Text classification to predict skin concerns over skincare using bidirectional mechanism in long short-term memory

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ABSTRACT

There are numerous types of skincare, each with its own set of benefits based on key ingredients. This may be difficult for beginners who are purchasing skincare for the first time due to a lack of knowledge about skincare and their own skin concerns. Hence, based on this problem, it is possible to find out the right skin concern that can be handled in each skincare product automatically by multi-class text classification. The purpose of this research is to build a deep learning model capable of predicting skin concerns that each skincare product can treat. By comparing the performance and results of predicting the correct skin condition for each skincare product description using both long short-term memory (LSTM) and bidirectional long short-term memory (Bi-LSTM), the best results are given by Bi-LSTM, which has an accuracy score of 98.04% and a loss score of 19.19%. Meanwhile, LSTM results have an accuracy score of 94.12% and a loss score of 19.91%.

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1. INTRODUCTION

Skincare products are the most mainstream cosmetics that maintain skin integrity, appearance, and condition. The high market demand has made skincare products one of the most popular ways to deal with skin concerns [1]. What's more, skincare trends began to rise drastically in 2020, when the COVID-19 pandemic began [2].

Skincare has various types and benefits according to the active ingredients contained in it [3]. Active ingredients here play an important role in the performance of every skincare product because these ingredients are chemicals that actively work on a specific target skin concern [4]. For example, salicylic acid can reduce sebum secretion so that it can control oily skin and acne, but on the other hand, it can also cause inflammation in sensitive and dry skin [5]. This is what makes skincare products difficult to use and unsuitable for beginners; the user must thoroughly understand what is contained in them in order to meet their skin care concerns and expectations [6].

Most beauty stores already manually sort all of their skincare products based on brands, skin types, and skin concerns. But it will take a long time and require someone who knows about skincare products. Instead, by collecting all information that relates to skincare products, such as the function of the product in dealing with certain skin concerns, we might be able to build a model that can automatically classify and predict the benefits of those skincare products quickly.
The information given to classify and predict is in the form of text data, which is a description of skincare products, so it is called a text classification. Text classification is one of the tasks in natural language processing (NLP), which aims to assign labels or targets to textual features or classes such as sentences, queries, paragraphs, and documents [7]. There are two problems in text classification: binary and multi-class classification. Binary classification is made up of only two labels, one of which is assigned a value in an arbitrary feature space $X$ [8]. Whereas multi-class classification has more than two labels [9].

There are various kinds of research on multiclass classification problems, despite the different uses of domains or topics, data types, and algorithms. Although there is currently no research related to skin care products, there are several studies that discuss the dermatology domain. The goal of Indriyani and Sudarma's [3] study was to categorize facial skin types, which were divided into four categories: normal, dry, oily, and combination skin. They used an image-type dataset of sixty facial images captured manually with a digital camera. Although this makes it into computer vision instead of NLP, at least with a case that aims to classify multiclass facial skin types and also by using a supervised learning algorithm, support vector machine (SVM), the result is an average accuracy score of 91.66% and an average running time of 31.571 seconds, which is higher than in previous studies [10]. The following study made extensive use of deep neural network algorithms such as convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) [11]. Although there are a few cases of binary classification because some datasets only have two classes, the majority of the datasets have between five and ten classes. The research combines several of those algorithms into a hybrid framework. Not only that, some algorithms are also modified into a bidirectional mechanism. The proposed model achieved excellent performance on all tasks. A bidirectional recurrent convolutional neural network attenuation-based (BRCAN) gave accuracy scores on the four multiclass classification tasks of 73.46%, 75.05%, 77.75%, and 97.86%; those results are higher than all comparison algorithms.

In relation to the aforementioned studies, we proposed a comparison of unidirectional/regular LSTM and bidirectional long short-term memory (Bi-LSTM) in our own dataset collected from several skincare online stores to classify skin concerns of each skincare product. The main purpose of this research is to find out the difference between the performance results of the two proposed algorithms. In other research, bidirectional mechanisms, which have layers that work forward and backward in sequence, are able to outperform unidirectional LSTM [12].

