

Convolutional Neural Network for Halal Detection of Korean Cosmetic Composition

Diena Rauda Ramdania
Department of Informatics
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
diena.rauda@uinsgd.ac.id

Faiz M. Kaffah
Department of Informatics
Universitas Islam Negeri
Bandung, Indonesia
faiz@uninus.ac.id

Rizky Maulana Aziz
Department of Informatics
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
rizkymaulana3812@gmail.com

Dian Sa'adillah Maylawati
Department of Informatics
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
diansm@uinsgd.ac.id

Edy Mulyana
Department of Electrical Engineering
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
edim@uinsgd.ac.id

Muhammad Insan Al-Amin
Department of Informatics
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
muhammad.insanalamin@uinsgd.ac.id

Muhammad Ali Ramdhani
Department of Informatics
UIN Sunan Gunung Djati Bandung
Bandung, Indonesia
m_aliramdhani@uinsgd.ac.id

Abstract—Korean cosmetics occupy the position as the best and most favorite cosmetics in Indonesia with a user percentage of 46.6%, beating domestic cosmetics with 34.1%. Unfortunately, Hangeul's writing on Korean cosmetic packaging often confuses the contents of the cosmetics. In fact, as a country with the most significant Muslim majority in the world, Indonesian people are required to use everything halal. A halal detection application for Korean cosmetic compositions was created by implementing the Convolutional Neural Network. The test results show that the application can detect material doubts with an accuracy rate of 95.56%. This indicates that the Korean cosmetic halal detection application is in a suitable category.

Keywords—cosmetic, CNN, halal detection, Korean cosmetic

I. INTRODUCTION

Korean Cosmetics is the best and most favorite cosmetics in Indonesia. It is proven by the percentage of 46.6% of users, beating Indonesian cosmetics with a portion of 34.1 [1]. Unfortunately, this consumption pattern is not supported by awareness of the ingredients in the cosmetics used. Only 0.1% of millennial women check the label/information about the composition of the beauty products they buy. Most teenagers under 18 pay more attention to price than the safety and halalness of the cosmetic products they buy [1].

In Indonesia, the country with the largest Muslim population in the world [2], Halal regulations for cosmetic products has been regulated since 2013 by the Indonesian Ulema Council in the MUI Fatwa No. 26 concerning Halal Standards for Cosmetic Products and Their Use. In the fatwa, it is written that every Muslim must use cosmetics made from halal and holy fields [3].

Although customers can know the halal standards and ingredients for cosmetic products, this is still difficult for Korean cosmetic products that use the Korean language and writing (Hangeul). Difficulties in understanding foreign languages can certainly be solved by utilizing technology. Many methods can be used to recognize letters or characters, including the Neural Network. This Neural Network method represents human nerves that learn something to achieve high

accuracy [4][5]. One of the developments of this Neural Network is the Convolutional Neural Network which can process two-dimensional data to process image data or images [4].

In previous studies, the Convolutional Neural Network has been used for various purposes, for example, detection of compositions on non-halal food packaging [6], facial skin type classification [7], age group classification from face image [8], extraction of recipes from food images [9], et cetera. In terms of the use of foreign language writing, CNN is used to recognize signs in various foreign languages, [10]–[16], and Japanese characters (Hiragana, Katakana, and Kanji) with an accuracy of up to 96.2% with cross-validation reaching 86% [4]. In addition, in 2015, a study successfully applied the Convolutional Neural Network to recognize Chinese handwriting with an accuracy of 96.35% [17]. Therefore, Convolutional Neural Network is the proper method to identify Korean writing (Hangeul). This study aims to create an application to detect the halal composition of Korean cosmetics using the Convolutional Neural Network. Furthermore, the application was tested to determine the accuracy level of CNN in detecting doubtful, haram, and halal materials.

II. METHODOLOGY

A. Convolutional Neural Network

One of the derivatives of the Neural Network, which is the development of the Multilayer Perception method, is the Convolutional Neural Network (CNN). CNN is widely used for processing grid-shaped data such as digital images because it has a high network depth and is included in the Deep Neural Network [4]. The name convolutional comes from the linear mathematical operation, the convolution operation. This convolution operation is used at least once on each CNN layer [18].

