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Deep Learning-Based Implementation of Convolutional Neural Networks for Skin Disease Detection Through Image Classification on Mobile Platforms

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Abstract

Maintaining skin health is essential, as poor skin conditions can lead to various diseases. To address this, early detection and classification of skin disorders is crucial. This study presents a deep learning-based Android application that enables users to detect and classify types of skin diseases through image input. The application integrates a Convolutional Neural Network (CNN) trained on labeled image datasets. The model achieved a training accuracy of 96% and validation accuracy of 83%. To provide a more comprehensive performance evaluation, metrics such as precision (87.75%), recall (84.29%), and F1-score (85.20%) were calculated. The evaluation was conducted using confusion matrix analysis based on eight skin disease classes. The implementation of CNN into an Android-based platform provides a practical and accessible tool for early skin disease detection and classification for the general public.

Keywords: Image, Skin disease, Android, CNN

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1. Introduction

The skin is the outermost organ of the human body that functions as a protector and a link between internal organs and the external environment [1]. Maintaining healthy skin is very important because untreated skin conditions can trigger various types of skin diseases [2]. Therefore, efforts to care for and maintain skin health need to be carried out early on to prevent more serious problems in the future [3]. In Indonesia, which is a tropical country and is known for its natural wealth, there are specific health challenges. Some of the main factors causing skin diseases in Indonesia include high air temperatures, environmental cleanliness, and personal hygiene [4]. In addition, infections, socio-economic conditions, and low public awareness of the importance of maintaining skin cleanliness are also factors that worsen the spread of skin diseases [5].

Skin diseases are often considered trivial because they tend not to be directly dangerous or fatal. Lack of public knowledge about the importance of skin care, as well as the assumption that the cost of treatment is expensive, leads to low awareness of carrying out routine skin health checks. In fact, it should be realized that skin diseases can spread quickly and become difficult to treat if not treated immediately [6]. In Indonesia, the prevalence of skin diseases is still relatively high and is a fairly serious public health problem. This is due to low awareness and ignorance of the public about the conditions of the surrounding environment, which ultimately accelerates the spread of skin diseases. The causes of skin diseases are very diverse, ranging from unhygienic living habits, climate change, viral or bacterial infections, allergic reactions, immune system disorders, and so on.

Alongside these challenges, recent advances in Artificial Intelligence (AI), especially deep learning methods like Convolutional Neural Networks (CNNs), have shown great potential in the automatic classification of skin diseases through image-based diagnosis [7], [8]. Studies have also explored the deployment of these AI models on mobile platforms, enabling wider access to early detection tools in remote or underserved areas [9], [10]. These developments highlight the growing role of AI in dermatology and support the relevance and novelty of this study, which implements a mobile-based CNN approach using EfficientNetV2S to classify skin diseases efficiently and accurately.

Lack of knowledge about the types of skin diseases and how to treat them can increase a person's risk of developing acute skin conditions. A study reported that individuals with low levels of knowledge are 1.5 times more likely to experience skin diseases compared to those with better understanding [11]. This condition is generally influenced by several contributing factors, such as limited financial resources, low health literacy, and feelings of embarrassment when consulting a specialist directly. Strengthening public education and awareness regarding skin health is therefore essential in reducing the prevalence and severity of dermatological diseases.

Based on the previously described issues, there is a need for technology that can assist the public in identifying and understanding skin diseases, particularly through automated classification of skin disease types [12]. To address this, the researchers propose an Android-based application designed to help users identify the type of skin disease they may be experiencing.

This application leverages Artificial Intelligence (AI), specifically image classification using Convolutional Neural Networks (CNNs), which enables the system to analyze skin images and recognize patterns based on previously trained data [13]. CNNs are a type of deep learning model that mimic human visual perception and have been widely adopted in the field of medical image analysis due to their high accuracy in feature extraction and classification. By utilizing this approach, the system can provide early indications of skin disease types, supporting users in making informed decisions about further medical consultation [14].

In this study, one of the artificial neural network architectures known as Convolutional Neural Network (CNN) was used, which is able to detect certain types of skin diseases through image data processing. CNN is a method based on deep learning and is widely used to solve problems related to object detection [15]. CNN is often chosen because it has a high level of accuracy and is able to provide good results in recognizing objects in the digital image recognition process. Meanwhile, the Android platform was chosen as the basis for application development because it is a popular operating system and is widely used by the public today [16]. In addition, Android is also considered practical because it allows users to access applications anytime and anywhere. The use of smartphones itself has reached almost all levels of society, so this application is expected to be used widely and effectively.

