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OPTIMIZATION THE PERFORMANCE OF CONVOLUTIONAL NEURAL NETWORKS TECHNIQUE FOR CLASSIFICATION MULTI-CLASS SKIN LESION DIAGNOSIS USING PRIVATE DATASET

Ahmed A. Alani [1,2]*, Jyoti Pareek [1], Vishal Prajapati [1]

[1]Department of Computer Science, Gujarat University, Ahmedabad, India

[2] Department of Accounting ,Baquba Technical College, Middle Technical University, Baghdad, Iraq

*Corresponding author E-mail: ahmed.abdulrahman@mtu.edu.iq

Abstract

Skin cancer and other cutaneous diseases are a significant global health issue, where early and precise diagnosis is critical in minimizing mortality and enhancing patient outcomes. Deep learning, especially Convolutional Neural Networks (CNNs), has proven to be incredibly successful in the analysis of medical images in recent years. Most current research, however, addresses binary or small-class issues and does not address the challenges of multiclass classification in actual clinical situations. This paper proposes an optimized multiclass skin lesion diagnosis system using a tailored multi-layer CNN structure. The model is trained and cross-validated on an Iraqi private dataset obtained from Iraqi patients with 3,057 dermoscopic images from six classes: Nevus, Vitiligo, Baghdad boil, Tinea, Dermatitis, and Melanoma. To address class imbalance and data limitation, aggressive data augmentation methods like random cropping, rotation, flipping, color jittering, and shearing were utilized. The network architecture involves convolutional layers with ReLU activation, max-pooling, dropout regularization, and fully connected layers, followed by a SoftMax classifier to make the final prediction. Experimental analysis was conducted by using precision, recall, F1-score, and accuracy as performance measures. The designed CNN system performed excellently, yielding precision, recall, and F1-score of 99%, and overall classification accuracy of 99.33%. The obtained results exceptionally surpass numerous state-of-the-art models, verifying the efficiency of the proposed strategy in managing multiclass dermatological diagnosis. The results indicate that this CNN-based system can be used as an effective clinical decision-support tool for dermatologists, minimizing the likelihood of diagnostic errors and allowing for early treatment. In future research, the pipeline can be extended by incorporating larger global datasets, adding explainable AI methods, and implementing lightweight models for mobile applications to provide greater accessibility in real-world healthcare settings.

Keywords: Skin Lesion; CNN; AI; Dermoscopic images ; Multi Layers CNN

1. Introduction

The skin is the outer covering and the largest organ in the human body., The construction consists multi- layers that cover and protect the inside organs.. The concept that skin condi-

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tion may influence the integumentary system, which involves various disorders like dermatoses, warrants more examination. [1][2]. Skin are classified into two categories: primary and secondary.. The primary include pimples, spots, discoloration, plaque, tumors, nodules, bullae, vesicles, cysts, and pustule While, the secondary skin lesions involve erosion, crust, scale, excoriation, fissure, ulcer, atrophy, induration, phyma, umbilication, and maceration. However, the primary types of skin infections mostly covered in the literature include melanoma, seborrheic keratosis, and squamous cell carcinoma [3][4]. Healthcare providers often face difficulties of diagnosing skin lesions and are looking at deep learning systems for handling this issue, aiming to cure or, at a minimum reducing the impact. Convolutional Neural Networks (CNNs), as a kind of deep learning systems, are very effective in the classification and analysis of medical pictures . In the diagnosis of skin lesions, it has been said that CNNs may achieve an accuracy level comparable to that of dermatologists . Therefore, CNN-based diagnostic systems need to be used in clinical environments. However, the erroneous designation of skin cancer as a benign lesion might result in significant clinical effects. Consequently, it is important to comprehend the possible failure mechanisms associated with CNN [5][6]. Dermoscopy is an analysis of skin lesions by using a dermatoscope, that includes a magnifying lens and a high-quality polarized lighting system. Smartphone camera attachments and high-resolution digital single-lens reflex cameras may be used for obtaining dermoscopic pictures. The processing of these images with CNN is becoming popular in research due to the introduction of multiple publicly accessible big dermoscopic datasets, which include diverse types of malignant and benign skin diseases.[7]. This study analyzes several challenges associated with skin lesion diagnosis as well as obtaining a high level of accuracy . The residual of this study will operate as follow: in section 2 summarizes the recently existing relevant works ; while section 3 clarify the proposed multiclass skin lesion diagnosis system based on CNN is explained; the results are described in details in section 4, and the last section shown conclusions .