CNN can be used in classifying labeled data using the supervised learning method. In supervised learning, there are training data and target variables where each data will be grouped and targeted to the existing data [19]. Convolutional Neural Networks use three main architectures: local receptive

fields, shared weight in the form of filters, and spatial subsampling in the form of a pooling [19]. The name convolution comes from the operation of linear algebra, which becomes a layer in CNN, namely the convolution layer. The convolution layer works by multiplying the matrix of the filter on the image to be processed [20] (see Fig. 1).

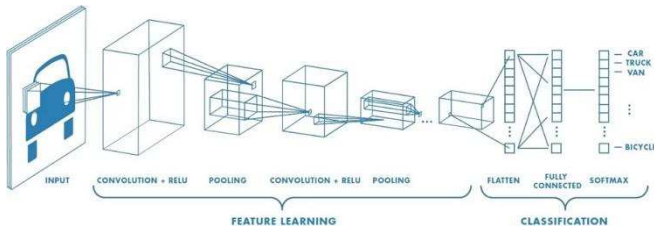


Fig. 1. CNN Architecture

The following are the layers or layers in the Convolutional Neural Network [21]–[23].

1). Convolution Layer

The convolutional layer is the layer that is the core of this CNN. In this layer, the image will be represented in the filter matrix and multiplied by each other. This filter has a length, width, and thickness, which are then initialized to a value where this value becomes a parameter that will be updated in the learning/training process [24]. The convolution process represents the image in a box with a specific value. In the box, there is a kernel indicating the convoluted value. This kernel will move from top left to bottom right (Fig. 2) [20].

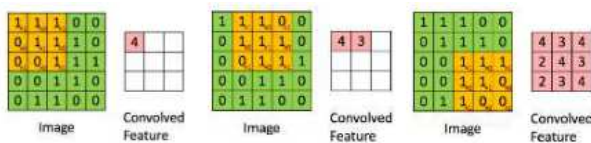


Fig. 2. Convolutional layer process

This convolution layer is a linear transformation of the input data. The result has a weight that specifies the kernels in the convolution layer so that the kernel can be trained based on the input to the CNN.

2). Pooling Layer

The next layer is the pooling layer. This layer aims to reduce the results of the previous layer by reducing the number of parameters using down-sampling operations. The max-pooling method is a popular method in applying the pooling layer. Max-pooling is used to take the highest value from the output convolutional layer which is divided into several grids (Fig. 3).

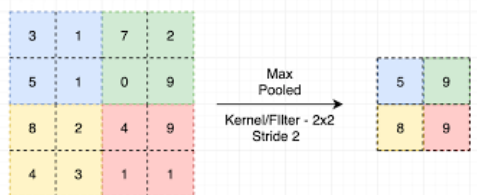


Fig. 3. Max-pooling on pooling layer

Signal will be greater when the grid is large. This layer is applied to each convolutional layer so that it can respond to any changes in the previous layer and increase the spatial abstractness.

3). Fully Connected Layer

To be classified, the data must first be processed using the Fully Connected Layer method that applies Multi-Layer Perception. A fully Connected Layer allows all activation neurons from the previous layer to be connected to the next layer.

B. Non-halal and doubtful cosmetic ingredients

Basically, the problem with non-halal cosmetic ingredients lies in their origin (human or non-halal animal) and the "unclean" status of these ingredients. So from various cosmetic ingredients, the following are non-halal ingredients and doubtful (doubtful) [3]. The list of ingredients for non-halal products can be seen in Table I.

