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Study of Public Sentiment Towards Beauty Products Using A Machine Learning Approach: Random Forest Analysis On Social Media

Tresya Noviania Pasaribu[1], Juliansyah Putra Tanjung[2)*], Dosma Hutauruk[3], Endang Sapriana Hutagalung[4], Saputra Silitonga[5]
[1,2,3,4,5] Prima Indonesia University, Indonesia
[1]tresyapasaribu23@gmail.com ,[2]juliansyahputratanjung@unprimdn.ac.id,
[3]dosmahuaturuk6284@gmail.com,
[4] endanghutagalung5@gmail.com [5]saputrasilitonga06@gmail.com

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Abstract: In this digitalized era, the development of technology and the internet has brought significant changes in various aspects of life, including the way we shop. The trend of online shopping is increasingly prevalent and favored by the public, not least for cosmetic products. This research uses a quantitative approach to analyze public opinion or sentiment towards beauty products, especially beauty products. The data used in this research comes from online platforms. This research uses a beauty product dataset obtained from Kaggle. This research uses the Random Forest algorithm to analyze the data and produce findings, This algorithm is one of the advanced tools in Machine Learning that is focused on sorting data into the right categories, which in this context is used to classify public sentiment towards beauty products into categories such as positive, negative or neutral. Random Forest achieved a very high accuracy rate of 94.68% in the evaluation. However, it should be noted that the positive class has a low recall (25%) and a low F1-score (40%), indicating that the model may struggle to detect positive sentiment towards beauty products beauty products. In general, the model did well in classifying neutral and negative sentiments. Sentiment analysis shows that the majority of public sentiment towards beauty products is neutral, with a significant amount of negative and positive sentiment. It is evident that user opinions are informative or descriptive without conveying strong positive or negative emotions.

Keywords: Sentiment Analysis; Social Media Data; Beauty Products; Machine Learning; Random Forest;

INTRODUCTION

While women crave good looks and a face that is pleasing to the eye, true beauty does not only come from clothes and accessories. The key lies in the health of the skin(Pratiwi Wijayatun, 2021). Technological advancements and easy access to the internet are driving a shift in cosmetic shopping trends. People now prefer to shop for cosmetics online (Fadila Putri et al., n.d.). Consumer foresight is very important in choosing cosmetic products in a diverse market because not all products have guaranteed quality and are safe to use (Sari1 et al., 2020). One product that attracts attention on social

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media is Skintific. Skintific is known for its innovative and effective skincare products and is widely used by consumers from all walks of life.

Nowadays, consumers often do cosmetic research to buy products. They will compare prices and discuss other consumers about their opinions, or read product reviews (Yulianti Prastika et al., 2021). Information from product reviews (5.06) is more trusted and able to attract consumers' interest than marketing information (4.36), which is subjective (Astuti & Astuti, 2022). Reading all reviews is ideal, but it can take a long time. Selecting only a few reviews is practical, but the risk is that the judgement is not objective. Sentiment analysis enables an efficient and objective review process, which saves time and results in more accurate judgements (Arsi & Waluyo, 2021).

Sentiment analysis is an automated process for understanding and analyzing opinions in unstructured text, such as reviews, by extracting, processing, and understanding them(Darwis et al., n.d.). Sentiment analysis is an automated process for understanding and analyzing opinions or opinions in unstructured text, such as reviews, by extracting, processing, and understanding them(Ambika Hapsari & Dwi Indriyanti, 2023). Sentiment analysis classification can be done with classification algorithms such as Decision Tree, Naive Bayes, Bayes Networks, Support Vector Machine (SVM), Random Forest, and others (Putra & Santika, 2020).

Machine learning is artificial intelligence that allows computers to learn and improve their own performance without being explicitly programmed, based on given data (Bayu Baskoro et al., n.d.). Machine learning approaches, specifically the Random Forest algorithm, offer an effective solution to analyse the abundant sentiment data from social media. Random Forest, an effective classification method, is used to automatically identify sentiment (positive, negative, or neutral) in customer comments (Machine et al., n.d.). Breiman introduced the Random Forest algorithm which has several advantages, namely it produces relatively low errors, has good performance in classification, is able to handle large-dimensional training data efficiently, and is an effective method for estimating datasets containing missing data (Farley Rafa Aurellia et al., 2023).

