CHAPTER 1

INDTRODUCTION

1.1 Rationale

In this era, the development of technology is getting faster. This has led to many advantages, one of which is the lifestyle of people about shopping and selling online [5]. The techniques used by humans in carrying out activities will change due to the development of the internet and technology, such as the process of buying and selling face to face, but because there is an easier medium supported by the development of the internet, many companies have begun to add marketing channels for their products via the internet [41]. The many conveniences offered in e-commerce today, make people interested in using it [53]. People often use this information technology to buy and sell goods through e-commerce, one of which is beauty products that will be made in this study [6].

Beauty products today have a variety of brands and the functions they offer [9]. In e-commerce, product reviews are a big consideration for potential buyers because they can display other buyers' experiences when using a product [3]. Product reviews can also provide information on whether the product is suitable or not for prospective buyers because the public must also be aware of the quality of a beauty product so as not to cause physical damage that could potentially be experienced if using a product that is not of quality or does not have BPOM standardization [11]. Based on research conducted by Jain et al. (2021) a review has a strong influence on consumer decision making in buying a product [17]. However, it is often found that reviews on a product have different aspects and content [50] [3], making it difficult for consumers to find all reviews from different aspects and content quickly [44], and requires a short time to analyze, therefore a system is needed that can process and summarize review data containing sentiments or emotions expressed by buyers on a content according to its aspects [32]. Sentiment analysis is performed as a process to generate categorization of opinions through reviews given on a topic into positive, negative, or neutral labels [26]. Based on the level, sentiment analysis is divided into three levels: document level, word level, and aspect level [3], so that from these problems aspect-based sentiment analysis is needed to get more specific sentiment results.

Related research has been conducted by Zing Fang and Jie Tao [12] discusses aspect-based sentiment analysis using BERT is not classifier. The background of the research is the need to understand the sentiment of online restaurant consumer reviews that can help various decision-making processes. The aspects contained in the study are aspects of food, price, service, atmosphere, and variety. The results showed that the approach with the BERT method obtained an accuracy of 61.65%. Further research conducted by Murthy, Allu, & Andhavarapu [28] discusses sentiment analysis on movie reviews and

Amazon products using the Long Short-Term Memory (LSTM) method. The background of the research is that to analyze textual information with large amounts manually will be difficult and time consuming. So that in the study sentiment analysis was carried out using the Long Short-Term Memory (LSTM) method. The results of the study found that the LSTM method can produce an accuracy of 85%.

Other research related to sentiment analysis has been conducted by Singh, Jakhar, Pandey [42] discusses sentiment analysis on the impact of the corona virus in social life. The background of this research is to study the wishes and opinions of people regarding the mental conditions affected by the corona virus, so that in this study sentiment analysis using BERT was carried out with datasets originating from Twitter. The study found that the BERT model was able to produce high accuracy of 94%. While further research conducted by Rai, et al [34] discusses the classification of fake news using LSTM. In this research, a transformer using BERT is applied. The BERT model output is connected to the LSTM layer. The problem behind this research is to verify the validity of the news manually is very difficult. So that classification is needed on the news data. The test results obtained an increase in accuracy of 2.50% and 1.10% on the PolitiFact and GossipCop datasets using the vanilla pre-training BERT model. The accuracy obtained on the PoliticFact dataset using LSTM + BERT is 88.75%, while on GossipCop it is 84.10%.

Based on the description above, this research will conduct sentiment analysis of beauty product reviews using aspect-based sentiment analysis with the aim of getting more specific sentiments based on their aspects [3]. The aspects used include packaging, moisture, price, staying power, and aroma. The aspects used are based on the research of Yutika, et al [54] is price, packaging, aroma. Meanwhile, aspects of moisture and staying power based on research by Tran, et al [**?**]. In conducting sentiment analysis, researchers use a combination of BERT embedding and LSTM as a classification method to produce good performance. The use of LSTM as a classification method is because LSTM has the advantage of being able to model and learn long-term relationships between data, and has strong potential in dealing with complex high dimensions in very large data [23], so that the LSTM can recognize patterns in the data to make predictions about sentiment [40]. The use of LSTM as a classification method is also due to the fact that it is a deep leaning model with a type of RNN architecture that is dedicated to sequential modeling such as text classification, and this sequential modeling capability is not possessed by other deep learning models [24]. While the use of BERT in this research is because the model has provided output in the form of pre-trained models that can be adopted for various NLP tasks, such as text classification [27]. From this description, the researcher will conduct a combination of BERT Embedding and LSTM because this combination has the advantage of increasing the ability of the model [16] because BERT has a contextualized sentence-level representation that can help LSTM better understand sentence semantics [34].