TABLE I. HARAM AND DOUBTFUL COSMETIC INGREDIENTS

No	Ingredients Name	Product	Description
1	Placenta	Lipstick, lip balm, perfume, face cream, lotion, bath soap, powder	Materials become haram if they come from humans or haram animals. It is permissible if it comes from halal animals through childbirth.
2	Keratin	Hair dye	Protein is found in human hair and soybeans. It becomes haram if it comes from human hair or haram animal protein.
3	Albumin	Solvent active cosmetic ingredients	Haram because it comes from human serum to be precise in human blood.
4	Amniotic Fluid	Moisturizer, shampoo, scalp care products.	It is a protective fluid for the fetus. Haram if it comes from humans or animals, is haram.
5	Glycerin	Body soap, lotion, sunscreen, lipstick, moisturizer, mask, lip gloss, toothpaste	Is a derivative of animal fat, plant, propylene gas, or microbial products (synthetic). Haram if it comes from haram animal fat.
6	Collagen and Elastin	Moisturizer, hand & body lotion	Is a connective tissue found in the skin of humans, pigs, goats, cows, etc. Haram if it comes from humans or animals, is haram.
7	Allantoin and its derivatives (Aluminum Chlorhydroxy Allantoinante, Aluminum dihydroxy Allantoinante, Allantoinante N Acetyl DL Methionine, etc.)	Deodorant, anti-irritant for babies, moisturizing, toothpaste, shampoo	Found in living fetuses, dog urine, wheat germ, earthworms, and other organic components. If the material comes from humans or animals, then the law is haram.
8	Hyaluronic Acid	Whitening cream	Found in eye fluid and fetus. Haram if it comes from humans and animals, are haram.

C. Confusion Matrix

Confusion Matrix is a method used to measure the work of Machine Learning. This method compares the classification results from the application with the actual classification. The results of this method are represented in 4 types, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [25] as shown in Fig. 4 [25].

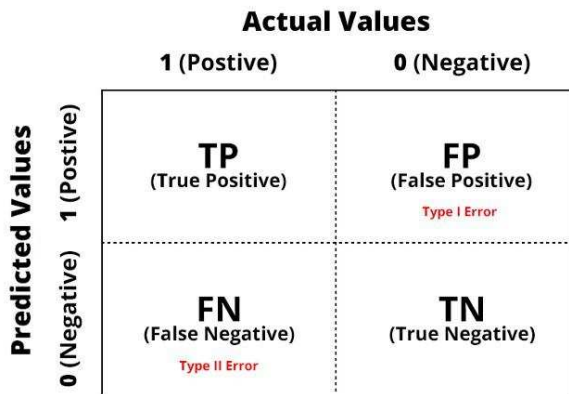


Fig. Confusion Matrix Representation

III. RESULT

The implementation stage is where the application is built according to the design. In developing applications for the detection of halal Korean cosmetics, there are three implementation processes: dataset implementation, CNN algorithm implementation, and interface implementation.

A. Dataset Implementation

The dataset is a collection of data used during the model training process. The data is in the form of images of Korean cosmetic ingredients/composition pieces in .jpg format. The total data collected is 900 images consisting of 9 classes of doubtful material. Each class has 100 images which are contained in a folder with the folder name according to the name of the subject matter of the class. Table II below is a breakdown of the class and the amount of data used.

TABLE II. CLASS DETAILS AND AMOUNT OF DATA

No	Ingredients Name	Name of Ingredients in Korean	Image Example	Amount of Data
1	Glycerin	글리세린		100
2	Niacinamide	나이아시나마이드		100
3	Allantoin	알란토인		100
4	Ethyl hexyl glycerin	에틸헥실글리세린		100
5	Hydrolyzed Collagen	하이드로라이즈드 콜라겐		100
6	Polysorbate (10, 20, 60, 80)	폴리소르바이트 (10, 20, 60, 80)		100
7	Xanthan Gum	산탄검		100

No	Ingredients Name	Name of Ingredients in Korean	Image Example	Amount of Data
8	Sodium Hyaluronate	소듐하이알루로나트		100
9	Arginine	알지닌		100

B. Precision Test Result

Precision testing is an algorithm test using test data that has been split when creating the dataset. This test is carried out after the model has been trained. This test aims to validate the training results' correctness and the maximum level of accuracy obtained. This test is carried out in each class to measure the algorithm's precision in predicting each class. The following is a test table for each class.