LITERATURE REVIEW

Random Forest

This research uses quantitative methodology. This research aims to analyze public opinion or sentiment towards Beauty Products, especially skintific products quantitatively by utilizing data from online platforms, in this case, using datasets obtained from Kaggle. This research uses the Random Forest, a sophisticated data classification method in the realm of Machine Learning. which in this context is used to classify public sentiment towards beauty products into categories such as positive, negative or neutral. Random Forest has several advantages, namely producing relatively low errors, having good performance in classification, being able to handle large-dimensional training data efficiently, and is an effective method for estimating datasets that contain missing data.

Sentiment Analysis

Sentiment analysis is a technique in natural language processing used to identify and categorize the emotions or attitudes contained in text. It is commonly used to determine whether a particular text, such as a product review, tweet, or comment, has a positive, negative, or neutral tone. The sentiment analysis process begins with data collection from relevant sources, such as social media, forums, or customer surveys. Once the data is collected, the next step is text pre-processing which involves cleaning the text from non-text elements, such as numbers and punctuation marks, as well as a tokenization process to break the text into words or phrases. Next, common words that have no specific meaning (stop words) are removed and text normalization, including stemming or lemmatization, is performed to convert words to their base form.

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METHOD

Each stage has its own role in ensuring the success and accuracy of the research conducted. The work procedure of this research can be seen in the following Flowcart:

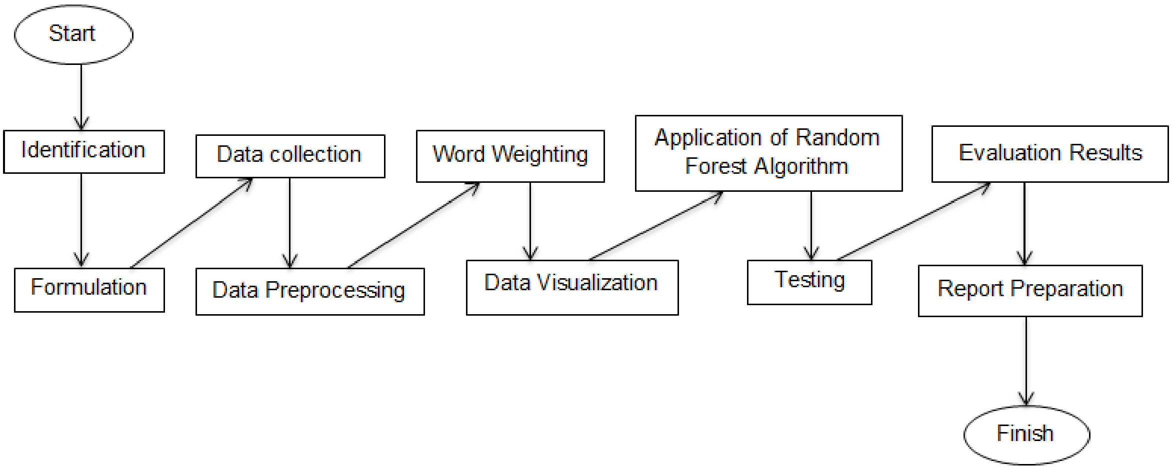

Figure 1. Flowchart of Work Procedure

Identification

This stage involves identifying the problem or issue to be studied, namely the analysis of public sentiment towards skintific beauty products. The research objectives must be clearly formulated to provide the right direction in the research.

Formulation

Preparation of a conceptual framework and formulation of research problems based on the background and research objectives.

Data collection

This research data is obtained through data collection from various relevant sources, namely from Kaggle to get datasets regarding public sentiment towards skintific beauty products.

Data Preprocessing

a) Cleaning is cleaning data from datasets that are NaN or empty.
b) Case Folding is a text pre-processing technique that converts all letters in the document into lowercase letters.
c) Tokenising is the process of separating text into pieces as tokens used for analysis.
d) Filtering, also known as Stopword Removal, is the process of separating important words from the tokenisation results.
e) Stemming is the process of removing word inflection to the basic form.
f) Labelling is the division of data or making classes into 3 parts including Positive, Negative or Neutral.