2. METHOD

This section of the paper presents the research methodology. When doing research, researchers must obtain data that will be studied for later processing. After obtaining the data, the data is still in the form of raw data, which then the researcher must prepare the data to become a data set that can be processed. After the data has gone through the processing stage, the last stage the researcher must do is to evaluate the research model or instrument to understand their performance, as well as its strengths and weaknesses. More details, there are several stages can be seen in Figure 1.

![Figure 1. The proposed research methodology](image)

2.1. Data collection

In this research, data collection was implemented by using the Web Scraping technique. Web Scraping is used to convert unstructured data into structured data that can be stored and analyzed in a central
local database or spreadsheet [13]. The data is collected on a beauty online store website which is lookfantastic.com, dermstore.com, allbeauty.com, sokoglam.com, and spacenk.com which market products such as skincare, makeup, and beauty tools.

2.2. Data merging

The data collected are divided into three categories according to the seven skin concerns handled by each skincare product, due to having similar symptom treatment. The three categories are dryness, redness; anti-aging, wrinkles; acne, big pores, blemish. Data has 6 attributes which is skincare name, skincare price, how to use, skin concerns, product description, ingredients, and active ingredients. The data that has been collected is merged into one dataset with a total of 5183 rows.

2.3. Data cleaning

Due to data that has the same value (duplicate data) and data that has no value (null data), then data cleaning is carried out by removing duplicate and null data evenly. Data cleaning greatly improves the accuracy of machine learning models, which however requires broad domain knowledge to identify examples that will influence the model [14]. After that, the total dataset is reduced to 5152 rows. However, in this study, we will focus on the attributes of product descriptions that will become features and skin problems that will become labels. So, we will delete the other columns that are not necessary to make the process easier going forward.

2.4. Text preprocessing

Before fed the dataset to our models, it’s necessary to perform a data pre-processing stage. According to the Figure 2, there is a several data pre-processing task including Case Folding, Punctuation Removal, Whitespace Removal, Numbers Removal, Stopword Removal, Lemmatization. Case folding is the process to convert all input words into the same form, for instance uppercase or lowercase [15]. So, we transform all our text in description product as the features to lowercase. After that, our text data must be clean from punctuation marks and symbol, so we applied punctuation removal. Next, we applied whitespace removal to remove an unpredicted extra spaces between every word and line or paragraph spacing [16]. We must make sure that our texts only contain meaningful words which aim to represent the essence of each text. So, we need to apply stopword removal. Stopwords are actually the most common words in any language that appears too much in a text does not add much information, such as articles, prepositions, pronouns and conjunctions. Final step in text preprocessing is lemmatization. Lemmatization works to reduce a word variant to its lemma and uses vocabulary and morphological analysis for returning words to their dictionary form [17]. This step converts all of word in our texts to its basic form. Generally, lemmatization and stemming is a similar approach and often produce same results, but sometimes the basic form of the word may be different than the stemming approach e.g. ”caring” is stemmed to ”car”, but in lemmatization you will get ”care” which more appropriate than stemming. Also, in Boban [17] study, Lemmatization produces better results.

2.4.1. Create data tensor

After our text successfully passing data preprocessing stage. We need to vectorize our features by convert our text data into either a sequence of integers and mapping it into real-valued vector, so we can feed it through input layer in our deep neural network models. Also, we limit the total number of words in our text features to the most frequent words, and zero out the rest. We determine the maximum sentence length (number of words) in each text features that will truncating long reviews and pad the shorter reviews with zero values in the next process. According to Figure 2 there are some steps in converting our text data after lemmatizing step called creat data tensor. First, we use tokenizer to split each word in the text. Second, we create an index-based dictionary on each word based on the text we have or the description of skincare products. Next, we transform our tokens from first step into sequence of integer based from our index-based dictionary. Then, truncate and pad the input sequences, so they are all in the same length for modeling. Last step is converting our categorical labels to numbers.