TABLE III. TESTING FOR THE INGREDIENT ALLANTOIN

No	Image Dataset	Prediction result	Accuracy	Result
1		Allantoin	0.9911972	Right
2		Xanthan Gum	0.9997435	Wrong
3		Allantoin	0.9979227	Right
4		Allantoin	0.9976618	Right
5		Allantoin	0.9983827	Right
6		Allantoin	0.9879749	Right
7		Allantoin	0.99725014	Right
8		Allantoin	0.9978654	Right
9		Allantoin	0.9934006	Right
10		Allantoin	0.9976101	Right

From the data above, the following information is obtained:

Number of correct (TP) = 9

Number of errors (TN) = 1

Total data = 10

Then the level of precision/precision algorithm in detecting the doubtful material Allantoin is as follows.

$$\text{precision} = \frac{9}{10} \times 100\% = 90\%$$

The following is a test table for the Arginine class/material in Table IV below.

TABLE IV. TESTING FOR THE INGREDIENT ARGININE

No	Image Dataset	Prediction result	Accuracy	Result
1		Arginine	0.82758003	Right
2		Arginine	0.93719894	Right
3		Arginine	0.59215444	Right
4		Hydrolyzed Collagen	0.8404101	Wrong
5		Arginine	0.8315795	Right
6		Arginine	0.9993988	Right

No	Image Dataset	Prediction result	Accuracy	Result
7	알지닌	Arginine	0.98720807	Right
8	알지닌	Arginine	0.80537516	Right
9	알지닌	Hydrolyzed Collagen	0.7876047	Wrong
10	알지닌	Arginine	0.82758003	Right

From the data above, the following information is obtained:

- Correct number (TP) = 7
- Number of errors (TN) = 2
- Total data (TP+TN) = 9

Then the level of accuracy of the algorithm in detecting Arginine doubtful materials is as follows.

$$precision = \frac{7}{9} \times 100\% = 77,7778\%$$

The following is a test table for the EthylHexylGlycerin class/material in Table V as follow.

TABLE V. TESTING FOR THE INGREDIENT ETHYLHEXYLGLYCERIN

No	Image Dataset	Prediction result	Accuracy	Result
1	에틸헥실글리세린	Ethylhexylglycerin	0.999999	Right
2	에틸헥실글리세린	Ethylhexylglycerin	0.999999	Right
3	에틸헥실글리세린	Ethylhexylglycerin	0.99999917	Right
4	에틸헥실글리세린	Ethylhexylglycerin	0.9994729	Right
5	에틸헥실글리세린	Ethylhexylglycerin	0.9999988	Right
6	에틸헥실글리세린	Ethylhexylglycerin	0.9999995	Right
7	에틸헥실글리세린	Ethylhexylglycerin	1.0	Right
8	에틸헥실글리세린	Ethylhexylglycerin	1.0	Right
9	에틸헥실글리세린	Ethylhexylglycerin	0.9999999	Right
10	에틸헥실글리세린	Ethylhexylglycerin	1.0	Right
11	에틸헥실글리세린	Ethylhexylglycerin	0.9999999	Right
12	에틸헥실글리세린	Ethylhexylglycerin	1.0	Right

From the data above, the following information is obtained:

- Correct number (TP) = 12
- Number of errors (TN) = 0
- Total data (TP+TN) = 12

Then the accuracy level of the algorithm in detecting doubtful materials Ethylhexylglycerin is as follows.

$$precision = \frac{12}{12} \times 100\% = 100\%$$

Table VI is the test results for the Glycerin class/material.

TABLE VI. TESTING FOR THE INGREDIENT GLYCERIN

No	Image Dataset	Prediction result	Accuracy	Result
1	글리세린	Glycerin	0.9803774	Right
2	글리세린	Glycerin	0.9850916	Right
3	글리세린	Glycerin	0.99663264	Right
4	글리세린	Glycerin	0.5912468	Right
5	글리세린	Glycerin	0.96999985	Right
6	글리세린	Glycerin	0.9781351	Right
7	글리세린	Glycerin	0.9895275	Right
8	글리세린	Glycerin	0.94521165	Right

From the data above, the following information is obtained:

- Total correct (TP) = 8
- Number of errors (TN) = 0
- Total data (TP+TN) = 8

Then the level of accuracy of the algorithm in detecting the doubtful material Glycerin is as follows.

$$precision = \frac{8}{8} \times 100\% = 100\%$$

The following is a test table for the class/material of Hydrolyzed Collagen in Table VII below.

