

## PAPER

# Convolutional Neural Network with Feature Extraction to Improve the Classification Accuracy of Multi-Class Facial Skin Disorders

Rismayani<sup>1,2</sup>, Amil Ahmad  
Ilham<sup>3</sup>(✉), Andani  
Achmad<sup>1</sup>, Muhammad Rifqy  
Yudhiestra Rachman<sup>3</sup>

<sup>1</sup>Département of Electrical  
Engineering, Universitas  
Hasanuddin, Gowa, Indonesia

<sup>2</sup>Département of  
Information System,  
Dipa Makassar University,  
Makassar, Indonesia

<sup>3</sup>Département of Informatics,  
Universitas Hasanuddin,  
Gowa, Indonesia

[amil@unhas.ac.id](mailto:amil@unhas.ac.id)

## ABSTRACT

This study aims to improve the accuracy of multi-class facial skin disorder classification using a convolutional neural network (CNN) enhanced with feature extraction. The CNN method for classifying multi-class facial skin disorders uses color feature extraction using color moment (CM) and Laplacian of Gaussian (LoG) for direct shape with image data. Multi-class facial skin disorders include oily, hyperpigmentation, acne, redness, blackhead, and normal. A public dataset is used with 7151 images with a balanced number of data classes. Researchers divided the data set into 80% for training and 20% for testing. Experiments are carried out through training and testing with 100 epochs, resulting in an accuracy of 85% for CNN, 66% for the CM-CNN, 80% for LoG-CNN, and 91% for CM-LoG-CNN. The highest classification accuracy is achieved with the CM-LoG-CNN combination.

## KEYWORDS

convolutional neural network (CNN), color moment (CM), facial skin disorder, laplacian of gaussian (LoG), multi-class

## 1 INTRODUCTION

Various facial skin problems, such as oily skin, dark spots, acne, redness, and blackheads, can change the appearance and feel of the skin. Due to artificial intelligence (AI), technology that can recognize and classify images has developed rapidly [1], [2]. Traditional methods that rely on physical examinations by dermatologists are often time-consuming and not easily accessible to everyone. Developing deep learning technologies, especially in computer vision, enables the development of more effective and accurate diagnostic methods for facial skin disorders. Correct diagnosis is needed for proper treatment because facial skin disorders are a common health problem. Image processing techniques and AI have opened up new avenues

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for effectively diagnosing facial skin disorders. Using efficient convolutional neural network (CNN), such as Efficient Net, is a widely used technique [3].

Research on CNN with feature extraction to improve multi-class classification of facial skin disorders has the potential to enhance facial skin diagnosis and treatment. Classifying various skin disorders accurately is a challenge due to their similar appearances. By utilizing effective feature extraction, CNN can boost classification accuracy by recognizing intricate patterns in facial skin images. This approach streamlines the classification process, increasing diagnostic extraction efficiency and enhancing classification accuracy.

Previous research has been conducted on predicting facial skin disorders with types of disorders such as acne, hyperpigmentation, and normal, which applies a model from artificial neural network (ANN) that uses information in the form of non-visual data and produces high accuracy [4]. However, to obtain results with high accuracy, it is necessary to conduct experiments on other models with information data in the form of facial skin disorder images and classify them with other facial skin disorders related to aesthetics.

The problem is how can the combined feature extraction method improve the accuracy of multi-class classification of facial skin disorders by combining color moment (CM), Laplacian of Gaussian (LoG), and CNN features based on image data. This study aims to improve the accuracy of multi-class facial skin disorder classification using CNN enhanced with feature extraction, where the main focus is to develop a more accurate CNN model compared to the basic CNN using a relevant feature extraction method.

This study contributes by incorporating feature extraction in CNN architecture to enhance the model's ability to learn more complex and subtle patterns in image data, resulting in higher classification accuracy. Then, this study shows a comprehensive method to prepare data and extract important features for multi-class classification of facial skin disorders using CM for color and shape with LoG. In addition, this study improves the understanding of the capacity of CNN models in distinguishing and categorizing various multi-class facial skin disorders. This study evaluates the model performance by analyzing the accuracy, precision, recall, and F1 score metrics.

