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OPTIMIZATION OF HYPERPARAMETERS FOR LSTM-BASED SENTIMENT ANALYSIS ON FACIAL SERUM DATASETS

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Abstract

Air pollution and environmental pollutants directly exposed to the skin can damage the skin by accelerating premature aging, increasing the risk of acne, and causing hyperpigmentation. Skincare products such as facial serums containing vitamin C, niacinamide, and vitamin E can effectively address these issues. Awareness of the importance of using facial serums is increasing, so information about product quality through user reviews is essential before placing an order. Sentiment analysis used to classify product reviews into positive or negative, thus providing an overview of the product quality sought before placing an order. This research uses the Long Short-Term Memory (LSTM) method for the sentiment classification process. In this process, the text is converted into a number vector through feature extraction using Word2Vec. In addition, several hyperparameters such as the number of epochs, batch size, and activation function are tested to obtain optimal accuracy results. Testing the number of epochs was conducted with variations of 10, 15, and 20 to determine the performance of the resulting model as the number of epochs increased. Testing the batch size is done to evaluate the batch size in influencing the performance of the model. The batch sizes tested were 16, 32, and 64. In addition, choosing the best activation function can help the LSTM model learn more complex patterns and improve performance in sentiment analysis. The activation functions tested were Softmax, Sigmoid, and Softplus. The results of this study show that the optimal combination of the number of epochs 20, batch size 16, and Softmax activation function can provide optimal accuracy of 96.45%.

Keywords: *Activation function, Batch size, Epoch, LSTM, Word2Vec.*

1. INTRODUCTION

Indoor and outdoor air pollution has turned the environment into an increasing hazard to human health worldwide [1]. According to the World Health Organization (WHO) definition in 2019, air pollution refers to outdoor or indoor environmental pollution caused by chemical, physical, or biological agents that can alter the natural properties of the atmosphere [2]. The skin is an organ directly exposed to air pollution and various environmental pollutants [3] that can cause skin damage, accelerate the aging process of the skin, and increase the risk of acne and hyperpigmentation [4].

Facial serum skin care products contain active ingredients such as Vitamin C, Niacinamide, and Vitamin E. Some of these ingredients can help overcome skin damage caused by exposure to air pollution. Research conducted by Hyoung Moon Kim, et al. in 2022 showed that Vitamin C has the ability as an antioxidant, preventing and reducing skin cell damage due to free radicals. In addition, Niacinamide is also proven to increase skin elasticity, reduce skin pigmentation, and fade dark spots on the skin [5]. Other studies have also revealed that Vitamin E can accelerate the regeneration of damaged skin cells [6].

Today, various online platforms, such as the Sociolla website, provide specialized forums for sharing cosmetic product reviews [7], including facial serums. In these forums, consumers can read various product reviews from other users through posts or threads. These reviews can be an overview of the quality product before placing an order [8].

Reading all reviews to get information about a product certainly takes a long time. Therefore, sentiment analysis is applied to classify product reviews into positive or negative reviews [9]. This research uses the Long Short-Term Memory (LSTM) method to classify user opinions on facial serum products. LSTM is one of the techniques in deep learning that can be used in various fields, such as Natural Language Processing (NLP), including speech recognition, text translation, reading, and updating previous information [10].

Research by Amrustian et al. evaluated lecturers who teach in universities using the LSTM method, resulting in an accuracy value of 91.08% [11]. These findings demonstrate the successful use of LSTM in text classification with high accuracy. In learning the various properties of objects, a feature extraction process is necessary to convert text into number vectors. One of the models used to generate word embedding is the Word2Vec model. This model produces a vector space based on the similarity of words in the corpus that are close to each other [12]. Gondhi et al. research on Efficient Long Short-Term Memory-Based Sentiment Analysis of E-Commerce Reviews resulted in an accuracy value of 93% [13]. This shows that using Word2Vec extraction in the LSTM algorithm can produce a good model performance in sentiment analysis.