Considering the background of the problems that have been explained, this study proposes the development of a system for classifying types of skin diseases based on image images using the Android-based Convolutional Neural Network method. This technology is expected to help the community, especially patients, in conducting independent examinations of their skin conditions for free without having to consult a doctor directly [17]. In addition, this application can also be a solution to reduce queues at health care facilities, because patients can carry out early detection of skin diseases independently through their smartphone devices.

2. Methods

The deep learning algorithm of Convolutional Neural Network (CNN/ConvNet), which is an advancement of the Multilayer Perceptron (MLP) architecture, is designed to process two-dimensional data such as images or audio. CNNs have the ability to classify labeled data using a supervised learning approach, where the dataset includes labels or target variables, allowing the model to categorize new input based on patterns learned from previously trained data [15]. CNN is widely applied in various tasks, including detection, segmentation, and object recognition [18].

A typical CNN architecture consists of several types of layers, including convolutional layers that extract features from the input image, activation layers such as ReLU (Rectified Linear Unit) that introduce non-linearity, and pooling layers that reduce the spatial dimensions of the feature maps. After several convolution and pooling stages, the extracted features are passed to one or more fully connected (dense) layers, followed by an output layer. In image classification tasks, the output layer generally uses the softmax activation function to produce probabilities across multiple classes.

The CNN model used in this study is trained using labeled skin disease images, where the input is an RGB image and the output is the predicted category of skin disease. The classification process is divided into two main stages: the training phase, where the model learns features and patterns from the training dataset, and the testing phase, where model performance is evaluated using unseen data.

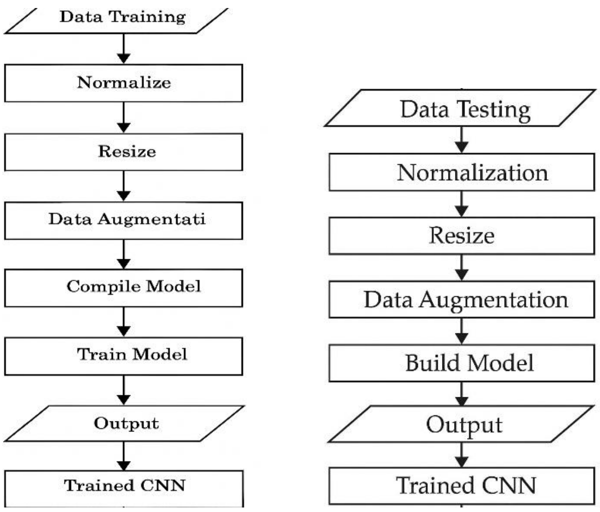


Figure 1. CNN Training and Testing Flowchart

The image classification process begins with collecting a dataset of skin disease images, which is split into 80% training and 20% testing data. The images undergo normalization to ensure consistent pixel ranges, resizing to fit the CNN input layer, and data augmentation (e.g., rotation, flipping, zooming) to increase variation and reduce overfitting, as seen in **Figure 1**. Finally, the CNN model is trained to recognize patterns and classify new images accurately.