2. Literature Review

Deep learning is an evolving tool for skin lesion diagnosis providing precise, remotely usable, and economical healthcare solutions [8][9]. Deep learning using CNNs and hybrid deep learning strategies on different dermoscopic datasets has been investigated by many studies. In the case of multiclass classification, [10] introduced a CNN integrated with error-correcting output codes SVM to distinguish eczema, acne, malignant, benign, and healthy lesions with an accuracy of 86.21% on 9,144 images. To make it more accurate, [11] enhanced this framework by using noise removal methods and incorporating machine learning techniques, achieving 96.5% accuracy on 3,672 images. In the same way, [12] proposed a CNN system for seven-class classification from the ISIC2018 dataset and achieved 94% accuracy. The limitation of this was it was hard to group classes into larger categories. In response to data sparsity, [13] proposed a fine-grained CNN trained on the HAM10000 dataset augmented images (256×256), yielding 66.1% average accuracy and notable recall gains for melanoma. Similarly, [14] showed a two-stage model integrating

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Mask R-CNN for segmentation and a 24-layer CNN for classification, with 86.5% accuracy on HAM10000. Aside from CNNs, [15] utilized SVM for BCC, SK, nevus, and melanoma classification, yielding better performance compared to other classifiers.

Some of them concentrated on particular diseases. In 2016, segmentation and SVM were utilized to automatically detect and measure eczema severity by studies. Likewise, [16] combined machine learning and computer vision, with a 95% accuracy rate for six skin diseases. Allugunti [17] introduced a CNN-based model for early detection of melanoma, and 88.83% accuracy was attained using DermNet images. Broadening CNN investigation, [18] compared 11 CNN architectures on HAM10000, where DenseNet169 yielded the best performance (92.25% accuracy, 93.27% F1-score). More extensive dermatological conditions were treated by [19], who suggested an ensemble meta-strategy for erythemato-squamous diseases (ESD) based on RF, DT, NB, KNN, and MLP algorithms with 97.8% accuracy after intensive preprocessing. To make it even more efficient, [20] presented a MobileNet-V2–based model that included squeeze-and-excitation networks, ASPP, and channel attention with 98.6% accuracy on various datasets.

Custom CNN designs have also been researched.[21] created a 15-layer HAM10000-trained CNN that was 95% accurate but had class imbalance with poor performance on melanoma (19% F1). Hybrid models have also performed well. [22] introduced an EfficientNetB0 system that utilized ant colony optimization for feature reduction and attained 98.43% accuracy and 99.01% in serial feature fusion. Along the same lines, [23] proposed a fusion-level model based on EfficientNet-B0, EfficientNet-B2, and ResNet50 that reported 99.14% accuracy on the Kaggle Skin Diseases Image Dataset. Even with such developments, precise diagnosis of multiclass skin lesions continues to be difficult because of shape variability, texture, color, lesion size, irregular border, and low image quality. Driven by such constraints, this paper suggests an efficient CNN-based system for the diagnosis of six skin lesion types to improve reliability and clinical value.

3. Suggested Multiclass Skin Lesion Diagnosis System using CNN

3.1 Dataset Overview

In this study, we developed a dedicated dataset of skin lesions pictures specific to the dermatological scenario in Iraq since available publicly available data did not cover the cases in detail. The data set consists of 3,057 dermatoscopic images that were divided into six categories: Nevus, Vitiligo, Baghdad boil, Tinea, Melanoma, and Dermatitis. These conditions are chosen based on consultation with specialists in dermatology, who pointed to their significance and the level in the region.

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Multiclass Skin Lesion	Associated	No. of Images

Figure 1. Dataset samples

3.2 Data Collection Process

The photographs were collected in the period between January 2023 and June 2025 in a number of medical centers, such as Sora Clinics Center, Baquba Clinics Center, and Baquba Hospital of Skin Diseases. To guarantee good quality and reliability of the dataset, we applied a stringent collection protocol:

- *Professional Supervision:* Dermatologists were close to the process to ensure that they made the correct diagnosis and each image was labeled correctly.

- *Constant Equipment:* The dermatoscopic device model used in all images was constant so that inconsistency due to hardware variation was eliminated, therefor used **camera type canon 850D** ,Lense volume ml70-24 .

- *Normalized Lighting*: To reduce noise, shadow or reflections, we took pictures under controlled conditions that had a consistent amount of light.

- *Quality Review:* following the collection, the medical experts went through the images to check the accuracy and clarity of the diagnoses and excluded those that were not clear.

Such a cautious procedure resulted in a dataset that is both clinically reliable and technically consistent, which is the best one to train deep learning models.