2.5. Model building and training

Next stages are model building and training. Before that, we split our dataset into three part for training, testing, and validating. We build our LSTM and Bi-LSTM model with a similar layer structur as illustrated in Figure 3.
2.5.1. Embedding layer

We put Embedding layer in first place as input layer ad map each word into a real-valued vector to represent each word. Embedding layers works by mapping a raw user/items features in a high dimensional space to dense vectors in a low dimensional embedding space [18]. Basically, embedding layer has similar purpose as popular word embedding frameworks (e.g word2vec and gloVe) which provide a dense representation of words and their relative meanings. However, there is a different between them, which are their training process. Popular word embeddings framework like word2vec and gloVe is trained to predict if word belongs to the context, given other words, e.g., to tell if “cuisine” is a likely word given the “The chef is making a chinese ... ” sentence begging. Word2vec learns that “chef” is something that is likely to appear together with "cuisine", but also with "worker", or "restaurant", so it is somehow similar to “waitress”, so word2vec learn something about the language. The conclusion is embeddings created by word2vec, gloVe, or other similar frameworks learn to represent words with similar meanings using similar vectors. Meanwhile, embeddings learned from layer of neural network may be trained to predict a specific case, in this case is text classification. So, the embeddings would learn features that are relevant for our text classification. If word2vec has a pre-trained corpus or dictionary, otherwise, embedding layers doesn’t have it. But we already created the index-based dictionary on each word from our features before and transform our features to sequence of integer through it. It’s more efficient, doesn’t need high computing resources, and useful for classification than using pre-trained word embedding like word2vec, even though embedding layer doesn’t capture the semantic similarity of words like word2vec does [19].

2.5.2. Spatial dropout 1D layer

Next, we adding spatial dropout 1D layer. This layer performs the same function as dropout. In standard dropout, the neuron on neural network drops independently as shown in Figure 4(a) [20]. Meanwhile, in spatial dropout it drops entire 1D feature maps instead of individual elements as shown in Figure 4(b).

2.5.3. Unidirectional and bidirectional long short-term memory (Bi-LSTM)

Next, we use the LSTM layer and the Bi-LSTM layer on each of the two architectural models created. LSTM is very popular for dealing with cases such as NLP, video, and audio where the data is in the...
form of a sequence. When compared with its predecessor vanilla RNN algorithm which is unable to use past information, LSTM outperforms it with its long-term memory. LSTM transforms the memory shape of cells within the RNN via way of means of reworking the tanh activation characteristic layer within the RNN right into a shape containing memory devices and gate mechanisms, pursuits to determine how to make use of and replace data saved in memory cells [21]. Now, there is a new concept of mechanism in those sequence feed-forward neural network which called bidirectional. Bidirectional is a mechanism that able to make a neural network works like two-way mirror, which trains an input data twice through past and future. With implementing the bidirectional concept, a regular LSTM not only capable train the input data forward, but also backward. According to Figure 5, Figures 6(a) and 6(b), those models are used the following formula to calculate the predict values.

\[ l_t (Input\ Gate) = \sigma_g(W_i X_t + R_i h_{t-1} + b_i), \]
\[ f_t (Forget\ Gate) = \sigma_g(W_f X_t + R_f h_{t-1} + b_f), \]
\[ C_t (Cell\ Candidate) = \sigma_g(W_c X_t + R_c h_{t-1} + b_c), \]
\[ O_t (Output\ Gate) = \sigma_g(W_o X_t + R_o h_{t-1} + b_o), \]

(1)

\( \sigma_g = \) The gate activation function
\( W_i, W_f, W_c, \) and \( W_o = \) Input weight matrices
\( R_i, R_f, R_c, \) and \( R_o = \) Recurrent weight matrices
\( X_t = \) The data input.
\( h_{t-1} = \) The output at the previous time \((t - 1)\)
\( b_i, b_f, b_c, \) and \( b_o = \) The bias vector

Figure 5. LSTM architecture

Figure 6. Shows the differences of LSTM in: (a) unidirectional and (b) Bidirectional mechanism
the forget gate counts the measure that decide to removes the previous memory values from the cell state. Just like the forget gate, the input gate determines the new input to the cell state. Then, the LSTM’s cell state \( C_t \) and the output \( H_t \) at time \( t \) are calculated,

\[
C_t = f_t \odot C_{t-1} + 1 \odot g_t \\
H_t = o_t \odot \sigma(C_t)
\]  
(2)

\( \odot \) denotes the Hadamard product (element-wise multiplication of vectors).