Word Weighting

The main purpose of this process is to generate the value of the identified root word. The meaning of the root word is converted into a numerical vector. This research utilises the TF method to calculate the word weight value that reflects its importance in the analysis. The following is the formula for calculating word weights using the TF-IDF method:

$$W_{t,d} = t_{f,t.d} \times idf_t = t_{f,t,d} \times \log(N|d,f,t)$$

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Description:
$W_{t,d}$: Frequency of word occurrence in the document
$t_{f,t.d}$: Inverse document frequency for each word
idf_t : Frequency of document occurrence for each word
N : Total number of documents

Data Visualization

Data visualisation is an effective method of presenting information to non-technical audiences, so that they do not have difficulty in reading and understanding the data. In addition, visualisation also helps decision makers in understanding complex concepts or identifying new patterns.

Application of Random Forest Algorithm

This stage involves applying the sentiment analysis method using Random Forest to classify sentiments from datasets related to skintific beauty products.

Testing

The testing stage is carried out on the classification model that has been built using test data to evaluate its performance and accuracy in classifying public sentiment towards beauty products.

Evaluation Results

The next stage is to evaluate the results that have been obtained. The results are presented in the form of accuracy calculations, where accuracy is calculated by measuring the ratio of true positive predictions to the entire data set. Precision is measured by comparing the number of true positive predictions to the total data categorised as positive, while Recall is calculated by comparing the number of true positive predictions to the total data that is actually positive. F1-score is then obtained by calculating the weighted average of precision and recall:

The equation of accuracy can be seen in the following equation formula:

$$\text{Accuracy}= \frac{TP+TN}{TP+TN+FP+FN}$$

The equation of precision can be seen in the following equation formula:

$$\text{Precision}= \frac{TP}{TP+FP}$$

The equation for recall can be seen in the following equation formula:

$$\text{Specificity}= \frac{TN}{TN+FP}$$

The equation of the f1-score can be seen in the following equation formula:

$$\text{F1 Score}= 2 \times \frac{Recall \times Precission}{Recall+Precission}$$

Report Preparation

The findings, analyses, and conclusions of the research that has been conducted are outlined in a comprehensive research report. This report will be an important document to share the research results.

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Tools and Materials

The tools and materials used in this research are divided into two categories, namely hardware and software. To support complex data processing and require large computing power, this research utilises sophisticated hardware, including computers with high specifications. For software, it uses Google colab, Python and libraries that will support this research. The dataset downloaded and used comes from kaggle. Here is the kaggle link.

	No	Medsos	Name	Profile ID	Date	Comment
0	1	Instagram	yoanangara	1927081761	05/12/23 09:09:59	????
1	2	Instagram	zuer.id	8089340592	05/12/23 10:05:58	Heran sama skintific ??, gue pake fw ini itu g...
2	3	Instagram	kosmetikashopsinar1	6980025161	05/12/23 10:36:57	????
3	4	Instagram	kosmetikashopsinar1	6980025161	05/12/23 10:36:58	????
4	5	Instagram	kosmetikashopsinar1	6980025161	05/12/23 10:37:00	????
...	...	...	...	...	...	...
467	468	Facebook	Ning Fiati	ID: 100003139516259	24/10/23 16:22:54	Ini bsa gk yah dipkai untuk kulit wajah yg kom...
468	469	Facebook	Mimih Riden	ID: 100017946678037	26/10/23 03:12:50	Buat flek hitam tebal melasma menahun bandel p...
469	470	Facebook	Raka Danuarta	ID: 100043905112462	26/10/23 09:31:47	Udah 3 bulan ini pake kata istri sama anak muk...
470	471	Facebook	Ipa Juliyanti	ID: 100030784879481	26/10/23 15:39:24	Cek harga
471	472	Facebook	Nina Bobo	ID: 100041232143153	29/10/23 08:56:24	NaN

Figure 2. Skintific dataset

RESULT

Data Collection

The data that has been collected is obtained by retrieving data from kaggle where there are comments from various Social Media such as, Instagram, Facebook, and Youtube. These comments include Negative, Positive and Neutral comments with a total of 958 comments. The following data is obtained:

Socmed	Name	Profile ID	Date	Comment
Instagram	Zuer.id	8089340592	05/12/23 10:05:58	I wonder about Skintific, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the name of acne on off. Is it true that there is a price there is quality? Btw my skin type is oily

Table 1. Dataset

Data Preprocessing

At this stage the data that has been obtained will be processed before the application of Random Forest Classification. There are 5 stages in this process, including:

Cleaning

In this stage, datasets that previously had columns and rows that were NaN and empty will be cleaned. Before cleansing the dataset, the amount of data is 958, after cleaning or removing

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columns and rows that are NaN and empty, the amount of data becomes 938. At this stage, punctuation, URL, html, emoticons, and numbers are also removed.

