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Research Article

Dermascan: Convolutional Neural Network-Based Skin Cancer Early Detection System

Arellia Agustin[1]*, Ida Nurhaida[2]

[1] Department of Informatics, Universitas Pembangunan Jaya, South Tangerang, Indonesia, 15413
[2] Center for Urban Studies, Universitas Pembangunan Jaya, South Tangerang, Indonesia, 15413
*Corresponding Author: arellia.agustin@student.upj.ac.id | Phone: +6285839927003

ABSTRACT

Skin cancer continues to show a significant global increase in incidence, and early detection remains essential to reducing mortality rates. Conventional diagnostic techniques such as biopsy are invasive, require considerable processing time, and are not always accessible, particularly in remote or resource-limited healthcare environments, indicating the need for an intelligent and efficient diagnostic support system. This study develops a lightweight Convolutional Neural Network (CNN) model designed to classify seven types of skin lesions using the HAM10000 dataset consisting of 10,015 dermatoscopic images. The preprocessing pipeline involved resizing, normalization, oversampling, and dataset splitting. The training process was conducted for a maximum of 40 epochs and concluded automatically at epoch 29 using early stopping to prevent overfitting. The experimental results demonstrated that the proposed model achieved an accuracy of 98%, and surpassed common pretrained architectures including ResNet50V2 (83%) and VGG19 (67%), with precision, recall, and F1-score metrics showing consistent performance across all lesion classes. The final trained model was integrated into the Dermascan web platform, enabling real-time automated lesion classification from user-uploaded images. These findings confirm that the lightweight CNN model offers a reliable, fast, and accessible tool for early skin cancer detection that can be beneficial for both clinical decision-support and wider public healthcare applications.

Keywords: Convolutional Neural Network; Dermatoscopic Images; HAM10000; Skin Cancer Classification; Web-Based Detection System.

1. INTRODUCTION

The skin is the body's outermost organ, functioning to protect humans from various environmental factors (Aji et al., 2023). Despite its important role, the skin remains vulnerable to disorders, including skin cancer, which generally appears in the epidermis and can be observed visually (Kassem et al., 2020). According to Globocan 2020 data, there are more than 18,000 cases of skin cancer in Indonesia, with a mortality rate of around 3,000 people (Primaya Hospital, 2023). These data highlight the urgency of increasing early detection efforts and public education regarding the risks and prevention of skin cancer. A global trend of increasing skin cancer cases has also been reported in recent years, making the need for diagnostic support technology a growing concern (Jeong et al., 2022).

Indonesia's geographical location on the equator causes high exposure to ultraviolet (UV) rays throughout the year. Excessive UV exposure is known to cause skin damage such as premature aging, pigmentation changes, and even skin cancer (Fauziah & Yushardi, 2024). Low public awareness of skin protection and limited access to medical examinations further exacerbate the high incidence of skin cancer in Indonesia (Sebayang, 2023). This condition is in line with the findings of Vieira et al. (2025), who stated that early detection remains a challenge in developing countries due to limited diagnostic facilities and dermatological examinations.

Skin cancer diagnosis is generally performed through a biopsy procedure, which involves taking tissue samples for analysis in a laboratory. Although accurate, this method is invasive, time-consuming, and not always accessible to all segments of society (Faruk & Nafi'iyah, 2020). A number of modern studies emphasize the importance of alternative digital imaging-based methods that are faster, more accessible, and still have a high level of diagnostic accuracy (Gusti et al., 2024).

Advances in artificial intelligence technology, particularly deep learning methods, have opened up new opportunities in medical image analysis. Convolutional Neural Networks (CNNs) have proven effective in extracting visual patterns in complex images such as X-rays, CT scans, and dermatoscopic images (AWS, n.d.; Jiang et al., 2023). Recent studies report that CNNs can achieve high accuracy in skin cancer classification, including on the multi-class HAM10000 dataset (Kestek & Aktan, 2023; Musthafa et al., 2024). In fact, several modern models have achieved accuracy rates above 95% through architecture optimization or data augmentation techniques (Mateen et al., 2024; Vieira et al., 2025). However, most previous studies used relatively heavy pretrained architectures that required large computational resources. In addition, there has not been much research in Indonesia that focuses on developing lightweight custom CNN models that are specifically optimized for skin lesion data and integrated into web-based systems for multi-class skin cancer detection (Jeong et al., 2022; Gusti et al., 2024). This condition is a research gap that this study aims to address.

This study aims to develop a custom CNN model for classifying seven types of skin lesions in the HAM10000 dataset and implement it in the Dermascan web system. This system is expected to provide fast, accurate, and easily accessible early detection, thereby supporting efforts to improve digital health services in Indonesia.