Also, we use another parameter in our hidden layer and output layer of both LSTM and Bi-LSTM which are dropout, recurrent dropout, recurrent regularizer, L2 regularizers. Recurrent dropout is a regularization that devoted recurrent neural network algorithms. Recurrent dropout works differently from the usual dropout, which is applied to forward connections of feed-forward architectures or RNNs, drop neurons directly in recurrent connections in away that does not cause loss of long-term memory instead [22]. There is a formula update on \( C_t \) when implementing recurrent dropout to the cell update vector \( g_t \),

\[
C_t = f_t \odot C_{t-1} + 1 \odot d(g_t)
\]  
(3)

Where \( d \) is dropout. Next parameter is usual dropout that we apply same with recurrent dropout where in both LSTM and Bi-LSTM layer. Last parameter is L2 regularizers which is a layer weight regularizers that enforce penalties on layer parameters or layer activity during optimization process. These penalties are added up in a loss function that optimizes the network applied on a per-layer basis there are three ways to apply these regularizer, in layer’s kernel, bias, and output. L2 regularizer summed the suared weights to the loss function. L2 are often to set a value on logarithmic scale between 0 and 0.1, such as 0.1, 0.001 and 0.0001.

2.6. Model evaluation and prediction

Final stages are model evaluation and prediction with a validation dataset. The evaluation contains a several score to measure the performance of model training and testing. We use an accuracy score by obtaining precision, recall, and f-measure.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]  
(4)

\( TP = \) True Positive is a skin concern that is in the actual label and appears in the prediction.

\( FP = \) False Positive is a skin concern that is in actual label but doesn’t appears in the prediction.

\( FN = \) False Negative is skin concern that is not in the actual label but appears in the prediction.

\( TN = \) True Negative is a skin concern that is neither in the actual label nor the prediction.

Precision is the percentage of positive cases that were actually predicted to be truly positive [23]. Precision is calculated,

\[
\text{Precision} = \frac{TP}{TP + FP}
\]  
(5)

Recall is the Percentage of actual positive cases that were correctly predicted. It actually measures the coverage of positive cases and accurately reflects the predicted cases [23]. Recall is calculated,

\[
\text{Recall} = \frac{TP}{TP + FN}
\]  
(6)

F1- Measure is a composite measure that captures the trade-offs related to precision and recall and calculated,

\[
F1-\text{Measure} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]  
(7)

loss function that being used is categorical cross-entropy. Categorical cross-entropy is specifically used for the case of multi-class classification which increasing or decreasing the relative penalty of a probabilistic false negative for an individual class [24]. The categorical cross-entropy loss function is used the following formula,

\[
\text{Loss} = -\sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i
\]  
(8)
\[ \hat{y}_i = i\text{-th scalar value in the model output} \]
\[ y_i = \text{Corresponding target value} \]

**Output Size** = The number of scalar values in the model output

This loss function measures the distance of dissimilarity between the true label distribution and the predicted label distribution. The \( y_i \) defines the probability that event \( i \) occurs. The sum of all \( y_i \) is 1 that means one event may occur. The minus sign guarantees that the closer the distributions are to each other, the smaller the loss. Also, we use a confusion matrix to calculate the total of true or false a prediction generated by the classification model. Confusion matrix is machine learning concept that contains information about the actual and predicted classifications performed by the classification system which has two dimension divided for indexing the actual class of an object, and the other is indexing the class that the classifier predicts [25].

3. **RESULTS AND DISCUSSION**

All stages of this research were carried out with the python programming language. The results of this research are measured using several scores. The scores measure the performance of the proposed model classification prediction, by looking at the accuracy and loss scores in each experiment carried out.

3.1. **Train-test-validation split evaluation**

The first experiment was carried out by splitting the dataset into three parts. The three parts of dataset used for train, test, and validation process. Table 1 shows the result of dataset splitting with the best result of 80% train dataset, 1% test dataset, and 19% validation dataset with an accuracy score of 98.04% and loss 19.19% from Bi-LSTM.

<table>
<thead>
<tr>
<th>Train/Test/Validation Split</th>
<th>LSTM Accuracy</th>
<th>LSTM Loss</th>
<th>Bi-LSTM Accuracy</th>
<th>Bi-LSTM Loss</th>
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<td>0.9804</td>
<td>0.1919</td>
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<td><strong>Best Score</strong></td>
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<td>0.9804</td>
<td>0.1919</td>
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</table>

3.2. **Hyper-parameters tuning**

There are several hyper-parameters used in model training. Memory units (Mu), Optimizers (O), Activity function (Af) tuning as shown in Table 2. The Bi-LSTM model still outperformed the LSTM with a memory unit setting of 100, RMSprop optimizers, and Activity function softmax.

