in this study are feature extraction, sentiment categorization, and data preprocessing. In the first stage, we preprocessed unstructured reviews, and in the second step, we categorized all of the reviews by computing the sentiment score with a rule-based classifier. The three classes in the labelled dataset are "positive," "neutral," and "negative." We used BERT and Zero-Shot algorithms to perform classification in the third stage. The performance of the suggested strategy is then evaluated empirically using K-fold cross-validation to gauge the system's precision.

We have used two deep learning approaches for sentiment classification: BERT and Zero-shot learning. The hyperparameter details of the deep learning model are also shown in Table II.

Table II: Summary of hyper-parameters of baseline models.

Model	No. of Components	No. of Iteration	Random State	Batch Size
Bert	10	5	None	-
Zero-Shot	50	20	-	64

By using the BERT for sentiment analysis, we achieved the highest accuracy of 93.21%. For the visual representation of the performance of our model, we also computed the accuracy and loss graph shown in Fig. 5.

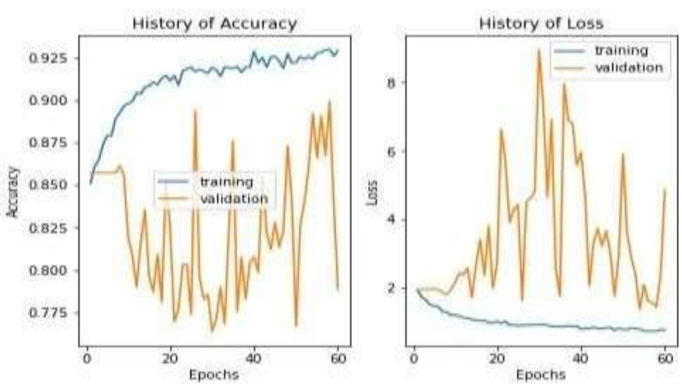

FIGURE 5: Accuracy and loss graph using the BERT model

Confusion matrices are typically used in deep learning and machine learning classification tasks to show the representation of statistical data collected during experimentation. Additionally, we generated a confusion matrix to depict the performance of our model, as seen in Fig. 6. Moreover, for further evaluation of our model in sentiment classification, we have also calculated precision, recall, and f-measure against each sentiment class, as shown in Table III.

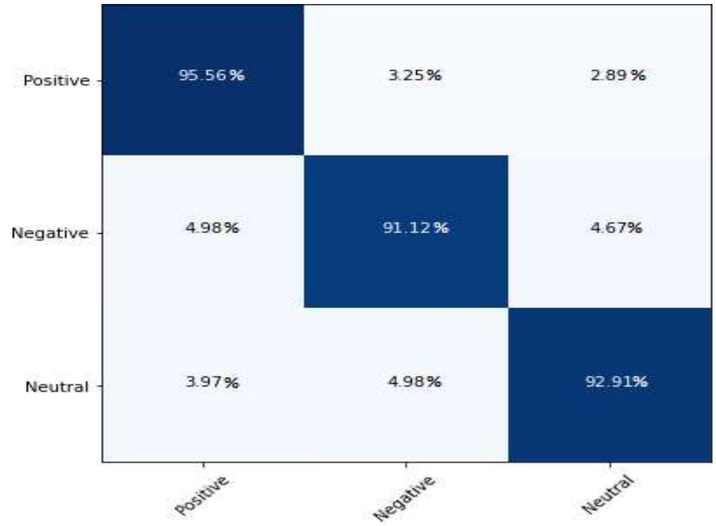

FIGURE 6: Confusion matrix using BERT model

We also evaluated the performance of our model according to accuracy, precision, recall, and f measure as explained by the mathematical equations shown as in (1) – (4), respectively.

$$Accuracy = \frac{TN + TP}{TN + TP + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F\ Measure = 2 * \frac{Precision * Recall}{Precession + Recall} \quad (4)$$

Table III: Performance Matrix of each sentiment class

Classes	Accuracy	Precision	Recall	F Measure
Positive	95.07%	0.94	0.91	0.93
Negative	94.08%	0.90	0.92	0.91
Neutral	94.41%	0.91	0.92	0.92

Furthermore, we also reported the comparative performance of our proposed model with previous research, as shown in Table IV.

Table IV: Performance evaluation of the proposed study with the previous state-of-the-art approaches

Study	Approach	Accuracy
[22]	Artificial Neural Network	88%
[23]	LDA	82.21%
[24]	Data Miner tool	73.28%
Our Proposed Approach	BERT	93.21%

V. CONCLUSION

Sentiment classification is a fascinating study area driven by the exponential rise in internet evaluations and recommendations availability. Organizations must investigate client review behaviour to evaluate the challenging business environment. This study uses transfer learning (TL) techniques to analyze and forecast customer opinions. Therefore, an annotation approach was suggested in this research to label unlabeled datasets. We present a deep learning-based methodology that develops an unsupervised ability to extract a meaningful representation for each review. In this study, we used cosmetics brands' datasets as textual reviews collected from Amazon. By using the BERT for sentiment analysis, we achieved 93.21% accuracy.

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CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest to report regarding the present study.

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