## **2 LITERATURE REVIEW**

### **2.1 Facial skin disorder**

These conditions can include changes in the color, texture, or function of the skin and can be caused by many things, such as genetics, environment, lifestyle, and certain diseases [5], [6], [7]. Facial skin disorders can cause discomfort, lack of self-confidence, and even cause serious health problems. [8], [9], [10]. Classification has a significant impact on its diagnosis and treatment. CNN is used to classify skin diseases automatically. Classification using CNN facilitates processing facial images segmented into more disease classes [11].

### **2.2 Convolutional neural network**

Convolutional neural network is a deep structure learning model that is very effective for image recognition. This model can be used to recognize and classify facial skin diseases. CNN utilizes its convolutional layers to extract hierarchical

features from images. CNN has a spatial hierarchy that allows the model to identify the uniqueness of each skin disease [12], [13]. This model can extract the grid pattern of pixel values that form interesting skin disease patterns and textures [14], [15]. Figure 1 shows CNN's basic architecture, starting with feature extraction, classification, and probabilistic distribution processes.

Previous authors produced different results by combining three different CNN models. Each model helps to extract specific features from skin images. These prediction results can be used to combine the predictions from each separate CNN model with an averaging method [16], intra-class variability and class homogeneity make classification more difficult. The class imbalance problem still exists, and the training amount is limited. Image pre-processing and scaling for model input and evaluation of eleven deep learning algorithms [17], still need to improve image pre-processing techniques for better accuracy. Classifying skin diseases using two group learning techniques, namely multimodal and multitask methods, with the aim of improving the accuracy of disease classification [18], limited multimodal and multitask network exploration. Overfitting and imbalance issues in very small datasets. The reduction stage in the ResNet50 model can reduce model complexity without sacrificing accuracy. Data augmentation techniques and mini-batch size adjustment are essential factors in achieving optimal accuracy in skin disease classification [19], however, the complex architecture is too complex for some classes. Reducing complexity can affect the performance model. Development of a mobile identification system that uses images for deep learning to detect biological butterfly characteristics [20] presents a CNN for image classification after training and characterization.

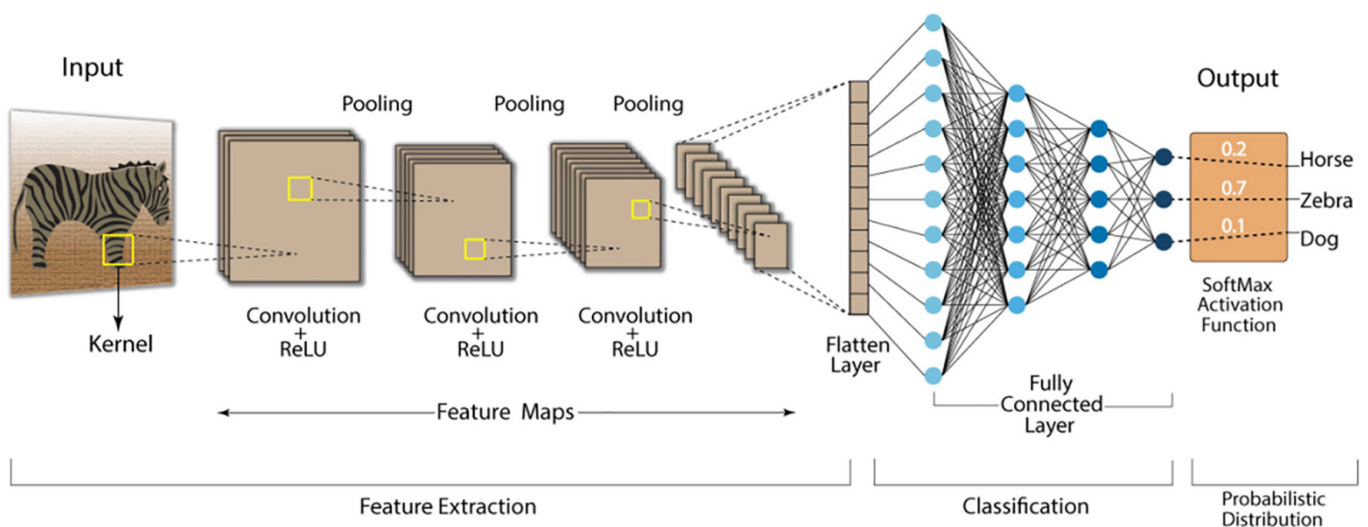


Fig. 1. Architecture CNN [21]