TABLE VII. TESTING FOR THE INGREDIENT HYDROLYZED COLLAGEN

No	Image Dataset	Prediction result	Accuracy	Result
1	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.9999678	Right
2	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.99997485	Right
3	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.9999863	Right
4	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.99720746	Right
5	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.9910115	Right
6	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.9995907	Right
7	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.99996984	Right
8	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.99992645	Right
9	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.9996718	Right
10	하이드롤라이즈드콜라겐	Hydrolyzed Collagen	0.99912745	Right

$$precision = \frac{10}{10} \times 100\% = 100\%$$

The following is a test table for the Niacinamide class/material in Table VIII below.

TABLE VIII. TESTING FOR THE INGREDIENT NIACINAMIDE

No	Image Dataset	Prediction result	Accuracy	Result
1	나이아신아마이드	Niacinamide	0.99930704	Right
2	나이아신아마이드	Niacinamide	0.9996182	Right

No	Image Dataset	Prediction result	Accuracy	Result
3	나이아신아마이드,	Niacinamide	0.9997949	Right
4	나이아신아마이드	Niacinamide	0.9998691	Right
5	나이아신아마이드	Niacinamide	0.99976546	Right
6	나이아신아마이드	Niacinamide	0.9999455	Right
7	나이아신아마이드	Niacinamide	0.9992181	Right
8	나이아신아마이드	Niacinamide	0.9998487	Right

$$precision = \frac{9}{9} \times 100\% = 100\%$$

The following is a test table for the Polysorbate class/material in Table IX below.

TABLE IX. TESTING FOR THE INGREDIENT POLYSORBATE

No	Image Dataset	Prediction result	Accuracy	Result
1	폴리소르베이트	Polysorbate	0.9986094	Right
2	폴리소르베이트	Polysorbate	0.9999957	Right
3	폴리소르베이트	Polysorbate	0.9999985	Right
4	폴리소르베이트	Polysorbate	0.9999857	Right
5	폴리소르베이트	Polysorbate	0.9999684	Right
6	폴리소르베이트	Polysorbate	1.0	Right
7	폴리소르베이트	Polysorbate	1.0	Right
8	폴리소르베이트	Polysorbate	0.9999807	Right
9	폴리소르베이트	Polysorbate	0.9999993	Right
10	폴리소르베이트	Polysorbate	0.9999976	Right

$$precision = \frac{10}{10} \times 100\% = 100\%$$

The following is a test table for the class/material of Sodium Hyaluronate in Table X below.

TABLE X. TESTING FOR THE INGREDIENT SODIUM HYALURONATE

No	Image Dataset	Prediction result	Accuracy	Result
1	소듐하이알루로네이트	Sodium Hyaluronate	0.9944179	Right
2	소듐하이알루로네이트	Sodium Hyaluronate	0.99846673	Right
3	소듐하이알루로네이트	Sodium Hyaluronate	0.99839526	Right
4	소듐하이알루로네이트	Sodium Hyaluronate	0.99744844	Right
5	소듐하이알루로네이트	Sodium Hyaluronate	0.99947196	Right
6	소듐하이알루로네이트	Sodium Hyaluronate	0.9998222	Right
7	소듐하이알루로네이트	Sodium Hyaluronate	0.9967847	Right

$$precision = \frac{7}{7} \times 100\% = 100\%$$

The following is a test table for the class/material Sodium Hyaluronate in Table XI below.