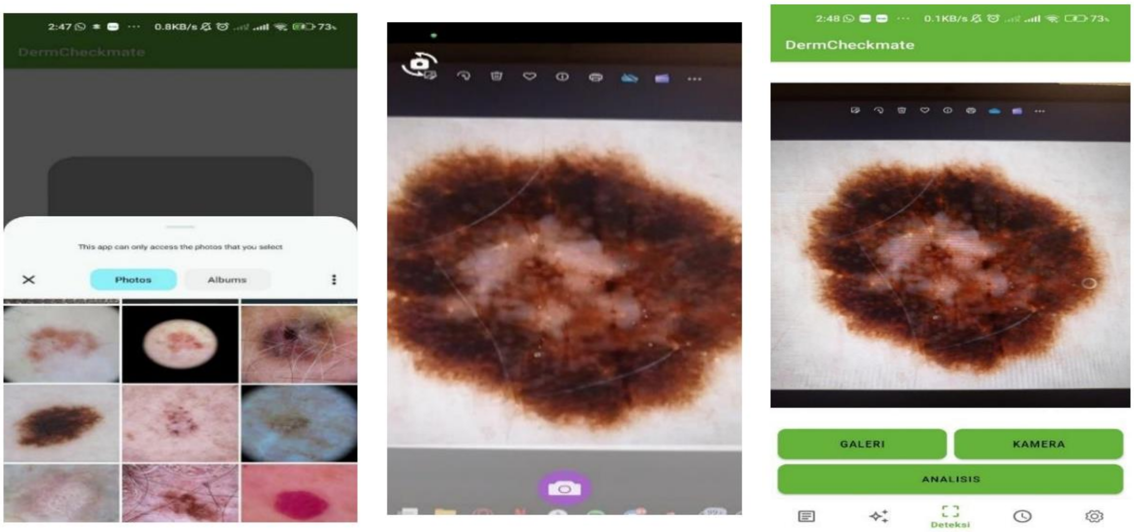
The testing process starts with preparing a separate dataset (20% of total data) to evaluate the trained CNN model's performance. Images are normalized to ensure consistent pixel values, resized to match the model's input, and optionally augmented to test robustness against slight variations. The trained CNN then analyzes and classifies the new images to assess accuracy and generalization capabilities.

3.Results and Discussion

This chapter discusses the results of the research that has been conducted and its discussion for the purpose of further evaluation and analysis. The implementation of this research is in the form of an Android-based application designed to classify types of skin diseases based on image images, by utilizing the Convolutional Neural Network (CNN) method. This application was developed as a technological solution that can help the process of identifying skin diseases automatically and efficiently.

3.1 Result

The image input process is the initial stage in the skin disease classification system based on Convolutional Neural Network (CNN). At this stage, the user takes or uploads an image of the skin to be analyzed through the Android application that has been developed, as seen in Figure 2. The image is then used as input data to be processed by the system.



(a) (b) (c)

Figure 2. (a) Image Input Process via Gallery, (b) Image Input Process via Camera, (c) Image Input Process Results

Input images undergo preprocessing, including normalization and resizing, to match the CNN model requirements. Normalization ensures consistent pixel values, while resizing adjusts image dimensions to the model's input size. After preprocessing, images are processed through a CNN-based skin disease classification system, consisting of training and testing stages using an 80:20 data split. The training data used in this study amounted to 20,495 images of skin diseases that have been classified into eight categories, namely:

- AK (Actinic Keratosis) as many as 690 images

- BCC (Basal Cell Carcinoma) as many as 2,665 images
- BKL (Benign Keratosis) as many as 2,088 images
- DF (Dermatofibroma) as many as 191 images
- MEL (Melanoma) as many as 3,607 images
- NV (Melanocytic Nevus) as many as 10,308 images
- SCC (Squamous Cell Carcinoma) as many as 524 images
- VASC (Vascular Lesion) as many as 191 images

After the image goes through the training stage using the Convolutional Neural Network (CNN) method, the model will produce final weights, as seen in **Tabel 1**. These weights represent the results of the model's learning of visual patterns from the training dataset, and are used as the main parameters in the testing process. By using the trained weights, the model can classify new images that have never been recognized before more accurately and efficiently.

Tabel 1. CNN Model Configuration

Maximum Number of Epochs	Initial Learning Rate	Callback
10	3.00000e-05 (Adam Optimizer)	o ModelChecpoint o Early Stopping o ReduceLROnPlateau o TensorBoard

The model training process is limited to a maximum of 10 epochs, with a learning rate value of 3.0000×10^{-5}, as seen in **Tabel 2**. Optimization is performed using the Adam Optimizer algorithm. The training results show that the model has achieved a training accuracy of 96%, while the validation accuracy obtained is 83%. This value indicates that the model has a fairly good performance in recognizing patterns from training data and has sufficient generalization capabilities when tested with validation data.

Training accuracy reflects the model's ability to correctly predict labels on training data, while training loss indicates prediction error during learning. Validation accuracy measures the model's performance on unseen data, and validation loss assesses its generalization capability. Lower loss and higher accuracy values indicate better learning and reduced overfitting.

After training, the model was tested using 5,067 unseen images to evaluate generalization and avoid bias. The CNN successfully classified 4,239 images into eight skin disease categories: AK, BCC, BKL, DF, MEL, NV, SCC, and VASC.