### 2.3 Feature extraction techniques

Various classification methods are used in CNN, and pre-trained CNN is one of the most widely used in facial skin disorder diagnosis. Pre-trained CNN classification methods use large datasets, which help CNN extract more complex features and correctly classify multiple classes [22], [23]. Pre-trained classification methods can identify facial skin diseases based on detected class differences, such as skin color and texture. CNN integration combines local binary patterns (LBP) and K-nearest

neighbors (KNN), achieves good feature extraction, and improves CNN classification methods by extracting features based on local image textures [24]. This new image feature extraction method relies on data symbols, such as the empirical cumulative distribution function (ECDF) and function distribution value (DFDV) [25]. This paper examines the problems associated with extracting features from remotely sensed data and discusses prospects in this field [26]. However, problems with extracting features from remotely sensed data are discussed, including atmospheric effects, radiometric distortions, and noise.

### 3 MATERIALS AND METHODS

Figure 2 illustrates the comprehensive research methodology employed in this study, depicting key stages such as pre-processing, feature extraction, dataset partitioning, implementation of the CNN model with feature extraction, performance evaluation, and interpretation of results.

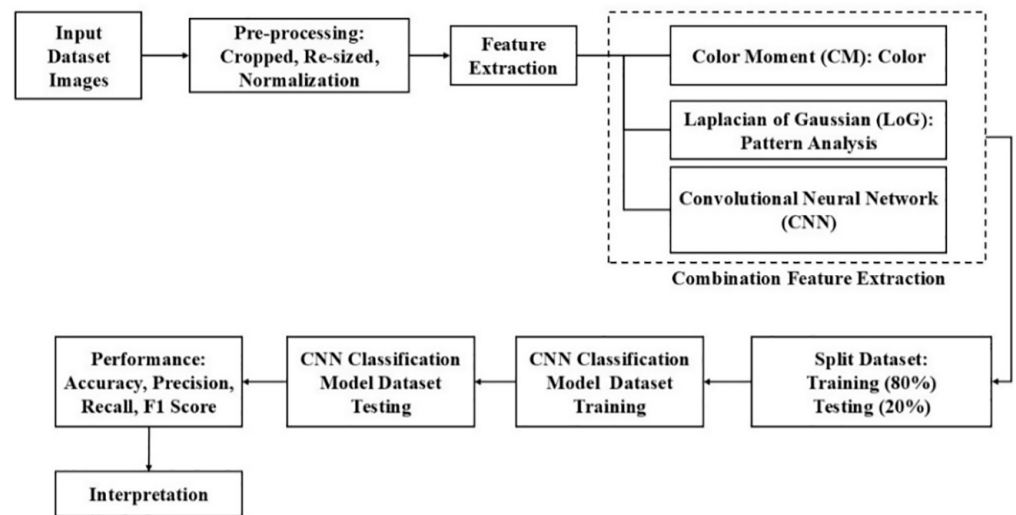


Fig. 2. The flow of research methodology with a combination extraction feature

#### 3.1 Data collection

The dataset used is a public dataset obtained from Roboflow Universe <https://universe.roboflow.com/keless/skin-problem-wqlfe>. The dataset consists of images of facial skin disorders such as oiliness, hyperpigmentation, acne, redness, blackheads, and normal. The number of datasets used is 7151 images. Then, the dataset is divided into 80% training data and 20% testing data, with a proportion of training data of 5723 and testing of 1428. Table 1 shows the division of data and Table 2 shows the proportion of the dataset.