This research uses the LSTM algorithm and Word2Vec feature extraction to perform sentiment analysis on facial serum product reviews. In addition, the goal of this research is to achieve optimal accuracy of the LSTM model in text classification. Changing the parameters of the algorithm model used can result in improved accuracy [14]. Comparison testing of epoch count and batch size can determine the hyperparameter of this model. The epoch is the iteration in which the entire training dataset is learned by the model. By varying the number of epochs tested, it can be seen how the model's performance evolves as the epochs increase. According to Hastomo et al. (2021) in their study entitled "Characteristic Parameters of Epoch Deep Learning to Predict Covid-19 Data in Indonesia", it was found that the LSTM model with 15 epochs has an RMSE of 68,417, fast processing time, and better accuracy than the GRU model which uses 400 epochs [15]. This research shows that changes in the number of epochs have an impact on the resulting accuracy. Then, testing on batch size is done to evaluate the batch size in influencing the model's performance. Batch size in deep learning models in the number of training samples at a time affects the quality and speed of model training [16]. In addition, choosing the best activation function can help the LSTM model learn more complex patterns and improve performance in sentiment analysis [17]. According to research by Munkhdalai et al. (2019), it has been found that the use of the Softmax activation function produces the highest level of accuracy [18].

Based on previous research, this study will conduct several comparisons to achieve the best accuracy of the LSTM model. The comparison includes:

1. Hyperparameter model with variations in the number of epochs and batch size.
2. Comparison of activation functions such as Softmax, Sigmoid, and Softplus.
3. Comparison with other deep learning models or machine learning models to validate the results obtained using the LSTM algorithm.

The dataset used in this study is based on an infographic provided by an online media, data, and research company in the economic and business field. The infographic includes data on the top five best-selling facial serum brands in e-commerce from June to August 2022. The five facial serum brands are Somethinc, Scarlett Whitening, Garnier, Avoskin, and Whitelab.

2. MATERIALS AND METHOD

2.1. Optimization

Optimization is a process to achieve the best results in a particular situation or system. The main goal is to improve efficiency, performance, or desired results [19]. According to [20] the purpose of performance optimization is to achieve an optimal level of performance or meet specific criteria. Optimization in sentiment analysis is an effort to improve the performance and accuracy of the model to predict sentiment in a text [21]. Based on the above statements, we conclude that optimization is a process that aims to achieve the best results in a particular situation or system and is an important thing to do because more accurate results can help make better decisions.

2.2. Long Short-Term Memory (LSTM)

Seep Hochreitern and Jurgen Schmidhuber created Long Short-Term Memory (LSTM) 1997 [10]. This method is a variation of the Recurrent Neural Network (RNN) designed to help the system maintain its condition to deal with long sequence data effectively [12]. The advantage of LSTM is that it has a cell memory mechanism that can store and remember long-term information and retain information throughout the data sequence in the decision-making process [22]. Each network in LSTM contains memory cells and gate units that function as memory regulators [23]. Memory cells in LSTM can be seen in Figure 1.

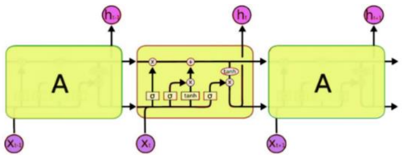

Figure 1. A memory cell in LSTM [23]

Long Short-Term Memory (LSTM) has gate units known as forget, input, cell, and output. These four gate units constitute the activation function process for each input the network receives [23]. The network architecture of LSTM can be seen in Figure 2.

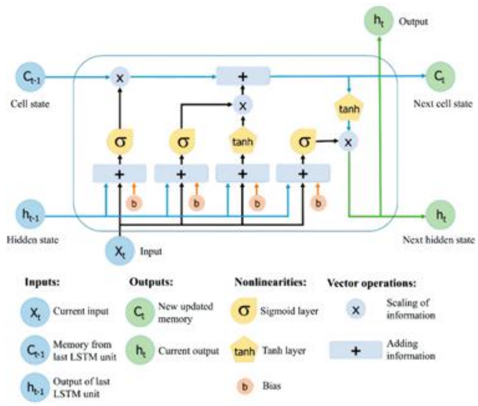

Figure 2. LSTM Network Architecture [24]