Detailed results show accurate label predictions for each class, as presented in Table 3.

Tabel 2. Training Process Results with Epoch 10

Epoch	Training Accuracy	Trainning Loss	Validation Accuracy	Validation Loss
1	0.5054	1.4674	0.7093	0.8460
2	0.7209	0.8058	0.7521	0.7123
3	0.7872	0.6140	0.7762	0.6403
4	0.8391	0.4670	0.7894	0.6032
5	0.8804	0.3491	0.8038	0.6021
6	0.9128	0.2539	0.8137	0.6104
7	0.9384	0.1908	0.8218	0.6133
8	0.9554	0.1373	0.8281	0.6536
9	0.9691	0.0986	0.8301	0.6609
10	0.9694	0.0883	0.8265	0.7208

Based on the prediction results obtained from the testing process, the distribution of the testing data image classification into eight categories of skin disease types was obtained. The visualization of the classification results can be seen in Figure 3 which displays the distribution of the number of images for each skin disease label predicted by the CNN model.

Tabel 3. Results of Classification of Skin Disease Types using CNN

No.	Label	Prediction Result								Total
		AK	BC	BKL	DF	MEL	NV	SCC	VASC	
1	AK	170	1	2	1	3	1	0	0	177
2	BC	39	374	52	25	37	41	10	34	658
3	BKL	8	9	478	5	10	13	7	6	536
4	DF	1	0	0	45	1	1	0	0	48
5	MEL	22	18	23	12	760	36	19	25	915
6	NV	27	34	51	41	55	2288	38	33	2567
7	SCC	2	5	3	4	6	8	69	7	107
8	VASC	0	1	1	0	2	2	1	55	62