Table 1. Split dataset

Split Data	Image	Percentage
Training	5723	80%
Testing	1428	20%
<b>Total</b>	<b>7151</b>	

**Table 2.** Proportion dataset

Multi-Class	Training Image	Testing Image
Oily	1276	319
Hyperpigmentation	862	215
Acne	1019	254
Redness	1123	197
Blackhead	653	163
Normal	790	280
<b>Total</b>	<b>5723</b>	<b>1428</b>

### 3.2 Pre-processing

The data preprocessing process for various models involves several steps, such as the original images from the dataset being resized to  $224 \times 224$  pixels to fit the model. The image dataset is cropped to focus on the face, removing irrelevant parts and normalizing to ensure all pixels are in the same range, thereby improving the model performance.

### 3.3 Feature extraction

Feature extraction is the process of extracting important information or characteristics from raw data, such as images, to transform it into a form easier for deep learning algorithms to process. This process aims to reduce the dimensionality of data and increase efficiency without losing important information [27]. There are some features extracted as follows:

- Color is one of the characteristics of facial skin disorders that uses the CM method with a graphical representation of the frequency distribution of intensity values in an image. CM is quite simple in image processing because it involves calculating the frequency distribution of pixel intensity values in an image as follows:

1. First moment (Mean): (1)

- a.  $\mu(R) = \frac{\Sigma(R(i))}{N}$

- b.  $\mu(G) = \frac{\Sigma(G(i))}{N}$

- c.  $\mu(B) = \frac{\Sigma(B(i))}{N}$

2. The second moment (Variants): (2)

- a.  $\sigma^2(R) = \frac{\Sigma((R(i) - \mu(R))^2)}{N}$

- b.  $\sigma^2(G) = \frac{\Sigma((G(i) - \mu(G))^2)}{N}$

- c.  $\sigma^2(B) = \frac{\Sigma((B(i) - \mu(B))^2)}{N}$

3. The third moment (Skewness): (3)

$$\text{a. } \gamma(R) = \frac{\Sigma((R(i) - \mu(R))^3)}{\left[ N \times (\sigma^2(R))^{\frac{3}{2}} \right]}$$

$$\text{b. } \gamma(G) = \frac{\Sigma((G(i) - \mu(G))^3)}{\left[ N \times (\sigma^2(G))^{\frac{3}{2}} \right]}$$

$$\text{c. } \gamma(B) = \frac{\Sigma((B(i) - \mu(B))^3)}{\left[ N \times (\sigma^2(B))^{\frac{3}{2}} \right]}$$

4. The fourth moment (Kurtosis): (4)

$$\text{a. } \kappa(R) = \frac{\Sigma((R(i) - \mu(R))^4)}{\left[ N \times (\sigma^2(R))^2 \right]}$$

$$\text{b. } \kappa(G) = \frac{\Sigma((G(i) - \mu(G))^4)}{\left[ N \times (\sigma^2(G))^2 \right]}$$

$$\text{c. } \kappa(B) = \frac{\Sigma((B(i) - \mu(B))^4)}{\left[ N \times (\sigma^2(B))^2 \right]}$$

Where:

$R(i), G(i), B(i)$  = The color intensity values at the  $i$  pixel for the red ( $R$ ), green ( $G$ ), and blue ( $B$ ) color channels

$N$  = The total number of pixels in the image

$\mu(R), \mu(G), \mu(B)$  = Average color for the red ( $R$ ), green ( $G$ ), and blue ( $B$ ) color channels

$\sigma^2(R), \sigma^2(G), \sigma^2(B)$  = Color variance for red ( $R$ ), green ( $G$ ), and blue ( $B$ ) color channels

$\gamma(R), \gamma(G), \gamma(B)$  = Color skewness for the red ( $R$ ), green ( $G$ ), and blue ( $B$ ) color channels

$\kappa(R), \kappa(G), \kappa(B)$  = Color kurtosis for the red ( $R$ ), green ( $G$ ), and blue ( $B$ ) color channels

$\Sigma$  = The count symbol indicates the number of all pixels in the image

- Then, for shape features that use the LoG, the Laplacian of Gaussian, or LoG, operator is used to identify corners and edges in the image. This operator works by convolving the image with a Gaussian kernel and then performing Laplacian [28].

$$LoG(x, y) = (x^2 + y^2 - 2\sigma^2) \times \exp\left(-\frac{(x^2 + y^2)}{(2\sigma^2)}\right) \quad (5)$$

Where:

$LoG(x, y)$  = LoG value at coordinates  $(x, y)$

$\sigma$  = Gaussian kernel standard deviation

$x, y$  = Coordinates of points in the image

### 3.4 Model

This study uses a CNN model to perform training and testing, which is explained as follows:

- CNN model training: The deep learning model, namely CNN, is used to train the combination of CM-LoG-CNN feature extraction. The CNN model used for the classification process has several convolutional, pooling, and fully connected layers. The parameters used include optimizer, learning rate, number of layers, and number of neurons.
- CNN model testing: The model obtained during training is used to test data to determine the optimal performance level of the CNN model. By testing the model on new data, researchers can assess how well it can generalize and predict outcomes.

### 3.5 Evaluation performance

To see how well the model works, we test it on a different set of data that it hasn't seen before. This helps us check if the model will perform well when given new information. which are defined in Eq. (6), (7), (8), and (9).

$$\bullet \text{ Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (6)$$

$$\bullet \text{ Precision} = \frac{TP}{(TP+FP)} \quad (7)$$

$$\bullet \text{ Recall} = \frac{TP}{(TP+FN)} \quad (8)$$

$$\bullet \text{ F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

Where:

$TP$  = True positive (True positive prediction)

$TN$  = True negative (True negative prediction)

$FP$  = False positive (False positive prediction)

$FN$  = False negative (False negative prediction)

### 3.6 Pseudocode feature extraction method

This code extracts various features from the image using CM, LoG, and CNN. Features are then combined to create a more complete feature representation, which can be used for image classification.

In this case, torch.cat combines feature vectors from three feature extraction methods: CM, LoG, and CNN. Torch.Cat creates a more information-rich feature vector by combining the three feature vectors. This data is then used as input for a classification model to determine the class of facial skin disorder. The goal of feature fusion is to improve classification accuracy by using more complete information from different methods and improving the model's ability to generalize to new data.

**Algorithm 1***Input* : Images dataset (loader)*Output* : Combined color moment, LoG features and CNN-based

```

FUNCTION extract_cnn_features(image)
  x_cnn = convolution(image)
  x_cnn = batch_normalization(x_cnn)
  x_cnn = relu(x_cnn)
  x_cnn = max_pooling(x_cnn)
  x_cnn = convolution(x_cnn)
  x_cnn = batch_normalization(x_cnn)
  x_cnn = relu(x_cnn)
  X_cnn = max_pooling(x_cnn)
  x_cnn = convolution(x_cnn)
  x_cnn = batch_normalization(x_cnn)
  x_cnn = relu(x_cnn)
  x_cnn = max_pooling(x_cnn)
  x_cnn = adaptive_average_pooling(x_cnn)
  cnn_features = flatten(x_cnn)
  RETURN cnn_features
END FUNCTION

FUNCTION extract_log_features(image)
  gray_image = grayscale(image) # using cv2.cvtColor with COLOR_BGR2GRAY
  log_feature = mean(gaussian_laplace(gray_image))
  RETURN log_features
END FUNCTION

FUNCTION extract_color_moment_features(image)
  channels = channel_split(image) # using cv2.split, data splitted to 3 channels (RGB)
  moments = []
  FOREACH channel in channels do
    BEGIN
      mean = mean(channel)
      std = standard_deviation(channel)
      skewness = skewness(channel, mean)
      moments += mean, std, skewness
    END
  ENDFOREACH
  RETURN moments
END FUNCTION

START
  INPUT image
  cnn_features = extract_cnn_features(image)
  log_features = extract_log_features(image)
  color_moment_features = extract_color_moment_features(image)
  combined_features = concat(cnn_features,
  log_features, color_moment_features) # using torch.cat
END

```

**4 RESULT AND DISCUSSION**

This study uses the Python 3 programming language and the PyTorch framework on the Jupiter Anaconda platform with a GPU accelerator. Researchers adjusted hyperparameters to maximize the performance of the model built. The experimental results will then be analyzed. The dataset consists of facial skin disorder images, including oily skin, hyperpigmentation, acne, redness, blackheads, and normal skin.