2. RESEARCH METHOD

The steps of this research are divided into five essential phases. First, the Dataset Collection phase involves the acquisition of dermatoscopic images or high-resolution medical images; this step is crucial because data quality greatly determines the performance of automatic diagnosis, as emphasized in research by Alsalemi et al. (2024), which explains the importance of dataset diversity in improving the performance of AI-based models. Second, the Preprocessing phase, where images undergo color normalization, lesion segmentation, size adjustment, and augmentation to reduce class imbalance and improve model generalization. This approach is supported by a study by Shah, Patel, & Gupta (2025), which shows that augmentation and segmentation can significantly improve the accuracy of skin cancer classification. Third, the Train Model phase uses a Convolutional Neural Network (CNN) architecture designed to recognize visual patterns in lesion images. In this phase, hyperparameter tuning, optimizer selection, and fine-tuning are performed a methodology consistent with current successful works in skin cancer detection (Musthafa et al., 2024). Fourth, the Testing phase is carried out using medical evaluation metrics such as Accuracy, Precision, Recall, F1-Score, Sensitivity, and Specificity to assess how well the system detects benign and malignant lesions; multiparameter evaluation has indeed become the standard in modern skin cancer detection research (Musthafa et al., 2024). Fifth, the Deployment phase is carried out by implementing the trained model into a web-based application prototype as an early detection tool that can be used in real time. In addition, system testing methods include performance testing, black-box testing, and white-box testing to ensure the accuracy, reliability, and stability of the system before it is applied in real-world scenarios (Shah et al., 2025).

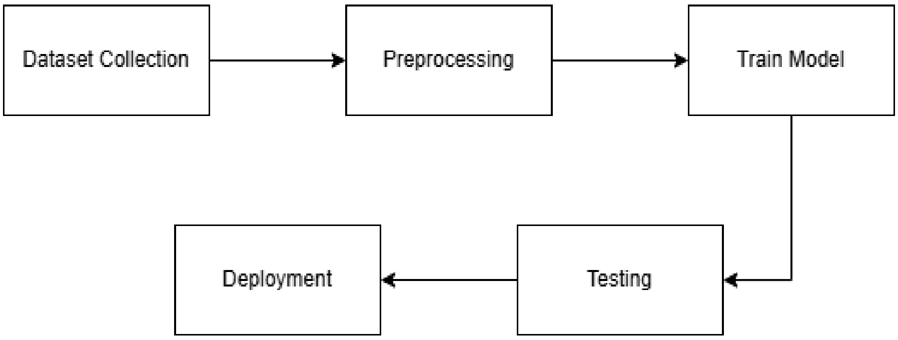


Figure 1. Implementation Steps Diagram

2.1 Data Collection

Data collection in this study was conducted through digital observation using the Kaggle platform, which provides various open datasets for artificial intelligence model development. The observation process focused on searching for datasets with complete annotations, adequate image quality, and coverage of skin lesion types suitable for multi-class classification needs. Based on the selection results conducted in March 2025, the Skin Cancer MNIST: HAM10000 dataset was selected, which is widely used in skin cancer detection research and has become an international benchmark for dermatoscopic lesion classification (Tschandl et al., 2018).

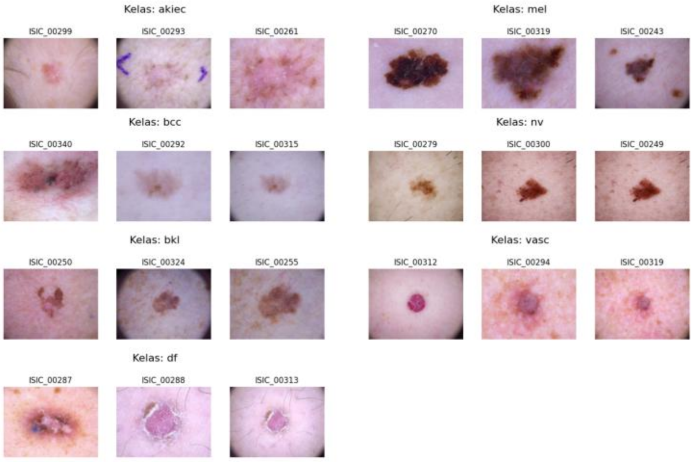


Figure 2. Skin Cancer Image Data

The HAM10000 dataset consists of 10,015 dermatoscopic images covering seven categories of pigmented skin lesions, namely Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic Nevi (NV), and Vascular Lesions (VASC) (Tschandl et al., 2018). The following table shows the distribution of the number of images in each class:

Table 1. Number of Image Data per Class in the HAM10000 Dataset

Class ID	Lesion Name	Number
AKIEC	Actinic Keratoses & Intraepithelial Carcinoma	327
BCC	Basal Cell Carcinoma	514
BKL	Benign Keratosis-like Lesions	1099
DF	Dermatofibroma	115
MEL	Melanoma	1113
NV	Melanocytic Nevi	6705
VASC	Vascular Lesions	142
Total		10,015

The distribution in Table 1 shows an imbalance in the amount of data between classes, especially in the NV class, which dominates the dataset, while the DF and VASC classes have relatively small sample sizes. This condition has the potential to cause bias in the model if not addressed, so the oversampling technique was applied at the preprocessing stage to balance the data distribution.

2.2 Data Preprocessing

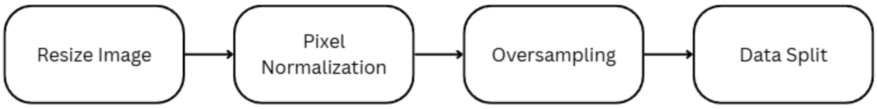


Figure 3. Data Preprocessing

Pre-processing steps are applied to ensure that images are in optimal condition before being used in the CNN model training process. First, each image is resized to a uniform size even though the ideal size varies. Research shows that the selection of input resolution needs to be adjusted based on the trade-off between computational efficiency and feature quality: resizing helps make the model lighter and more computationally efficient, making it more suitable for implementation on the web or devices with limited resources (Abir, Shoha, & Hossain, 2024). After the resizing process, each pixel value is normalized (e.g., to a range of 0–1) to speed up training and aid convergence stability (Faudya et al., 2024).