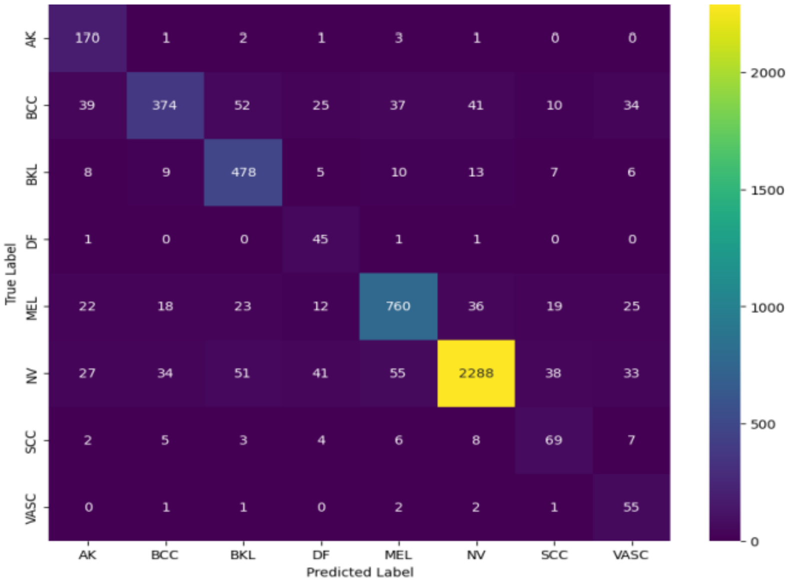


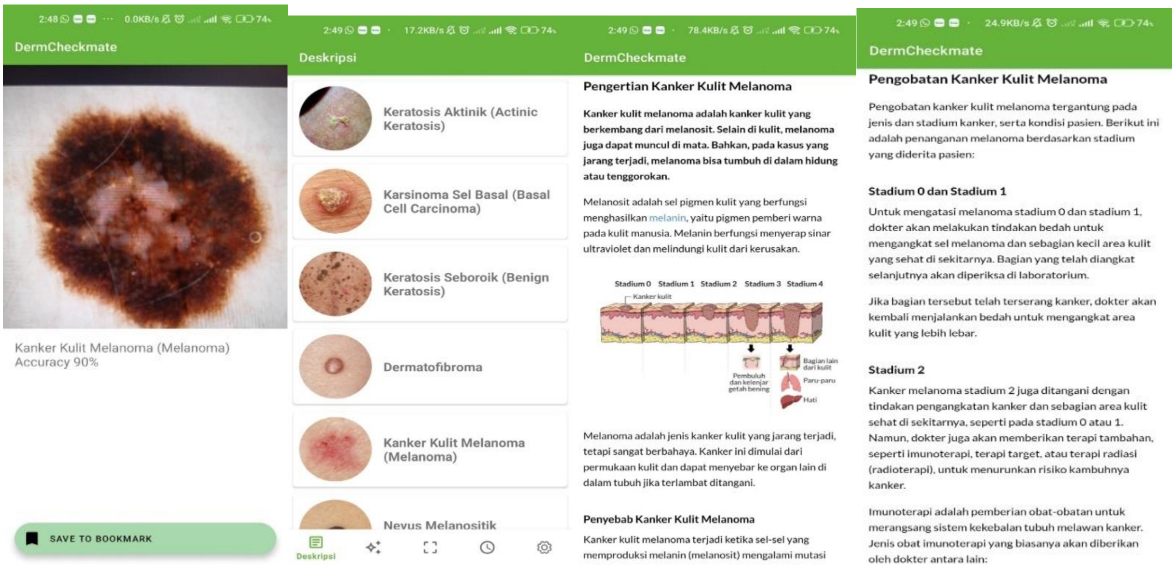
Figure 3. Distribution of Prediction Results of Test Data Image

Based on the distribution of prediction results obtained, an evaluation of the performance of the classification model was carried out using the Confusion Matrix to determine the percentage of correct predictions (true predictions) and incorrect predictions (false predictions) for each type of skin disease. The Confusion Matrix provides a comprehensive overview of the model's performance in classifying each category, including the number of correct and incorrect predictions for each class. Based on the resulting Confusion Matrix in **Tabel 4**, the following is a calculation of the accuracy of the CNN classification model on the test data.

Tabel 4. Accuracy Calculation Results using Confusion Matrix

	Prediction Result								**Accuracy (%)**
	AK	BC	BKL	DF	MEL	NV	SCC	VASC	
Correct Prediction (%)	96	57	89	94	83	89	67	89	83
Incorrect Prediction (%)	4	43	11	6	17	11	13	11	17

The processed image classification data will be displayed automatically on the results display after the feature extraction and classification process is complete. The information presented to the user is in the form of a label of the type of skin disease detected, accompanied by an accuracy score value that indicates the level of model confidence in the prediction results. The presentation of this information aims to provide an overview to the user regarding the type of skin disease experienced and the level of prediction accuracy of the system.



(a) (b) (c) (d)

Figure 4. Display Results on Android Devices

3.2 Discussion

This Android-based application identifies skin disease types through image analysis using the CNN method, as seen in **Figure 4**. It also provides medically reliable descriptions and treatment suggestions by integrating trusted health sources. The classification process involves automatic feature extraction, dimensionality reduction, and classification using the CNN model to deliver fast and informative results to users.

The model architecture employs EfficientNetV2S as the base feature extractor, pre-trained on the ImageNet dataset to enable effective transfer learning. Feature dimensionality is reduced using a Global Average Pooling 2D layer, while a Dropout layer is applied to prevent overfitting and enhance generalization.

The CNN model was trained using 25,331 skin disease images classified into eight categories **Tabel 4**, following the configuration in **Tabel 1**. Training was conducted for 10 epochs with a learning rate of $3.0000e^{-5}$ using the Adam Optimizer. The model achieved 96% training accuracy and 83% validation accuracy, demonstrating strong pattern recognition and generalization performance **Tabel 4**

Key findings from the training process include: (1) the importance of sufficient training data in optimizing CNN performance and classification accuracy; (2) successful classification of eight skin disease types with 96% training accuracy and 83% validation accuracy, confirming CNN's effectiveness; and (3) the EfficientNetV2S base model improved accuracy and convergence, with stable validation loss after the 4th epoch, indicating minimal overfitting and strong generalization.

4. Conclusion

This study concludes that a CNN-based classification system, supported by sufficient training data, can effectively identify eight types of skin diseases with high accuracy (96% training, 83% validation). The use of EfficientNetV2S improved both accuracy and convergence stability. Implemented as an Android application, the system offers practical and accessible early detection, supported by descriptive information and treatment solutions from trusted sources—making it beneficial for communities with limited access to healthcare services.

Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

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