Figure 3 shows the architecture of the feature combination with the CM-LoG-CNN method. This architecture combines the extraction of CM and LoG features before being fed into the CNN model. This feature combination aims to improve the CNN model's ability to classify facial skin disorders by utilizing image color and texture information.

Figure 4 is a flowchart of the process carried out by combining feature extraction to classify multi-class facial skin disorders. The initial stage of this study involved an input dataset of facial skin disorder images, which was then pre-processed by cropping, resizing, and normalizing. Experiments are carried out using extraction methods such as CNN, CM, and LoG and then combined. After that, a multi-class facial skin disorder classification is carried out, and the facial skin disorder classification results are displayed, such as oiliness, hyperpigmentation, acne, redness, blackheads, and normal.

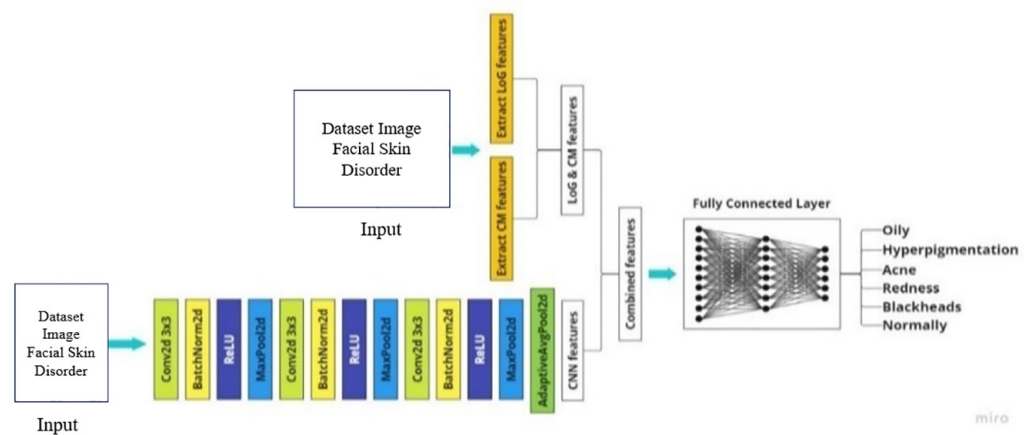


Fig. 3. Architecture system combination features

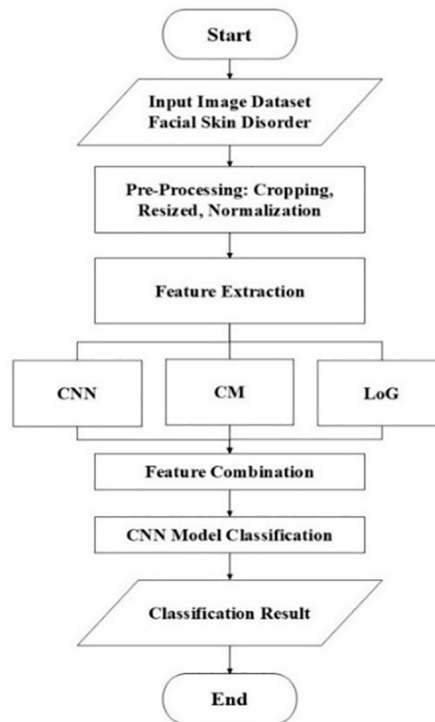


Fig. 4. Proposed model flow diagram

Table 3 displays the CNN model configuration with the Adam optimizer, which utilizes a learning rate of 0.0001 and is trained over 100 epochs. The model architecture includes Conv2D for detecting patterns in images, BatchNorm2D for stabilizing and accelerating network learning, rectified linear unit (ReLU) for introducing non-linearity, MaxPool2D for down sampling, AdaptiveAvgPool2D for resizing feature maps, Linear for final decision-making, and Dropout for preventing overfitting by enhancing generalization through neuron randomness.