Next, to address the imbalance between classes in skin lesion datasets that commonly occurs in clinical/dermatoscopy datasets, oversampling or data balancing techniques were applied to achieve an equal number of samples per class before model training, so that the model would not be biased towards the majority class (Thwin et al., 2024). After that, the dataset was divided into two parts, 80% for training and 20% for testing, with random_state set so that the experimental results were consistent and replicable, as was done in many skin lesion classification studies.

2.3 Training Model

The Convolutional Neural Network (CNN) model used in this study is a custom architecture designed to be lightweight and efficient for deployment on web-based systems. The custom architecture was chosen to keep the model size small and reduce inference time, so pretrained models such as VGG-19, ResNet, or other heavy architectures were not used. This choice is in line with findings that lightweight CNN models with a minimal number of layers and parameters offer computational efficiency and faster training times without sacrificing too much accuracy, making them suitable for applications with limited resources (Islam et al., 2025; Appasami et al., 2025). The CNN architecture consists of two convolution blocks with ReLU activation, each followed by max pooling to reduce feature dimensions and improve computational efficiency. After passing through all feature extraction stages, the network output is flattened using a flatten layer and passed to two dense layers for the seven-class skin lesion classification process. Details of the architecture are presented in the following table.

The training process was carried out using data that had undergone preprocessing stages such as normalization, oversampling, and augmentation to increase image variation. Model training was carried out using the model.fit() function with the following configuration:

- Batch size: 32
- Epoch: 40
- Optimizer: Adam
- Loss function: categorical cross-entropy
- Validation split: 20%
- Callback: early stopping to prevent overfitting

At each training iteration, the model learns visual patterns from dermatoscopic images and updates weights based on the resulting error. Validation data is used to monitor model performance during the training process so that the model can achieve a balance between accuracy and generalization.

Table 2. Custom CNN Model Architecture

No	Layer	Output Shape	Parameters
1	Input Layer	28x28x3	---
2	Conv2D (ReLU)	26x26x32	Kernel: 3x3, Filters: 32, Stride 2
3	MaxPooling2D	13x13x32	Pool Size: 2x2
4	Conv2D (ReLU)	11x11x64	Kernel: 3x3, Filters: 64, Stride 1
5	MaxPooling2D	5x5x64	Pool Size: 2x2
6	Flatten	1600	---
7	Dense (ReLU)	128	Units: 128
8	Dense (Softmax)	7	Units: 7 (Number of Classes)

2.4 Model Testing

Model testing was conducted to validate the generalization ability of the CNN model on unseen data. This evaluation was carried out quantitatively with two objectives: to measure overall performance and to analyze specific errors per disease class. First, the model was tested using Loss and Total Accuracy. These metrics provide an initial overview of how well the model minimizes errors and how often the model provides correct predictions on new data sets.

An in-depth analysis was conducted by creating a Classification Report and Confusion Matrix. The Classification Report presents performance per class, focusing on Precision, Recall, and F1-Score. In the context of medical diagnosis, the Recall metric is crucial because it measures the model's ability to correctly detect all positive cases (cancer), minimizing potentially fatal False Negatives. The Confusion Matrix then visually identifies where classification errors occur, such as when one type of lesion (e.g., melanoma) is incorrectly predicted as another type of lesion.

In addition to the final evaluation, visualization of the Training and Validation Loss curves and Accuracy during training is used to detect overfitting or underfitting problems. A significant difference between the training and validation curves indicates that the model fails to generalize, validating the need for parameter adjustment. Overall, this testing phase aims to prove that the model is not only accurate on training data, but also diagnostically reliable in simulated clinical scenarios.

A methodology that has been successfully applied in prior Indonesian CNN-based skin disease classification studies (Permana et al., 2024; Nurlitasari, 2022). This model testing stage serves as a complement to the black-box performance testing that was conducted previously. While black-box testing ensures that the system functions according to user requirements, Model Testing focuses on the quality of predictions generated by the CNN model in terms of classification performance. Overall, the results of this testing confirm that the Dermascan model is not only accurate on training data, but also reliable and consistent when applied to new data that reflects real-world conditions in the clinical early detection process.

2.5 Deployment

The implementation phase integrates the CNN model into the operational environment through a modular web service architecture, where Flask serves as the main backend framework (Gusti et al., 2024). The trained model is loaded using TensorFlow at application startup, making it ready for prediction. The detection process begins when an authenticated user uploads an image via the web interface. The image is then processed, including resizing to 28x28 pixels and normalization, before being fed into the CNN model for classification. The prediction results, in the form of disease class and confidence level, are immediately recorded in the SQLAlchemy database as the user's detection history (Chandra et al., 2025). This system is enriched with additional functionality that supports diagnosis. After detection, the system automatically calls the Groq API (using the LLaMA 3.3 large language model) to generate generative follow-up recommendations, providing personalized advice to users. User management and access are secured through Flask-Login, ensuring that all diagnostic features and sensitive histories are only accessible to the relevant users, so that the system functions not only as a detection tool, but also as an integrated skin health management platform.