Initial Text	Cleaning
wonder about Skintific??, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the name of acne on off. Is it true that there is a price there is quality? Btw my skin type is oily	wonder about Skintific I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the acne is off. It is true that there is a price there is quality Btw my skin type is oily

Table 2. Preprocessing Cleaning

Case Folding
Convert all text to lowercase

Initial Text	Case Folding
wonder about Skintific??, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the name of acne on off. Is it true that there is a price there is quality? Btw my skin type is oily	wonder about Skintific I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the acne is off. It is true that there is a price there is quality Btw my skin type is oily

Table 3. Preprocessing Case Folding

Tokenizing

Initial Text	Tokenizing
wonder about Skintific??, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the acne is off. It is true that there is a price there is quality? Btw my skin type is oily	['wonder', 'about', 'skintific', 'I', 'use', 'this', 'fw' , 'that', 'nothing', 'fits', 'even', 'more', 'acne', 'pustules', 'this', 'panthenol', 'is', 'immediately', 'better', 'the', 'acne', 'is', 'off', 'it', 'is', 'true', 'that', 'there', 'is' 'price', 'there', "is" 'quality', 'btw', 'my skin', 'type', 'is' 'oily']

Table 4. Prepropcessing Tokenizing

Filtering (Stopword Removal)
Removing common words that have no significant meaning in the analysis

Initial Text	Tokenizing
wonder about Skintific??, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the acne is off. It is true that there is a price there is quality? Btw my skin type is oily	['wonder', 'skintific', 'I', 'use', 'this', 'fw' , 'that', 'nothing', 'fits', 'even', 'more', 'acne', 'pustules', 'this', 'panthenol', 'is', 'immediately', 'better', 'the', 'acne', 'is', 'off', 'it', 'is', 'true', 'price', 'quality', 'btw', 'my skin', 'type', 'is' 'oily']

Table 5. Preprocessing Filtering (Stopword Removal)

Stemming
Change words into their base form.

Initial Text	Tokenizing
wonder about Skintific??, I use this fw that nothing fits even more acne & pustules. This Panthenol is immediately better, the acne is off. It is true that there is a price there is quality? Btw my skin type is oily	['wonder', 'skintific', 'I', 'use', 'this', 'fw' , 'that', 'nothing', 'fits', 'even', 'more', 'acne', 'pustules', 'this', 'panthenol', 'is', 'immediately', 'better', 'the', 'acne', 'is', 'off', 'it', 'is', 'true', 'price', 'quality', 'btw', 'my skin', 'type', 'is' 'oily']

Table 6. Preprocessing Semming

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Labelling

Grade the preprocessed reviews.

	processed_comment	sentimen
0	heran sama skintif gue pake fw ini itu ga ada ...	netral
1	abi moistur yg paket ata abi itu tahap nya bol...	netral
2	zuerid aku oili msih stay biru pen pindah ke p...	netral
3	zuerid kak sbelum pake skintif jetwatku brsih ...	netral
4	uuuu udhh mauu abi botol yg facial wash nyaa t...	netral
..	...	...
933	untuk menghlangkan plek itam adaklo ada brp hrg	netral
934	cek kak paket satu	netral
935	klo untuk kulit kere yang mana kak	netral
936	buat bumil aman gk kak	netral
937	udh beli ne photo httpsscontentlaxxxfbcdnnetvt...	netral

[938 rows x 2 columns]