**Table 3.** Layer model CNN

Layer Type	Output Shape	Parameter
Conv2d	None, 32, 224, 224	896
BatchNorm2d	None, 32, 224, 224	64
ReLU	None, 32, 224, 224	0
MaxPool2d	None, 32, 112, 112	0
Conv2d	None, 64, 112, 112	18496
BatchNorm2d	None, 64, 112, 112	128
ReLU	None, 64, 112, 112	0
MaxPool2d	None, 64, 56, 56	0
Conv2d	None, 128, 56, 56	73856
BatchNorm2d	None, 128, 56, 56	256
ReLU	None, 128, 56, 56	0
MaxPool2d	None, 128, 28, 28	0
AdaptiveAvgPool2d	None, 128, 1, 1	0
Dropout	None, 138	0
Linear	None, 128	17792
ReLU	None, 128	0
Dropout	None, 128	0
Linear	None, 6	774

#### 4.1 Result and performance of CNN-based model

Table 4 presents the results of CNN performance experiments using various feature extraction combinations. The experiments show that the CNN model achieves 85% accuracy, while the combination of CM and CNN (CM-CNN) achieves 66%, LoG and CNN (LoG-CNN) achieves 80%, and CM and LoG with CNN (CM-LoG-CNN) achieves 91%.

**Table 4.** Performance of CNN with feature extraction

Multi-Class	Precision	Recall	F1-Score	Accuracy
<b>CNN-Based</b>				
Oily	0.84	0.79	0.81	85%
Hyperpigmentation	0.84	0.83	0.84	
Acne	0.89	0.83	0.86	
Redness	0.81	0.88	0.84	
Blackhead	0.88	0.87	0.88	
Normal	0.82	0.88	0.85	
<b>CM-CNN</b>				
Oily	0.57	0.54	0.56	66%
Hyperpigmentation	0.66	0.43	0.52	
Acne	0.80	0.70	0.75	
Redness	0.59	0.89	0.71	
Blackhead	0.87	0.58	0.70	
Normal	0.59	0.83	0.69	
<b>LoG-CNN</b>				
Oily	0.73	0.71	0.72	80%
Hyperpigmentation	0.75	0.83	0.79	
Acne	0.94	0.76	0.84	
Redness	0.71	0.88	0.79	
Blackhead	0.89	0.79	0.84	
Normal	0.82	0.81	0.81	
<b>CM-LoG-CNN</b>				
Oily	1.00	1.00	1.00	91%
Hyperpigmentation	1.00	0.83	0.91	
Acne	1.00	0.50	0.67	
Redness	0.75	1.00	0.86	
Blackhead	1.00	1.00	1.00	
Normal	0.88	1.00	0.93	

## 4.2 Accuracy recapitulation

The experimental results in Table 4 show that the combination of CM and LoG feature extraction for multiclass facial skin disorder classification achieves an accuracy rate of 91%. This outperforms the CNN-based approach, which achieves an accuracy rate of 85%, where the recapitulation of the experimental results is shown in Table 5.

Previous studies have explored various CNN models and feature extraction techniques for classifying skin problems, disorders, and diseases, as summarized in Table 6. This table provides a comparative analysis of these studies, highlighting the various approaches used in the field. The method used by previous studies has used a lot of CNN, but previous studies still use CNN-based and CNN architecture for skin disease classes. However, this study combines feature extraction with the CM-Log-CNN method to improve accuracy in classifying facial skin disorders. The results show an increase in accuracy of 91% compared to without a combination of feature extraction.

**Table 5.** Accuracy recapitulation model with feature extraction

Model	Accuracy
CNN-Based	85%
CM-CNN	66%
LoG-CNN	80%
CM-LoG-CNN	91%

**Table 6.** Comparison research

Reference	Dataset	Class	Model/Feature Method	Accuracy
[29]	2475	Superficial Spreading Melanoma, Nodular Melanoma, Lentigo Maligna Melanoma	CNN	88.83%
[30]	5405	Melanoma, Basal Cell Carcinoma, Squamous Cell Carcinoma	ResNet50	83%
[31]	5289	Low risk or High risk for Melanoma	DenseNet121	84%
[32]	1612	Basal Cell Carcinoma, Squamous Cell Carcinoma, Actinic Keratosis, Seborrheic Keratosis, Melanoma, Melanocytic Nevus	ResNet50	67%
[33]	300	Melanoma and non	Shallow Network With 2 Convolutional Layers	61%
[34]	16720	Actinic Keratosis and Intraepithelial Carcinoma, Basal Cell Carcinoma, Benign Keratosis-Like Lesion, Dermatofibroma, Melanoma, Melanocytic Nevus, Vascular Lesion	AlexNet	79%
[35]	–	Acne, blisters, cold sores, psoriasis, and vitiligo	MobileNet, VGG19, ResNet, EfficientNet, Inception, and DenseNet	90%
[36]	10000	Acne, Eczema, Psoriasis, Dermatitis, and Skin Infections	CNN, VGG, MobileNet, MobileNetV2	85%
<b>Proposed Research</b>	<b>7151</b>	<b>Oily, Hyperpigmentation, Acne, Redness, Blackheads, Normal</b>	<b>Color (CM), Pattern (LoG), CNN Feature Extraction Feature</b>	<b>91%</b>