Forget gates are responsible for processing and selecting input data that should be kept or discarded in memory cells. The formula for forget gates is as follows [24]:

$$f_t = \sigma(W_f \ [h_{t-1} \ ] + b_f) \quad (1)$$

This formula, represents the sigmoid function, while and are the weight and bias matrices of the forget gates, respectively. Then, two gates in the input gates function to decide and store information. The first gate uses a sigmoid activation function to determine the value that should be updated or ignored. The second gate uses a tanh activation function to create a new value vector that will be stored in the memory cell. Here is the formula for the input gates [24]:

$$i_t = \ \sigma(W_i \ \ [h_{t-1}, X_t \ \ ] + b_i \quad (2)$$

$$N_t = tanh(W_n \ \ [h_{t-1}, X_t \ \ ] + X_t] + b_n \quad (3)$$

$$C_t = C_{t-1} \ \ f_t + N_t \ \ i_t \quad (4)$$

C_{t-1} and C_t are the cell states at time $t-1$ and t, while and are the weight and bias matrices of the cell states, respectively. Furthermore, cell gates function as a place to replace old memory cells with new memory cells whose values come from a combination of forget gates and input gates. The equation that explains the function of the cell gate is as follows [25]:

$$C_t = (f_t \cdot C_{t-1} + i_t \cdot C't) \quad (5)$$

Where f_t is forget gates, C_t is cell gates, i_t is input gates, and $C't$ is the activation cell.

Finally, the output gates use a sigmoid activation function to determine the value in the memory cell that will be output. The following formula explains the output gate process [24]:

$$O_t = \sigma(W_o \ [h_{t-1}, X_t] + b_o \quad (6)$$

$$h_t = O_t \ \ \ tanh(C_t) \quad (7)$$

In this formula, W_o and b_o are the weight and bias matrices of the output gate, respectively

2.3. Sentiment Analysis

Sentiment analysis is a Natural Language Processing (NLP) technique that aims to identify the emoticons contained in a text [26]. This technique can obtain users' opinions about products and services from their reviews and generate knowledge that is applied to an entity [27]. Sentiment analysis can evaluate product performance in customer reviews [28]. Based on some of the explanations above, it can conclude that sentiment analysis is a field of science that processes text or sentences to extract the sentiments, opinions, and emotions contained in them.

2.4. Facial Serum Reviews

A facial serum is a type of skin care product that contains a gel or lotion with a light moisturizing content and active ingredients that can penetrate deeper layers of the skin [29]. The facial serum contains a formula with a very high concentration of active ingredients, which can help treat various specific facial skin problems. The molecular content in facial serum which is easily absorbed by the skin, can provide optimal performance in protecting and helping to overcome various facial skin problems, ranging from signs of aging to uneven facial skin color [30]. A facial serum review is a comment or assessment of a face serum product.

2.5. Feature Extraction

This research uses Word2Vec as a feature extraction technique and a Long Short-Term Memory algorithm for classification. Word2Vec is an algorithm that uses neural networks to learn vector representations of different words in a text [31]. In generating word vector representations or word embedding, Word2Vec can predict word meanings based on context and usage history. This ability is used to determine the association relationship between words that have similar meanings [32]. The Word2Vec model used in this research is skip-gram because it is considered an efficient method for evaluating vector representations in an unstructured text by predicting words that appear before or after the current word, where the input used comes from the current word [33]. The architecture of the Skip-gram model can be seen in Figure 3.

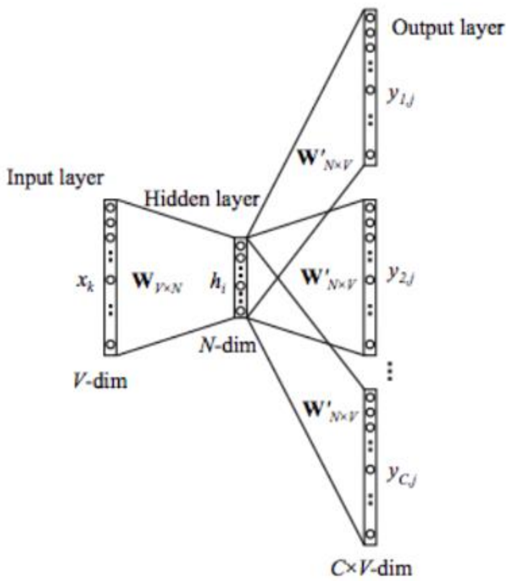

Figure 3. Skip-gram Model Architecture [31]

2.6. Text Preprocessing

Text preprocessing is carried out before feature extraction to prepare data using various techniques [34]. The text preprocessing techniques used in this research are:

1) Labeling

The dataset that has been obtained is labeled with two sentiment categories, namely positive and negative. This stage is carried out to categorize the dataset, which will be used as a reference in the data labeling process for training [35].