Figure 2. Labeling Result

Word Weighting

In the word weighting stage, there is a calculation of Term Frequency (TF) followed by Document Frequency (DF). The next step is to calculate Inverse Document Frequency (IDF), and finally combine the two to get the TF-IDF value. Then the calculation results obtained can be seen in the following figure:

```
Kata: yg, TF-IDF Rata-rata: 0.04589673111197903
Kata: kak, TF-IDF Rata-rata: 0.04479166344147587
Kata: pake, TF-IDF Rata-rata: 0.03693997830927779
Kata: ya, TF-IDF Rata-rata: 0.03180212484128497
Kata: untuk, TF-IDF Rata-rata: 0.03082981358711549
Kata: kulit, TF-IDF Rata-rata: 0.030450584123888152
Kata: aku, TF-IDF Rata-rata: 0.029565806805646896
Kata: pakai, TF-IDF Rata-rata: 0.029078457248596798
Kata: harga, TF-IDF Rata-rata: 0.02860764420474088
Kata: nya, TF-IDF Rata-rata: 0.027962414997462492
```

Figure 3.TF-IDF Word Weighting

The figure shows which words are most significant in the text analysis process.

Data Visualization

Word cloud visualization can be used to describe words that appear frequently in text data. In word cloud visualization, words that are displayed in large size indicate that they appear frequently, while words that rarely appear will be small. The results of the word cloud for positive, negative and neutral classes can be seen as follows:

Figure 4. Positive Word Cloud

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Positive sentiment totaling 33 data is the least data for users to have a positive opinion about Skintific Beauty Products on social media. The word cloud above displays the words that appear most often in the text with a positive sentiment class. Words such as "use", "and", "if", "this", "skin", "suitable", "good", and so on, show that they are frequently used in positive sentiment. This indicates that users have satisfaction with Skintific beauty products.

Figure 5. Negative Word Cloud

For negative sentiment, which amounts to 110 data, there is more data than positive sentiment for users in giving negative opinions about Skintific Beauty Products.

From the figure it can be seen that the words often used by users to give negative comments are "skin", "use", "yg", "I", "use", "oily", "dry", "dull", and so on. From these words have a relationship that shows information that users do not like Skintific Beauty Products because they feel less suitable for these products.

Figure 6. Neutral Word Cloud

As for neutral sentiment, which amounts to 795 data, it is much more than positive and negative data. The word cloud results above display words that often appear in texts with neutral sentiments. Words like "me", "kak", "use", "nya","wear", skintific", and so on indicate that the text is informative or descriptive without conveying strong positive or negative emotions.

Random Forest

Classification using Random Forest results in the percentage of positive, negative, and neutral classes shown in the following figure:

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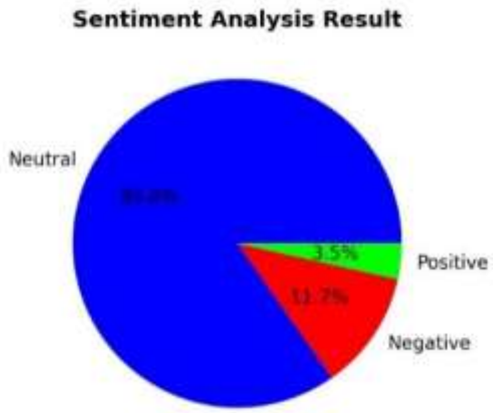


Figure 7. Diagram of Sentiment Analysis Results

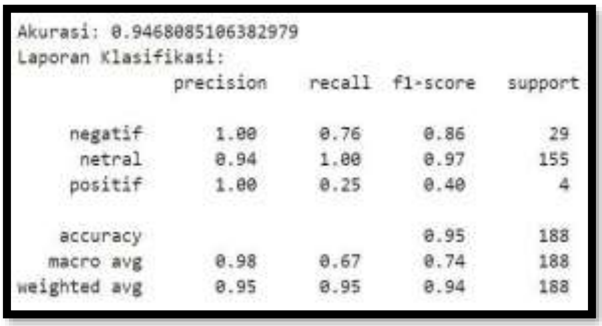
The diagram shows the percentage of classification results with the Random Forest algorithm. The results show that the sentiment tends to be more neutral, which is 84.8%, while for negative sentiment it is 11.7%, but when compared to the sentiment looking at the diagram the lowest sentiment with a total percentage of 3.5% is positive.

Testing

The classification model that has been built will be tested using test data to evaluate its performance and accuracy in classifying public sentiment towards skintific beauty products. Test data is part of the dataset that is not used in model training, so the test results provide an overview of the model's ability to generalize to new data. For data division, namely training and testing with a ratio of 80:20.