3.3 Data Augmentation

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Alt-

	Label	Original Images	Train and Augmented Images
Nevus	0	901	1000
Vitiligo	1	452	1000
Baghdad boil	2	450	1000
Tinea	3	399	1000
Dermatitis	4	449	1000
Melanoma	5	406	1000

hough the dataset was quite diverse, it had issues related to its size and uneven representation of categories to train CNNs. In order to counter this, we used data augmentation to increase the dataset size, balance the classes, and increase features variety. The augmentation methods contained:

3.3.1 Geometric Transformations

- Rotation: The pictures were flipped to simulate different orientations of lesions by rotating them in other angles.
- Flipping: Horizontal and vertical flips were employed to get lesion symmetry and variations.
- Translation and Cropping: The appearance of lesions was altered randomly by shifts and crops.
- Shearing: Used to make perspective different.

3.3.2 Photometric Transformations

- Color Adjustments: adjustments to brightness, contrast, saturation and hue to simulate the lighting conditions found in the real world.
- Color Space Shifts: Tests feature consistency across representations by converting some representations to grayscale or HSV.
- Intensity Changes: Customizations to simulate varying lighting.

3.3.3 Filtering Techniques

Table 1. local dataset, labels and number of images

- Gaussian Blur: This is added to determine the model robustness against minor focus changes.
- Edge Detection: This is employed in order to highlight the borders of lesions and the structural features.

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These extensions increased the scale of the dataset a great deal, giving the model a better generalization potential and minimizing overfitting. They further made sure that the model could cope with real differences in image capture.

3.4 Data Splitting

In order to have a fair and unbiased analysis we divided the data set into three parts:

- Training Set: This is employed to train the CNN and optimize the parameters.
- Validation Set The validation set is one that is observed as training progresses to tweak hyperparameters and monitor performance.
- Test Set: This is the set saved to be tested at the end of the model to determine how the model works with previously unseen data.

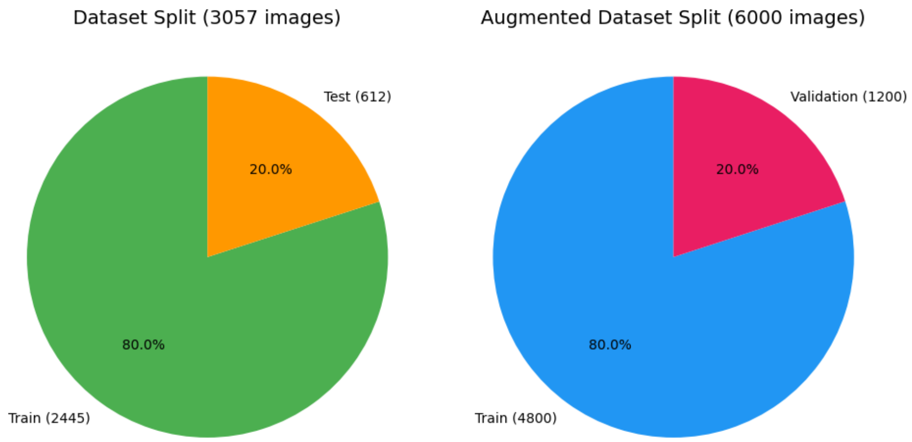

Figure 2. Split Percentage of data

Such a train-validation-test division is crucial in ensuring that the model has been trained well, has been validated appropriately, and tested in an unbiased manner, providing the actual picture of its diagnostic ability. For the purpose of ensuring proper model training and testing, the 3057 original images database was divided first in an 80:20 ratio, where 2445 images were used as the training, and 612 were reserved as the testing. However, the dataset was bi-ased in terms of the disease classes and this can bias the model to the dominant classes. To remedy this, we employed data augmentation methods which involved rotation, flipping, scaling, and brightness adjustment that helped augment the dataset artificially while keeping it diverse at the same time. The result of this operation was balanced dataset of 6000 images (1000 per class). The enriched dataset was also split into 80 percent train-ing (4800 images) and 20 percent validation (1200 images). While the model was trained with the training set,

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the validation set was crucial in hyperparameter tuning and re-tuning of weights such that the model performs optimally before being executed on the unseen test set.

3.5 Model Architecture and Training:

The proposed system of diagnosing skin lesions in the guise of a real multiclass was brought into practice through a tailored Convolutional Neural Network (CNN), tailored to dermoscopic images. The structure was split into two stages namely feature extraction and classification. In feature extraction, two convolutional layers with 64 3x3 filters were employed to yield low- to high-level image features. Following each convolution, a Rectified Linear Unit (ReLU) activation function was employed to introduce non-linearity and accelerate convergence. Between convolutional layers, max-pooling layers were applied to progressively down sample spatial resolution of feature maps, keeping dominant visual patterns. For improved generalization, dropout layers were employed in this phase to randomly deactivate neurons while training, which further reduced the risk of overfitting.

The classification stage was done using full connected layers that integrated the extracted features and passed them to the final prediction. The last layer employed the SoftMax activation, which gave a probability distribution of the target classes, which were Nevus, Vitiligo, Baghdad boil, Tinea, Melanoma and Dermatitis. The maximum probability score in this output vector was used to get the predicted class.