2) Tokenization

Tokenization is a process of separating words according to the order of the words contained in them [36]. The output of the word separation process is known as a token [37]. This stage makes the text data more structured and can be processed further for analysis [38].

3) Case Folding

Case folding is converting all letters in the dataset into lowercase letters [22]. To facilitate data search, analysis, and processing using text processing techniques [39].

4) Stopword Removal

Stopword removal is removing words irrelevant to a particular topic [40]. Examples of stopwords are "which, or, and, really, also, only, early, from" and so on. These words are irrelevant to a topic, so they should be removed to reduce the dimension of the input text that is not important. In addition, stopword removal can also help speed up the analysis process [41].

5) Stemming

Stemming is converting words into their basic form [42]. The goal is to reduce the variety of words with the same meaning into a uniform form, making it easier to compare and analyze words [43]. In addition, this stage also aims to remove affixed words such as conjunctions, pronouns, and prepositions [44].

2.7. Method

The method used in this research is deep learning by utilizing the LSTM algorithm, Word2Vec feature extraction, and optimization experiments to perform sentiment analysis on datasets obtained from the Sociolla site. The stages of this research can be seen in Figure 4.

Based on Figure 4 above, the flow of this research begins with the data acquisition stage, text preprocessing, the use of the word embedding method using Word2Vec feature extraction, the classification process using the Long Short-Term Memory (LSTM) algorithm, and optimization through several experiments to achieve the highest or optimal accuracy.

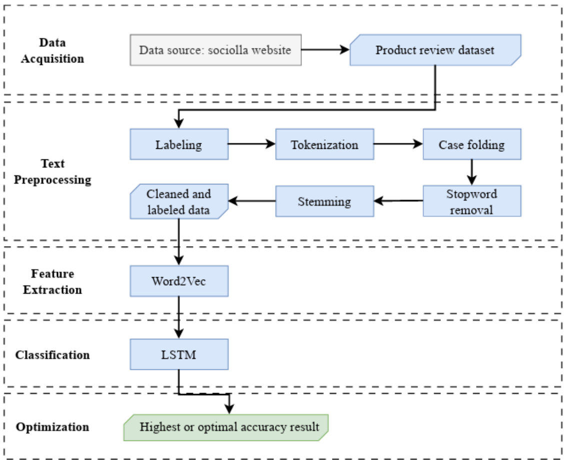

Figure 4. Research Method

3. RESULT

3.1. Data Acquisition

At this stage, the data collection process was carried out with the help of a tool from the Google extension called Web Scraper on February 26 to 28, 2023. Data scraping is conducted by taking reviews on the Sociolla website, and the facial serum brands used for datasets in this sentiment analysis are Somethinc, Scarlett Whitening, Garnier, Avoskin, and Whitelab. The number of datasets obtained for each brand can be seen in Figure 5.

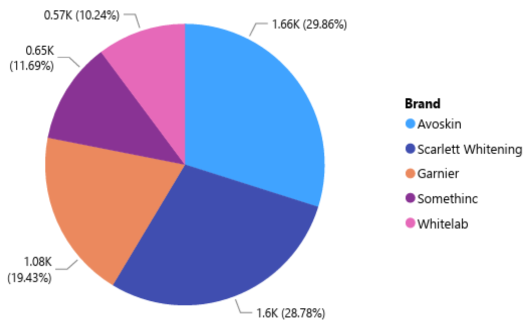

Figure 5. The Number of Datasets

Figure 5 above illustrates the number of reviews obtained for each brand, namely Avoskin with 1,660 data, Scarlett Whitening with 1,600 data, Garnier with 1,080 data, Somethinc with 650 data, and Whitelab with 570 data.