The implications of this study include the potential to classify multi-class facial skin disorders more accurately and reliably using advanced technologies such as

CNN enhanced with feature extraction methods. By achieving significant improvements in classification accuracy, this study opens up opportunities to improve the diagnostic process, treatment strategies, and overall health outcomes associated with skin disorders. Furthermore, the successful application of CM and LoG together with CNN highlights the importance of integrating multiple techniques to improve artificial intelligence systems' performance in dermatology. This study paves the way for further advancements in the automated classification of skin disorders, which will ultimately benefit patients and healthcare professionals. In dermatology, CNN integration improves diagnostic accuracy and makes skin disorder classification more accessible, especially in areas with limited medical resources. However, ensuring that models are applicable to diverse populations and addressing class imbalance remain ongoing challenges.

## 5 CONCLUSION

This study concludes that it successfully improves the classification accuracy of multi-class facial skin disorders by combining CNN with feature extraction methods such as CM and LoG. By applying this technique to a public image dataset consisting of 7151 images of various skin conditions, including oily skin, hyperpigmentation, acne, redness, blackheads, and normal skin, significant progress in classification accuracy is achieved. This study produces good results through rigorous experiments and training for more than 100 epochs, with the combination of CM-LoG-CNN showing the highest accuracy rate of 91%.

Future work efforts should focus on improving data representation and model accuracy through the exploration of more sophisticated feature extraction methods. The incorporation of additional layers and hyperparameter optimization has the potential to enhance CNN model performance further. Leveraging larger and more diverse datasets may contribute to better model generalization and enable comprehensive evaluation of model performance across different skin conditions and demographic groups.

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## 8 AUTHORS

**Rismayani** is a doctoral student at the Universitas Hasanuddin in Electrical Engineering concentration Informatics, faculty of Engineering, Indonesia. Also, currently, she is Associate Professor at the Dipa Makassar University, department of Information System and she fields of interest are artificial intelligence, deep learning, and machine learning. She has several publications in these fields. She can be contacted at email: [rismayani22d@student.unhas.ac.id](mailto:rismayani22d@student.unhas.ac.id), [rismayani@undipa.ac.id](mailto:rismayani@undipa.ac.id).

**Amil Ahmad Ilham** is a Professor at the Department of Informatics, Faculty of Engineering, Universitas Hasanuddin, Indonesia. He is currently the Vice Dean for Academic and Student Affairs at the Faculty of Engineering, Universitas Hasanuddin. His research interests include various fields in information systems, big data, cloud computing, and computer systems. Additionally, he also has interests in image processing, data mining, machine learning, deep learning, and artificial intelligence. He can be contacted at email: [amil@unhas.ac.id](mailto:amil@unhas.ac.id).

**Andani Achmad** is a Professor at the Department of Electrical Engineering, Faculty of Engineering, Universitas Hasanuddin, Indonesia. Additionally, he also has interests in artificial intelligence, machine learning, deep learning, and the Internet of Things. He can be contacted at email: [andani@unhas.ac.id](mailto:andani@unhas.ac.id).

**Muhammad Rifqy Yudhiestra Rachman** is a Bachelor student at the Universitas Hasanuddin in Department of Informatics. He fields of interest are artificial intelligence, deep learning, mobile Android, and machine learning. He can be contacted at email: [rachmanmry20d@student.unhas.ac.id](mailto:rachmanmry20d@student.unhas.ac.id).