3. RESULTS AND DISCUSSION

3.1 Model Training Results

The Convolutional Neural Network (CNN) model training process was carried out using the HAM10000 skin cancer image dataset that had undergone preprocessing and data augmentation (Tschandl et al., 2020). The model was trained for 40 epochs with a batch size of 32, using the Adam optimizer and categorical cross-entropy loss function, a configuration that is also widely adopted in similar studies on skin cancer classification. During the training process, accuracy and loss were monitored on both the training and validation datasets to evaluate the stability of the learning process. The training results show that the training accuracy consistently increased, while the validation accuracy also demonstrated a strong upward trend without significant divergence from the training accuracy, indicating the absence of major overfitting issues. These observations are consistent with recent findings showing that CNN-based skin lesion classifiers using standard training pipelines such as Adam optimizer and categorical cross-entropy produce stable learning behavior and high classification performance for multi-class skin cancer detection (Houssein et al., 2024).

3.1.1 Analysis of Accuracy and Loss Graphs

From the training results, it can be seen that the training accuracy value increased consistently to nearly 1.00 (100%), while the validation accuracy also showed an upward trend to nearly 0.97 (97%). This pattern indicates that the model is able to learn image patterns well without experiencing significant overfitting, and these findings are in line with research showing that CNN models with lightweight architectures can achieve high performance on the HAM10000 dataset. On the loss graph, it can be seen that the training loss value drops dramatically from the beginning to the end of the epoch, reaching close to 0.00, while the validation loss decreases to around 0.10–0.15 and tends to stabilize at the end of training. The small difference between training and validation loss indicates that the model generalizes well to new data, and the training process has successfully produced optimal model weights.

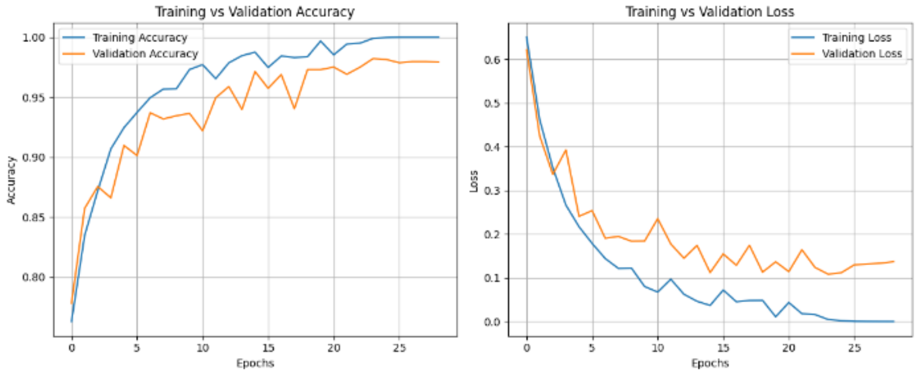


Figure 4. Comparison Chart of Accuracy and Loss on Training and Validation Data

Table 3. Custom CNN Model Training Result

Epoch Index	Accuracy (Train)	Accuracy (Val)	Loss (Train)	Loss (Val)
1	0.7316	0.7782	0.7434	0.6219
2	0.8180	0.8573	0.5009	0.4249
3	0.8651	0.8755	0.3654	0.3370
4	0.9027	0.8660	0.2821	0.3931
5	0.9132	0.9097	0.2497	0.2411
6	0.9368	0.9013	0.1860	0.2542
7	0.9450	0.9370	0.1542	0.1909
8	0.9563	0.9318	0.1246	0.1951
9	0.9519	0.9345	0.1357	0.1841
10	0.9743	0.9365	0.0800	0.1844
11	0.9761	0.9220	0.0705	0.2357
12	0.9579	0.9495	0.1198	0.1779
13	0.9778	0.9589	0.0672	0.1451
14	0.9831	0.9398	0.0499	0.1747
15	0.9845	0.9714	0.0450	0.1123
16	0.9776	0.9574	0.0633	0.1550
17	0.9780	0.9688	0.0625	0.1290
18	0.9891	0.9403	0.0317	0.1747
19	0.9737	0.9730	0.0790	0.1134
20	0.9965	0.9730	0.0138	0.1370
21	0.9824	0.9751	0.0521	0.1146
22	0.9916	0.9691	0.0246	0.1645
23	0.9947	0.9750	0.0183	0.1241
24	0.9986	0.9822	0.0063	0.1087
25	0.9996	0.9815	0.0028	0.1120
26	1.0000	0.9787	7.0067e-04	0.1301
27	1.0000	0.9796	4.0893e-04	0.1319
28	1.0000	0.9796	2.5861e-04	0.1338
29	1.0000	0.9792	2.2009e-04	0.1373

The results in Table III show that the CNN model training process experienced consistent performance improvement from the initial epoch to the 29th epoch. Training accuracy increased steadily from 0.7316 in the first epoch to 1.0000 in the

26th epoch, while validation accuracy ranged from 0.97 to 0.98 in the final stage of training. The training loss value also decreased significantly to 2.20×10^{-4}, with the validation loss value remaining low and relatively stable (around 0.11–0.14).