TABLE XI. TESTING FOR THE INGREDIENT POLYSO

No	Image Dataset	Prediction result	Accuracy	Result
1	전탄검	Xanthan Gum	0.9987534	Right
2	전탄검	Xanthan Gum	0.99999213	Right
3	전탄검	Xanthan Gum	0.9999968	Right
4	전탄검	Xanthan Gum	0.9999995	Right
5	전탄검	Xanthan Gum	0.99998736	Right
6	전탄검	Xanthan Gum	0.9999821	Right
7	전탄검	Xanthan Gum	0.9996784	Right
8	전탄검	Xanthan Gum	0.99999464	Right
9	전탄검	Xanthan Gum	0.9999963	Right
10	전탄검	Xanthan Gum	0.9996275	Right
11	전탄검	Xanthan Gum	0.9999981	Right

$$precision = \frac{11}{11} \times 100\% = 100\%$$

From all the precision test results in each class, it can be taken the average of the precision values as follows.

$$means = \frac{90 + 77,7778 + 100 + 100 + 100 + 100 + 100 + 100 + 100}{9} \% = 96,4198\%$$


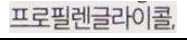
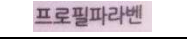
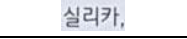
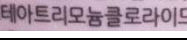
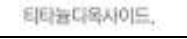
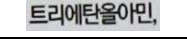
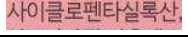
C. Recall Test Result

Recall testing is an algorithm testing with halal or doubtful criteria. This test is carried out by entering the data of halal ingredients per the LPPOM MUI Decree. The application will assess the accuracy of the input, if it is less than 0.59 in any class then the material is categorized as halal material. This is determined by referring to the minimum value of accuracy obtained when testing precision using test data.

The data used is an image of pieces of halal material with a total of 50 images. Furthermore, the level of accuracy is calculated using the Recall formula in the confusion matrix method. The following is a table of the results of tests on the application. Table XII show the recall test result.

TABLE XII. RECALL TEST RESULT

No	Ingredients Name	Image	Prediction Result
1	Aloe Barbadensis leaf Juice	알로에베라잎즙	Syubhat
2	1,2- Hexanediol	1,2-헥산디올	Syubhat
3	Acrylate Copolymer	크릴릭애씨드코폴리머	Syubhat
4	Butylethylglycol	부틸렌글라이콜	Syubhat
5	C13-14 Isoparaffin	C13-14이소파라핀	Syubhat
6	Chlorophenesin	클로페네신	Halal
7	Cyclohexasiloxane	사이클로헥사실록산	Syubhat
8	Dimethicone	디메치콘	Halal
9	Disodium EDTA	디소듐이디티에이	Halal
10	hydroxyethylcellulose	하이드록시에틸셀룰로오스	Syubhat
11	Methyl Propanediol	메틸프로판디올	Halal
12	Phenoxy Ethanol	페녹시에탄올	Halal

No	Ingredients Name	Image	Prediction Result
13	Poly Acrylate 13		Syubhat
14	Propylene Glycol		Syubhat
15	Propyl Paraben		Syubhat
16	Silika		Syubhat
17	Steartrimonium Chloride		Syubhat
18	Titanium Dioxide		Syubhat
19	Triethanolamine		Syubhat
20	Cyclopentasiloxane		Syubhat

From these tests, only 5 were categorized as halal ingredients. Then the recall from the test is as follows.

$$Recall = \frac{5}{20} \times 100\% = 25\%$$

The results of the training model process on the training data produce an accuracy level of 0.9708 with a validation accuracy of 0.9667 and a training loss level of 0.1337 with a validation loss = 0.0650. The evaluation and testing of the algorithm using test data show an accuracy level of 0.9556 with a loss of 0.2396. The results of validating doubtful materials show the average precision of 9 classes of precision using test data of 96.4198%. The results of testing using halal material data show a result of 25%.

CONCLUSION

An application has been built to detect the halal composition of Korean cosmetics. The system is created by applying the CNN algorithm. The process of detecting the halal ingredients of Korean cosmetics is carried out in several stages: creating a dataset, defining the training model, the training model stage, predicting the image, and creating the interface. The level of system accuracy testing is at 96%. This shows that the system can function correctly.

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