3.2. Text Preprocessing

Text data that has been cleaned and processed at the previous stage of text reprocessing can be seen in Table 1.

Table 1. Result of Text Preprocessing

Sentiment	Review	Clean Review
Positive	Beli 2 karena pas promo hehe. Teksturnya ringan dan gampang ngeresap di muka, serumnya juga gak lengket. Emang bikin muka jadi cerah, tapi	beli pas promo tekstur ringan gampang ngeresap muka serum gak lengket emang bikin muka cerah

	semuanya butuh proses gak instan. Aku rekomendasiin ke teman dan ternyata pas pake juga pada cocok.	butuh proses gak instan rekomendasiin teman pas pake cocok
Negative	GAK COCOK!! muncul jerawat baru terus menerus ditempat yang gak biasanya jerawatan. sempet mikir kalo ini purging, tapi gatahan deh akhirnya stop aja.	gak cocok muncul jerawat gak jerawat sempet mikir kalo purging gatahan deh stop aja

Table 1 shows the results of cleaned and labeled data obtained through text preprocessing including the stages of tokenization, case folding, stopword removal, and stemming.

3.3. Feature Extraction

There are several parameters used in training the Word2Vec model. First, the MIN_COUNT parameter used to ignore words with a total frequency lower than the specified value. The WINDOW parameter determines the maximum distance between the current word and the predicted word in a sentence. The EPOCH parameter determines the number of iterations performed during the training process. The SG parameter specifies the training algorithm used, with a value of 1 for skip-gram and 0 for CBOW. Finally, the SIZE parameter determines the dimension of the generated word representation vector. By setting these parameters, the program can train the Word2Vec model according to the specified configuration. The Word2Vec parameters used can be seen in Table 2.

Table 2. The Word2Vec Parameters

Parameter	Amount
MIN_COUNT	1
WINDOW	5
EPOCH	15
SG	1
SIZE	5

3.4. Classisification

The sentiment analysis classification in this study uses the LSTM algorithm and Word2Vec feature extraction, with initial parameters including the number of epochs 10, batch size 16, and Softmax activation function. Table 3 contains the accuracy results in the initial conditions.

Table 3. Initial Conditions

Accuracy	Val Accuracy	Recall	F1-Score
87.81%	71.30%	75.00%	76.00%

3.5. Optimization

1) Hyperparameter model

There are two parameters that we make as hyperparameters of the model, namely the number of epochs and batch size. Epochs are the iterations of model training, while the batch size is the amount of sample data in an iteration. This experiment was conducted to obtain the best parameters for the LSTM model. The results of the hyperparameter model testing can be seen in Table 4.

Table 4. Result of The Hyperparameter Model

Epoch \ Batch Size	10	15	20
16	87.81%	92.44%	**96.45%**
32	83.49%	87.04%	91.51%
64	83.80%	85.19%	89.97%

Table 4 above shows that the results of the best model hyperparameter tuning are achieved using the number of epochs 20 and batch size 16, which resulted in an optimal accuracy of 96.45%.

2) Comparison of activation functions

After obtaining the best hyperparameter model results, the next experiment was carried out to compare activation functions such as Softmax, Sigmoid, and Softplus to see the accuracy results obtained. The results of this comparison can be seen in Table 5.

Table 5. Result of The Activation Function

Activation Function	Accuracy	Recall	F1-Score
Softmax	**96.45%**	**74.00%**	**75.00%**
Sigmoid	95.99%	76.00%	76.00%
Softplus	93.83%	73.00%	70.00%

Based on the results of Table 5 above, optimal accuracy is achieved by using the Softmax activation function of 96.54%, recall of 74%, and F-1 Score of 75%.

3) Comparison of model classification

After obtaining the best model hyperparameters and activation functions, the next step is to compare the classification model with other types of Recurrent Neural Networks, such as Gated Recurrent Unit (GRU), as well as machine learning classification models such as Support Vector Machine (SVM). The results of the classification model comparison can be seen in Table 6.