The consistency between the accuracy and loss trends in the training and validation data shows that the model is able to converge well without experiencing significant overfitting a behavior also observed in other skin-cancer/CNN-based classification studies in Indonesia (Wona et al., 2025; Ramdhana, 2023). Early stopping at epoch 29 indicates that the model reached optimal validation performance earlier than the maximum training limit, demonstrating that the learning process had converged effectively without overfitting. The training configuration including the Adam optimizer, batch size of 32, and the use of callbacks successfully maintained a balanced trade-off between learning capability and generalization. Based on these results, the lightweight Custom CNN model proves highly effective for multi-class skin lesion classification, achieving strong performance while requiring significantly lower computational resources compared to pretrained architectures. These findings confirm that the proposed model is suitable for deployment in practical clinical support systems, particularly for web-based platforms that demand fast inference and efficient resource utilization.

3.1.2 Model Evaluation Results

The Confusion Matrix in Figure 5 shows the distribution of model predictions across seven classes of skin cancer images. It can be seen that the main diagonal values are very high, indicating that the model is able to correctly predict most samples for each class. Some classification errors appear in class 4 (BKL), which slightly overlaps with other classes, but the number is relatively small compared to the total test data.

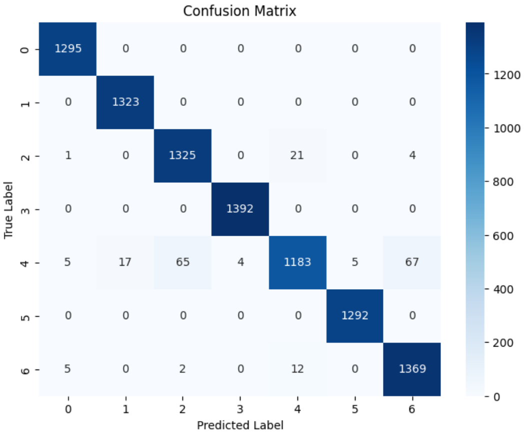


Figure 5. CNN Model Confusion Matrix

From the classification report, the overall accuracy average was 0.98 (98%), with precision, recall, and F1-score values also averaging 0.98. This shows that the model has excellent detection capabilities for distinguishing various types of skin lesions, both benign and malignant.

Table 4. Model Performance Evaluation Result

Classification Report:

	precision	recall	F1-score	support
0	0.99	1.00	1.00	1295
1	0.99	1.00	0.99	1323
2	0.95	0.98	0.97	1351
3	1.00	1.00	1.00	1392
4	0.97	0.88	0.92	1346
5	1.00	1.00	1.00	1292
6	0.95	0.99	0.97	1388
accuracy			0.98	9387
macro average	0.98	0.98	0.98	9387
weighted average	0.98	0.98	0.98	9387

These results show that custom CNN models built without using pretrained architectures such as VGG19 or ResNet are capable of achieving high performance with lighter parameter efficiency. The high precision and recall values indicate that the model can minimize detection errors for both positive and negative classes.

3.1.3 Discussion of Results

From the results obtained, it can be concluded that the CNN model successfully classified skin cancer images accurately and stably. The high accuracy and consistency between training and validation data indicate that the designed CNN architecture is capable of capturing important features such as texture, pigment patterns, and lesion shapes effectively. Minor errors in several classes were likely due to visual similarities between lesions especially between BKL (Benign Keratosis-like Lesions) and AKIEC (Actinic Keratoses) which is a common challenge in skin lesion classification due to overlapping visual characteristics (Naqvi et al., 2023). Moreover, similar studies have shown that lightweight or optimized CNN architectures can achieve competitive performance for multi-class skin lesion classification while maintaining computational efficiency, making them suitable for deployment in resource-limited or web-based systems (Musthafa et al., 2024; Ding et al., 2023).

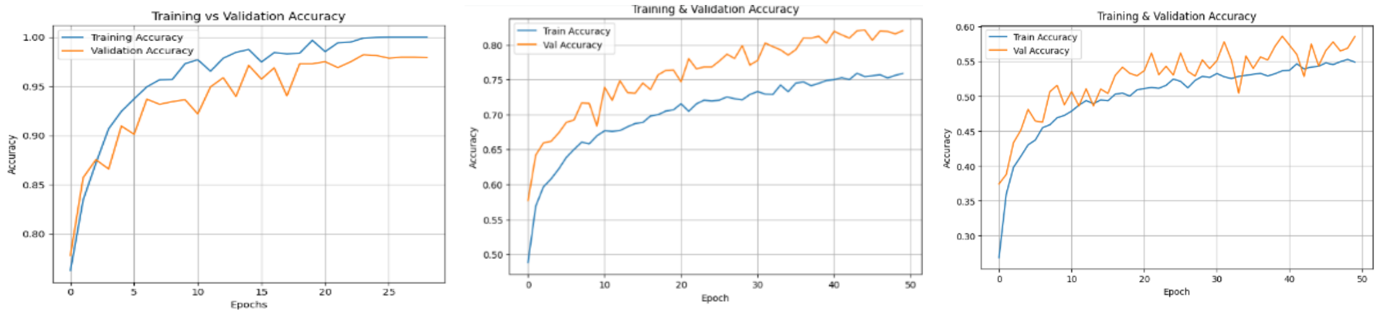
3.1.3 Comparison of Results Between Models

To assess the superiority of the custom CNN model, a comparison was made with two popular pretrained models, namely VGG19 and ResNet50. This comparison is descriptive, where each model is tested using the same dataset, but with training settings that adjust to the characteristics of each architecture, such as input image size, augmentation methods, and the proportion of training and validation data division.