Next, early stopping callback is a parameter that stop the training process when metric has stopped improving by stores the model’s weights at the optimal epoch. These parameter attain the highest accuracy in training regardless of the epoch setting [26]. These parameter has two hyper-parameter which is patience (p) and minimal delta (-Δ). The result of tuning these two hyper-parameter as shown in Table 3. The Bi-LSTM model still outperformed the LSTM with a patience of 5 and min delta of 0.0001.

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3.3. Model evaluation and prediction

After the hyper-parameter tuning, we get the best settings as shown in Table 4. We evaluate our proposed models with a validation dataset as much as 980 skincare products. To measure the performance of model training and testing, we used an accuracy score by obtaining precision, recall, and f-measure as shown in Table 5. Testing and validation confusion matrix in Bi-LSTM models are shown in Figures 7(a) and 7(b).
Table 4. The best models’ settings

<table>
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<tr>
<th>Hyper-Parameter</th>
<th>LSTM</th>
<th>Bi-LSTM</th>
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<td>80/1/9</td>
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<td>Min. Delta</td>
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<td>0.9412</td>
<td>0.9804</td>
</tr>
<tr>
<td>Loss Score</td>
<td>0.1991</td>
<td>0.1919</td>
</tr>
</tbody>
</table>

Table 5. Classification report on the validation data in the proposed models

<table>
<thead>
<tr>
<th>Model</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Avg. Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM</td>
<td>0.9012</td>
<td>0.8939</td>
<td>0.8975</td>
<td>Micro Avg</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.9004</td>
<td>0.8797</td>
<td>0.8894</td>
<td>Macro Avg</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.9015</td>
<td>0.8939</td>
<td>0.8972</td>
<td>Weighted Avg</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.8939</td>
<td>0.9939</td>
<td>0.8939</td>
<td>Samples Avg</td>
</tr>
<tr>
<td>BI-LSTM</td>
<td>0.8981</td>
<td>0.8908</td>
<td>0.8945</td>
<td>Micro Avg</td>
</tr>
<tr>
<td>BI-LSTM</td>
<td>0.8905</td>
<td>0.8839</td>
<td>0.8866</td>
<td>Macro Avg</td>
</tr>
<tr>
<td>BI-LSTM</td>
<td>0.8994</td>
<td>0.8908</td>
<td>0.8946</td>
<td>Weighted Avg</td>
</tr>
<tr>
<td>BI-LSTM</td>
<td>0.8908</td>
<td>0.8908</td>
<td>0.8908</td>
<td>Samples Avg</td>
</tr>
</tbody>
</table>

Figure 7. BI-LSTM Testing, (a) validation and (b) confusion matrix

3.3.1. Models inference

After getting the fine-tuned in each model, we tested the models to predicting what’s skin concern that every skincare product overcomes by manually input the skincare product description to the models. The actual labels over skincare description that we manually input before are taken from official website of each skincare products. The results can be seen in Table 6.
4. CONCLUSION

The findings have produced a satisfactory performance, with an adequate score obtained both for accuracy and loss. The performance of the bidirectional LSTM model, which makes use of this bidirectional mechanism, outperforms that of the LSTM model, which makes use of the same mechanism and produces an accuracy score of 94.12% and a loss value of 19.91%. The bidirectional LSTM model produces a score of 98.04% for its accuracy and a loss value of 19.19% for its loss. The usage of an embedding layer where the data was previously transformed into a tensor form may be adjusted by employing a popular word embedding such as word2vec or gloVe, which requires a large amount of computer resources but can extract the semantic meaning of the features. Both of the models that have been provided have been able to effectively train on the dataset that we obtain from well-known websites that specialize in the sale of skincare items. Because of this, the prediction successfully maps the skin’s worries over the description of each skincare product, both with unseen data or validation data and the description that we manually enter into the models. Additionally, given the dataset that we have, this research has the potential to be further expanded into a recommendation system for online retailers that offer skincare goods as well as a mobile application.

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Text classification to predict skin concerns over skincare using bidirectional mechanism ... (Devi Fitrianah)