Table 6. Result of The Comparison Model Classification

Classification	Accuracy	Recall	F1-Score
LSTM	**96.45%**	**74.00%**	**75.00%**
GRU	95.83%	74.50%	75.00%
SVM	89.00%	88.50%	89.00%

LSTM produced the best accuracy compared to GRU and SVM. This shows that the LSTM algorithm can understand the context, in this case, study significantly better. GRU is a development of Recurrent Neural Network (RNN). SVM (Support Vector Machine) is a machine learning algorithm used for classification and regression. The results of this experiment show that LSTM is better than some of these models. Then the parameters that have been obtained are applied to the entire dataset. The accuracy results on the Somethinc dataset is 98.72%, Scarlett Whitening is 96.56%, Garnier is 96.45%, Avoskin is 95.58%, and Whitelab is 99.42%. The visualization results of the best accuracy of each dataset can be seen in Figure 6.

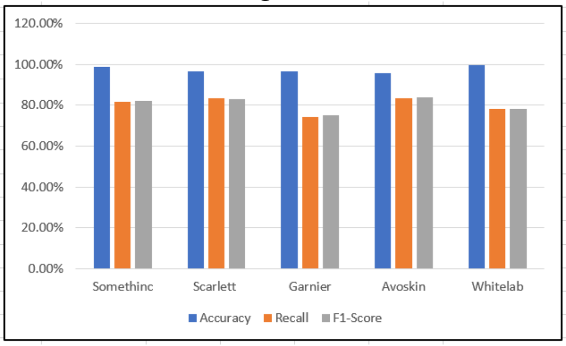

Figure 6. The Visualization of The Best Accuracy of All Datasets.

4. DISCUSSION

In this study, we successfully applied the Long Short-Term Memory (LSTM) algorithm for sentiment analysis on a facial serum review dataset. Previous research [45] has obtained excellent accuracy values in text classification using the LSTM algorithm, with accuracy rates reaching 96.45%. It proves the reliability and potential of the LSTM algorithm in sentiment analysis tasks. In comparison to traditional classification methods such as Support Vector Machine (SVM) or other Recurrent Neural Network (RNN) algorithms such as Gated Recurrent Unit (GRU), the LSTM algorithm was shown to be able to cope with the complexity and variation in text data and produce better performance in sentiment analysis.

Research on the effect of the number of epochs [21] shows that changes in the number of epochs have an impact on the resulting accuracy. In this study, the best results were achieved by using an epoch count of 20, after being compared to using epoch counts of 10 and 15. Furthermore, research on batch size [46] shows that the batch size of deep learning models, which refers to the number of training samples processed at a time, affects the quality and speed of model training. In this study, using a batch size of 16 resulted in the highest accuracy value, compared to batch sizes of 32 and 64, considering the number of datasets used.

In addition, research [47] shows that using the Softmax activation function produces the highest level of accuracy. In this study, using the Softmax activation function resulted in the optimal accuracy value, compared to other activation functions such as Sigmoid and Softplus.

These findings indicate that in this study, parameter settings such as the number of epochs, batch size, and activation function selection play an important role in achieving optimal accuracy in sentiment analysis using the LSTM algorithm. In future research, the effect of these parameters, and the potential use of other techniques to improve the performance of the LSTM algorithm in sentiment analysis, can be further explored.

5. CONCLUSIONS

In this research, several experiments were performed to achieve the highest accuracy in sentiment analysis. The experiments include model hyperparameter setting, activation function comparison, and comparison with other classification models. Model hyperparameter setting is done by comparing the number of epochs and batch size in the LSTM model. The experimental results show that the greater the number of epochs used, the more accuracy increases. However, the larger the batch size used, the more accuracy decreases. In this case study, it was found that the best model hyperparameters were the number of epochs 20 and batch size 16. In addition, a comparison of activation functions such as Softmax, Sigmoid, and Softplus was performed to achieve optimal accuracy results. The results show that the Softmax activation function produces the best accuracy, which is 96.45%. LSTM also proved to be the algorithm with the best accuracy in sentiment analysis on the facial serum dataset. This is proven by comparison with other RNN models such as GRU, and machine learning classification models such as SVM. For future research, it is recommended to use a larger dataset and explore other hyperparameters, such as the learning rate, number of LSTM layers, or number of neurons in the model. By studying the influence of these hyperparameters, an optimal configuration can be found to improve the performance of the LSTM model and achieve better accuracy.

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