Table 5. Comparative Performance Table

Model	Accuracy	Learning Rate	Optimizer	Epoch	Batch Size
Custom CNN	98	0.0001	Adam	50	32
ResNet50	83	0.001	Adam	50	32
VGG19	67	0.001	Adam	50	32

Figure 6. Comparison of Training Accuracy



(a) Custom CNN Training Accuracy (b) ResNet50 Training Accuracy (c) VGG19 Training Accuracy

The figure illustrates that the Custom CNN exhibits the most stable and consistent improvement in training accuracy, outperforming both pretrained networks. ResNet50 and VGG19 experienced fluctuating accuracy values in the early stages of training, which is commonly caused by the complexity and large number of parameters in pretrained architectures. Additionally, differences in training configurations—such as parameter size and transfer learning mechanisms make this comparison unsuitable for being interpreted as an absolute benchmark. However, it is sufficient to serve as a baseline evaluation to demonstrate the efficiency and suitability of the proposed Custom CNN architecture for the skin cancer dataset used in this research.

The Custom CNN model showed the best performance with an accuracy of 98%, surpassing the pretrained ResNet50V2 (83%) and VGG19 (67%) models with equivalent configurations, as shown in Table 5. These results indicate that the Custom CNN architecture, which was specifically designed for the research dataset, was able to adapt to skin image patterns more optimally. Meanwhile, pretrained models such as ResNet50V2 and VGG19 likely experienced a decline in performance due to differences in data characteristics compared to their original training data.

3.2 System Implementation and Interface

System implementation is realized as a web-based application powered by a CNN model for skin lesion detection, allowing users to upload lesion images and receive classification results in real time without requiring specialized software installation. Such a deployment model has been successfully demonstrated in recent studies, for example in a Flask-based web application for skin disease detection (Chandra et al., 2025), and in the SkinHealthMate platform which integrates deep learning diagnosis into a user-friendly web interface (Aboulmira et al., 2024). These works show that a web interface can make AI-powered skin cancer screening accessible both to healthcare professionals and general users, facilitating early detection efforts and providing scalable diagnostic support.

3.2.1 Login Page

This page serves as the entry point to the system. Users are required to enter their username and password. The system also provides an option for new user registration.

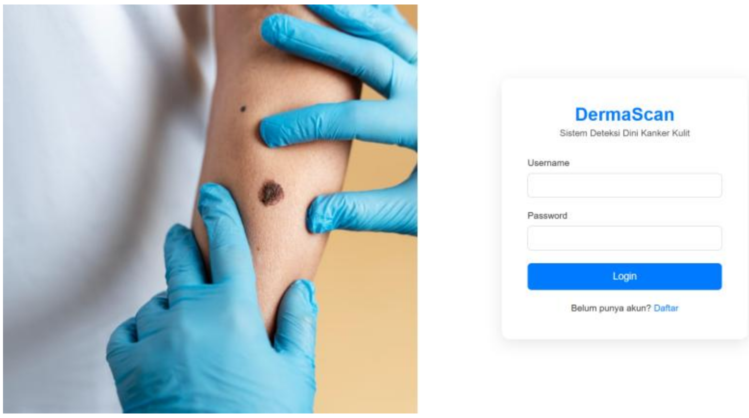


Figure 7. Dermascan Login Page Interface

3.2.2 Sign up Page

This page is used for new user registration in the DermaScan system. Users are required to fill in their username, email address, password, and password confirmation to create an account. The system also provides an option for users who already have an account to proceed to the login page.

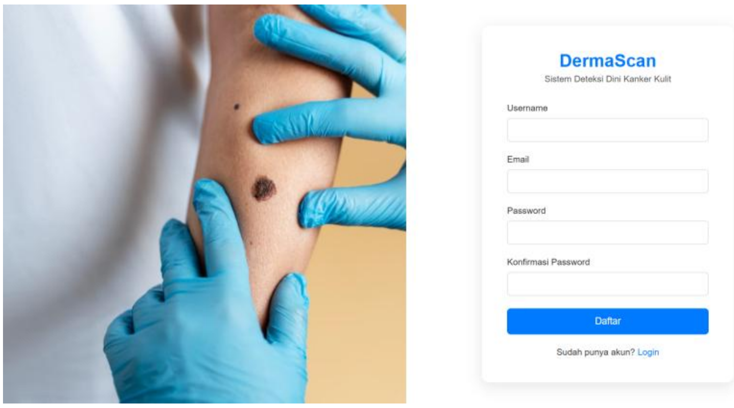
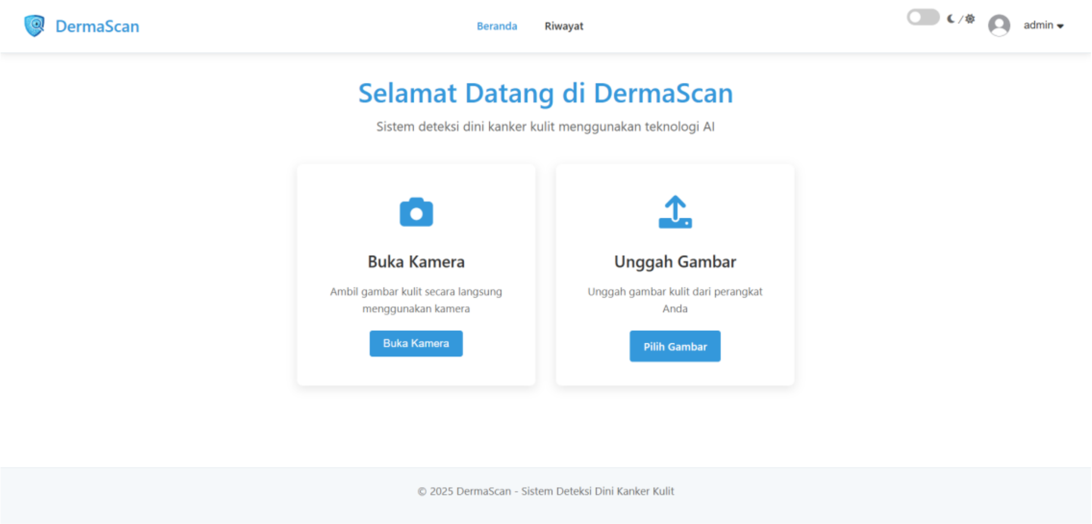