In this study, a beauty product review dataset will be used which consists of three classes, namely positive, negative, and unknown. The dataset experiences imbalance conditions or an unbalanced amount of data in each class, so it is necessary to apply an oversampling method using SMOTE which is used to handle imbalance data on the beauty product review dataset. The use of SMOTE in this study is because the SMOTE method can produce synthetic samples of minority classes by taking oversamples from each data point by considering a linear combination of existing minority class neighbors [49]. In addition, the SMOTE method was used because in Ade Nurhopipah and Cindy Magnolia's research [31] comparing resampling methods on imbalance datasets resulted in the best performance of the SVM classification model with the dataset resampling results of the SMOTE method getting an f-measure value of 0.9524. Another reason for using SMOTE is because SMOTE can provide better performance than without using SMOTE [36]. This is evidenced in the research that SMOTE can improve the performance of the LSTM model by 8% compared to not using SMOTE [37], so that the research conducted is expected to help consumers in choosing the best beauty products based on the results of sentiment analysis.

1.2 Theoretical Framework

The theoretical framework of this research is using the IndoBERT Embedding model and Long Short-Term Memory (LSTM). LSTM is an improvement of Recurrent Neural Network (RNN). LSTM proposes memory blocks compared to RNN units in solving vanishing and exploding gradients. The LSTM network can remember and connect previous information with the currently acquired data [15]. In addition, the advantage of LSTM as a classification method is that it can model and learn long-term relationships between data, such as in text that requires context for proper understanding. LSTM also has strong potential in dealing with complex high-dimensionality in very large data [23], so that the LSTM can recognize patterns in the data to make predictions about sentiment [40]. IndoBERT, on the other hand, provides output in the form of pre-trained models that can be adopted for various NLP tasks, such as text classification [27]. This was done in previous research by Rai, et al [34] which implements transformers using BERT. The output of the BERT model is connected to the LSTM layer to classify fake news. The test results obtained an accuracy of 88.75% on the PoliticFact dataset and 84.10% on the GossipCop dataset.

From this description, researchers will combine BERT Embedding and LSTM because this combination has advantages that can improve the model's capabilities [16] because BERT has a contextual sentence-level representation that can help LSTM understand the semantics of sentences better [34].

1.3 Conceptual Framework/Paradigm

The conceptual framework of this research employs a combination of the IndoBERT embedding model and LSTM to perform aspect-based sentiment analysis on beauty product reviews from the Female Daily Network website. The input data consists of reviews covering five aspects: packaging, moisture, price, staying power, and aroma. Each aspect is labeled with one of three sentiment classes: positive, negative, or unknown. The data is then preprocessed through case folding and tokenization to clean the text. After preprocessing, the dataset is split into training and testing sets with a ratio of 80% training data and 20% testing data [18]. IndoBERT is then applied to generate token embeddings, which are used in the classification process. To address class imbalance, SMOTE is performed on the training data to ensure the positive, negative, and unknown classes are equally represented. The LSTM model is subsequently implemented to carry out the aspect-based sentiment analysis, both with and without SMOTE. Finally, the classification results are evaluated using a confusion matrix to determine accuracy, precision, recall, and F1-score. The research paradigm is illustrated in Figure 1.1.