Evaluation Results

After testing and getting results to evaluate performance to ensure that the model can classify sentiment towards skintific beauty products accurately. This test results in accuracy, recall, precision, and F-1Score can be seen as follows:



Akurasi: 0.9468085106382979
Laporan Klasifikasi:

	precision	recall	f1-score	support
negatif	1.00	0.76	0.86	29
netral	0.94	1.00	0.97	155
positif	1.00	0.25	0.40	4
accuracy			0.95	188
macro avg	0.98	0.67	0.74	188
weighted avg	0.95	0.95	0.94	188

Figure 8. Results of Accuracy, *Precision*, *Recall*, *F1-Score*

The evaluation results show that Random Forest has a very good accuracy of 94.68%. However, it should be noted that the positive class has a low recall (25%) and a low F1-score (40%), indicating that the model may have difficulty in detecting positive sentiments towards skintifc beauty products. In general, the model is quite good at classifying neutral and negative sentiments.

Cross-Validation Scores: [0.17891374 0.18210863 0.17948718]
Rata-rata Cross-Validation Score: 0.1801698479014773

Figure 9. Cross-Validation Results

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From the figure above, it can be seen that the cross-validation value obtained is relatively low (around 0.18), which indicates that random forest is not good at classifying data. This happens because the class distribution in the dataset is not balanced. The class distribution can be seen in the following figure:

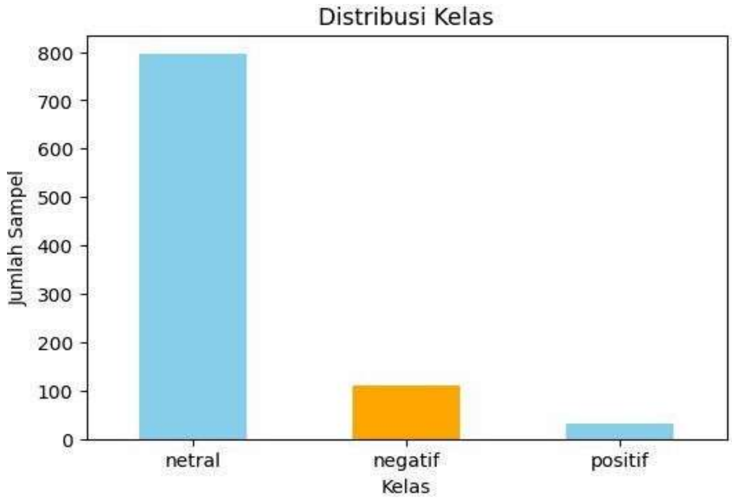

Figure 10. Bar Chart of Class Distribution Results

From the figure, it can be seen that the number of neutral class samples is much higher than the negative and positive classes. Where the number of neutral class samples is 795 data, the number of negative class samples is 110 data, and the number of positive class samples is 33 data.

DISCUSSIONS

The suggestions that must be considered and can be the basis for development in this study, namely:
In future research, it is necessary to expand the dataset by taking data from various media platforms and other sites. This aims to provide a more in-depth analysis. This research is recommended to use other Machine Learning algorithms such as Support Vector Machines (SVM), Neural Networks, or Gradient Boosting which may be able to overcome the weaknesses of Random Forest in terms of recall and F1-score.

CONCLUSION

From the results of research that has been conducted on the Study of Public Sentiment Towards Beauty Products with a Machine Learning Approach:

Random Forest Analysis on Social Media Data, it is concluded that. Random Forest algorithm proved to be less effective in classifying public sentiment towards skintific beauty products. Where the accuracy results are indeed very good, namely 94.68. However, please note that high accuracy does not necessarily indicate good performance results. Due to the unbalanced dataset, the model is only able to predict the dominant class.

In the neutral class, the model has a good performance where the precision is 94%, recall is 100%, and F1-score is 97%. The negative class has a high precision of 100% but, has a lower recall with a result of 76% and f1-score 86%. Meanwhile, the positive class has a high precision of 100%. However, the recall and F1-score are low at 25% and 40% respectively.

Sentiment analysis shows that the majority of public sentiment towards skintific products is neutral, with a significant amount of negative and positive sentiment. It is evident that opinions from users are informative or descriptive without conveying strong positive or negative emotions.

User reviews and opinions on social media play an important role in shaping public perception of beauty products. Usually, consumers tend to search for information and compare reviews before making a decision.

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