Figure 8. Dermascan Sign up Page Interface

3.2.3 Main Dashboard

This page is the main display after successful login. Users can choose to upload images or perform direct detection via the device's camera.



Selamat Datang di DermaScan

Sistem deteksi dini kanker kulit menggunakan teknologi AI

Buka Kamera

Ambil gambar kulit secara langsung menggunakan kamera

Unggah Gambar

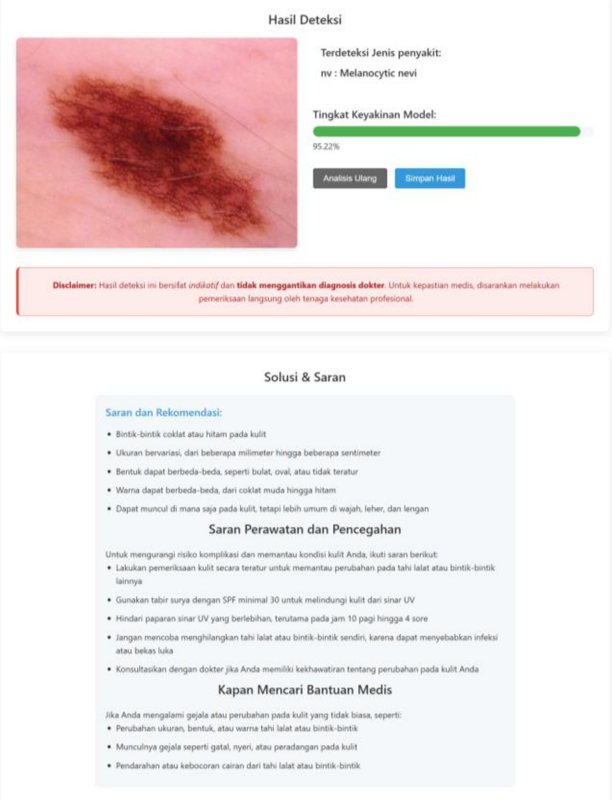
Unggah gambar kulit dari perangkat Anda

© 2025 DermaScan - Sistem Deteksi Dini Kanker Kulit

Figure 9. Dermascan Dashboard Interface

3.2.4 Detection Page

This page presents the results of skin lesion detection. The system displays the identified lesion category along with the model's confidence score. The output is intended for informational purposes only, includes a medical disclaimer, and is not designed to replace professional diagnosis by qualified healthcare practitioners. In addition, the system offers AI-based recommendations and suggestions as preliminary guidance for users.



Hasil Deteksi

Terdeteksi Jenis penyakit:

nv : Melanocytic nevi

Tingkat Keyakinan Model:

95.22%

Disclaimer: Hasil deteksi ini bersifat *indikatif* dan **tidak menggantikan diagnosis dokter**. Untuk kepastian medis, disarankan melakukan pemeriksaan langsung oleh tenaga kesehatan profesional.

Solusi & Saran

Saran dan Rekomendasi:

- Bintik-bintik coklat atau hitam pada kulit
- Ukuran bervariasi, dari beberapa milimeter hingga beberapa sentimeter
- Bentuk dapat berbeda-beda, seperti bulat, oval, atau tidak teratur
- Warna dapat berbeda-beda, dari coklat muda hingga hitam
- Dapat muncul di mana saja pada kulit, tetapi lebih umum di wajah, leher, dan lengan

Saran Perawatan dan Pencegahan

Untuk mengurangi risiko komplikasi dan memantau kondisi kulit Anda, ikuti saran berikut:

- Lakukan pemeriksaan kulit secara teratur untuk memantau perubahan pada tahi lalat atau bintik-bintik lainnya
- Gunakan tabir surya dengan SPF minimal 30 untuk melindungi kulit dari sinar UV
- Hindari paparan sinar UV yang berlebihan, terutama pada jam 10 pagi hingga 4 sore
- Jangan mencoba menghilangkan tahi lalat atau bintik-bintik sendiri, karena dapat menyebabkan infeksi atau bekas luka
- Konsultasikan dengan dokter jika Anda memiliki kekhawatiran tentang perubahan pada kulit Anda