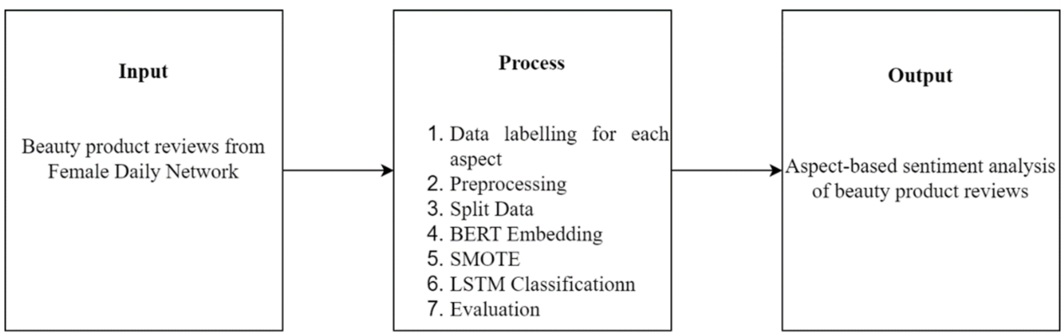

Figure 1.1: Research Paradigm

1.4 Statement of the Problem

The problem identified in this study is that product reviews often cover various aspects and content, making it challenging for consumers to quickly find and analyze reviews based on specific aspects. This process can be time-consuming, highlighting the need for a system that can efficiently process and summarize review data by capturing the sentiments or emotions expressed by buyers for each aspects. In addition, research conducted by Syiti Liviani Mahfiz and Ade Romadhony [25] classifying aspect-based reviews using the naïve bayes method produces an f1-score of 50.55% with the SMOTE method, this occurs due to classification errors because there are words that are often mixed in various aspects, languages that are mixed in one word, and non-standard words. Therefore, the study provides suggestions for applying the deep learning method with other classification methods to determine the comparison of model performance.

Based on the explanation above, this study aims to perform sentiment analysis on beauty product reviews from the Female Daily Network website using aspect-based sentiment analysis to obtain more detailed sentiment results for each aspect. It employs a combination of IndoBERT embeddings and LSTM to achieve optimal performance. The findings of this research are expected to assist consumers in selecting the best beauty products based on the sentiment analysis results.

1.5 Objective and Hypotheses

This study is designed to implement and comprehensively analyze aspect-based sentiment analysis on beauty product reviews by utilizing a combination of IndoBERT embeddings and the LSTM model. The motivation behind this approach stems from the limitations observed in previous studies, particularly the research conducted by Syiti Liviani Mahfiz and Ade Romadhony [25], which focused on aspect-based opinion extraction and polarity classification using the naïve Bayes method. In their study, the authors achieved an F1-score of 50.55% across all identified aspects. By applying the SMOTE technique alongside text preprocessing techniques such as filtering and stemming, they were able to slightly improve the F1-score to 53.04%. While their findings demonstrated the feasibility of aspect-based sentiment analysis, the results indicated room for improvement, particularly in achieving higher accuracy and more robust performance.

In light of these findings, the hypothesis of this study is that aspect-based sentiment analysis using an advanced combination of IndoBERT embeddings and LSTM can produce superior accuracy compared to the naïve Bayes-based approach presented by Syiti Liviani Mahfiz and Ade Romadhony [25]. By leveraging the contextual word representations of IndoBERT and the sequence modeling capability of LSTM, this research aims to enhance the performance of sentiment classification for each aspect of beauty product reviews. Furthermore, this study aspires to provide a more effective method that not only surpasses the previous results but also contributes to improving consumer decision-making by delivering more accurate and reliable sentiment insights from reviews.

1.6 Assumption

Sentiment extracted from textual data in the form of beauty product reviews can influence consumer decisions in purchasing a product. However, the large number of beauty product reviews containing different content makes it difficult for consumers to find reviews quickly. Therefore, by conducting aspect-based sentiment analysis, these reviews can be processed so that sentiments are obtained according to their aspects. The assumption of this study uses 5 aspects discussed, namely packaging, moisture, price, staying power, and aroma. Meanwhile, the sentiment classification class is divided into 3 classes, namely positive, negative, and unknown. Therefore, this study conducted an aspect-based sentiment analysis of beauty product reviews from the Female Daily website using BERT embedding and Long Short-Term Memory (LSTM).

1.7 Scope and Delimitation

To ensure that the research can be carried out effectively, certain limitations are defined. The scope of this study is as follows:

1. The dataset consists of beauty product reviews collected from the Female Daily Network website.
2. The sentiment analysis focuses on five specific aspects: packaging, moisture, price, staying power, and aroma.
3. Sentiment classification is categorized into three classes: positive, negative, and unknown.
4. he models employed in this study are IndoBERT embeddings and LSTM for the classification process.
5. Experiments are performed both with and without the application of SMOTE.
6. The outcome of this research is the F1-score achieved by the LSTM model combined with IndoBERT embeddings, evaluated on the classification of beauty product reviews from the Female Daily Network, both with and without the use of SMOTE.

1.8 Significance of the Study

This research aims to improve the accuracy of aspect-based sentiment analysis on beauty product reviews by leveraging a combination of BERT embeddings and LSTM. By doing so, it seeks to capture more specific sentiments related to aspects such as packaging, moisture, price, staying power, and aroma. Furthermore, the study aspires to aid consumers in making better choices by presenting insights derived from the analysis, thereby contributing both to the field of sentiment analysis and to informed consumer decision-making.