Kapan Mencari Bantuan Medis

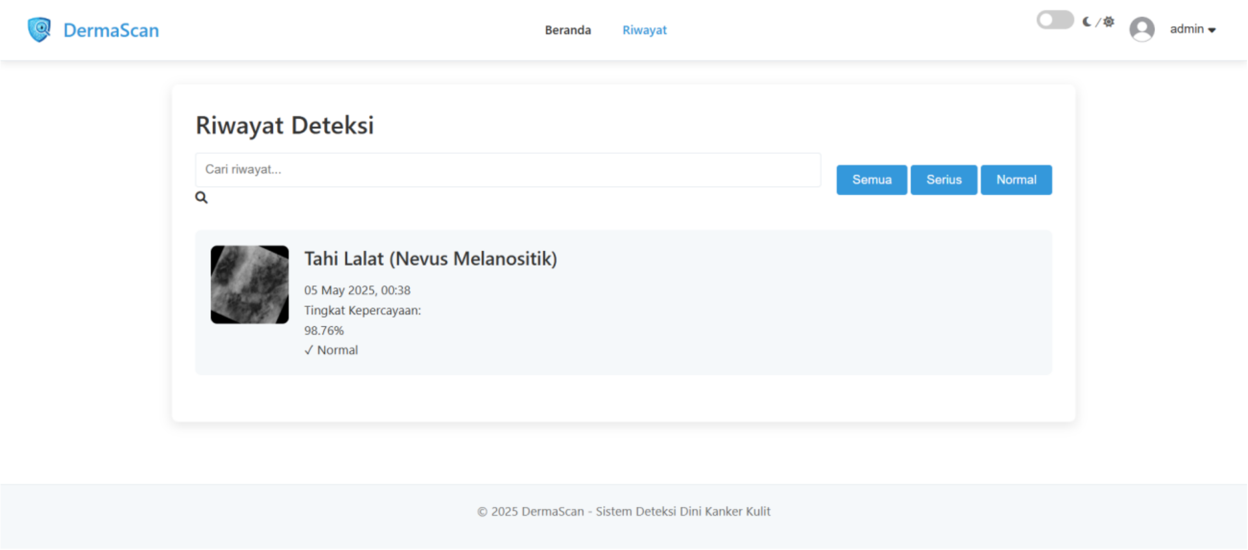
Jika Anda mengalami gejala atau perubahan pada kulit yang tidak biasa, seperti:

- Perubahan ukuran, bentuk, atau warna tahi lalat atau bintik-bintik
- Munculnya gejala seperti gatal, nyeri, atau peradangan pada kulit
- Pendarahan atau kebocoran cairan dari tahi lalat atau bintik-bintik

Figure 10. Dermascan Detection Page Interface

3.2.5 History Page

Contains a list of previous detection results, complete with the time of examination, type of skin lesion detected, and the confidence level of the prediction results.



Riwayat Deteksi

Cari riwayat...

Tahi Lalat (Nevus Melanositik)

05 May 2025, 00:38

Tingkat Kepercayaan:

98.76%

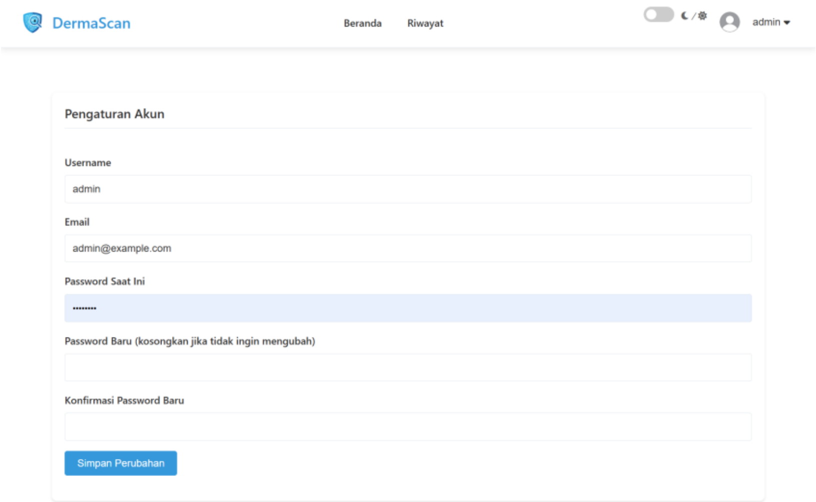
✓ Normal

© 2025 DermaScan - Sistem Deteksi Dini Kanker Kulit

Figure 11. Dermascan History Page Interface

3.2.6 Settings Page

Used to modify user profile data such as name, email, and password, as well as other system preference settings.



Pengaturan Akun

Username: admin

Email: admin@example.com

Password Saat Ini: ••••••••

Password Baru (kosongkan jika tidak ingin mengubah)

Konfirmasi Password Baru

Figure 12. Dermascan History Page Interface

4. CONCLUSION

This study successfully developed a custom Convolutional Neural Network (CNN) model to detect skin cancer types based on dermatoscopic images from the HAM10000 dataset (Tschandl et al., 2020). The model, designed without using a pretrained architecture, achieved an accuracy of 98%, surpassing the ResNet50V2 (83%) and VGG19 (67%) models. These results indicate that lightweight custom CNNs can outperform pretrained architectures for the HAM10000 dataset, making them suitable for implementation in low-performance web environments. The implementation of the model as a web-based system allows for faster and more practical early skin cancer detection. A lightweight CNN-powered diagnostic tool made available via a web interface can significantly improve accessibility, particularly in resource-limited settings and remote areas (Akinrinade & Du, 2025). This suggests that a properly designed web application could serve as an efficient, user-friendly, and accessible early-diagnosis tool suitable for both medical personnel and the general public.

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