Layer(type)	**Output shape**	**Param#**
conv2d_15 (Conv2D)	(None, 64, 64, 32)	3,488
max_pooling2d_15(MaxPooing2D)	(None, 32, 32, 32)	0

Table 2. The details of layered architecture of the proposed system

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dropout_20 (Dropout)	(None, 32, 32, 32)	0
conv2d_16(Conv2D)	(None, 32, 32, 64)	73,792
max_pooling2d_16(MaxPooling2D)	(None, 16, 16, 64)	0
dropout_21 (Dropout)	(None, 16, 16, 64)	0
conv2d_17(Conv2D)	(None,16,16, 128)	73,856
max_pooling2d_17(MaxPooling2D)	(None, 8, 8, 128)	0
dropout_22 (Dropout)	(None, 8, 8, 128)	0
flatten_5(Dense)	(None, 8192)	0
dense_10 (Dense)	(None, 128)	1,048,704
dropout_23 (Dropout)	(None, 128)	0
dense_11 (Dense)	(None, 6)	774

Total Parameters: 1,200,614 (4.58 MB)
Trainable Parameters: 1,200,614 (4.58 MB)
Non-trainable Parameters: 0 (0.00 MB)

All images were resized to a constant size beforehand for compatibility with CNN's input, and the pixel values normalized to the range [0,1] to minimize the illumination bias. Optimizing training was done through the Adam optimizer with the initial learning rate of 0.001 that is decayed gradually during subsequent epochs for stabilization of convergence. Categorical cross-entropy loss was used because it is particularly suitable for multiclass classification tasks. The model was trained on a batch size of 32 for 50 epochs, with early stopping to prevent training when validation performance ceased to improve.

Regularization and optimization strategies were also utilized to increase model robustness. Dropout with probability 0.5 was added in fully connected layers to prevent co-adaptation of neurons, and batch normalization after convolutional layers stabilized learning and sped up training. Data augmentation (outlined in Section 3.2) also enriched the data set with data transformations like flipping, rotation, color space changes, and intensity adjustments to expose the model to a broad spectrum of variations in lesions.

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3. Results and Discussion

The basic contribution of the given work is the complete analysis of a fifteen-layer CNN model for the diagnosis of multiclass skin lesions. The system's performance was evaluated based on four commonly used evaluation measures: Precision, Recall, F1-Score, and Accuracy.

$$Precision = \frac{true\ positive}{true\ positives + false\ positives}$$
(1)

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$
(2)

$$F1 - Score = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)}$$
(3)

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + True\ Negative + False\ Negative + False\ Positive)}$$
(4)

These measures were calculated based on the conventional equations (1–4) for classification problems.

Table 3. The obtained results of Precision, Recall, and F1-Score

Classes	**Precision**	**Recall**	**F1-score**	**Support**
Neavus	1.00	1.00	1.00	710
Vitiligo	0.99	0.99	0.98	698
Baghdad boil	0.99	1.00	0.99	698
Tinea	0.99	0.99	0.99	708
Dermatitis	0.99	0.99	0.99	744
Melanoma	1.00	1.00	1.00	754
avg / total	0.99	0.99	0.99	4312

The class-wise results in detail are captured in Table 1, which illustrates that the suggested model reported very high values for each of the classes with an average precision, recall, and F1-score value of 0.99, reflecting outstanding and well-balanced performance. More specifically, the Nevus and Melanoma classes reported perfect values of 1.00 on all three metrics, reflecting the model's capability to differentiate them with absolute confidence.

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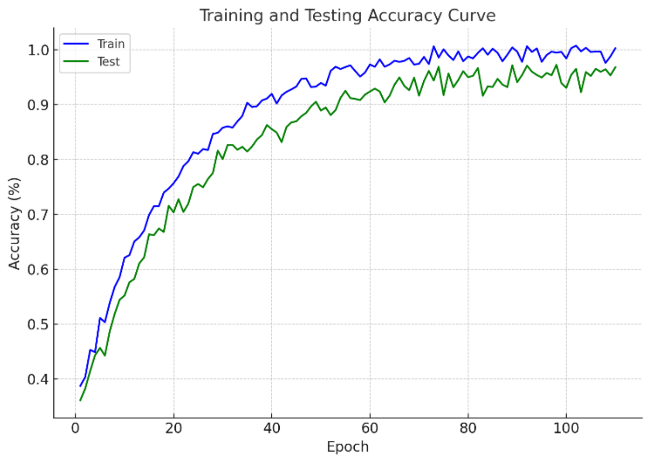

Figure 3. Accuracy vs Epoch

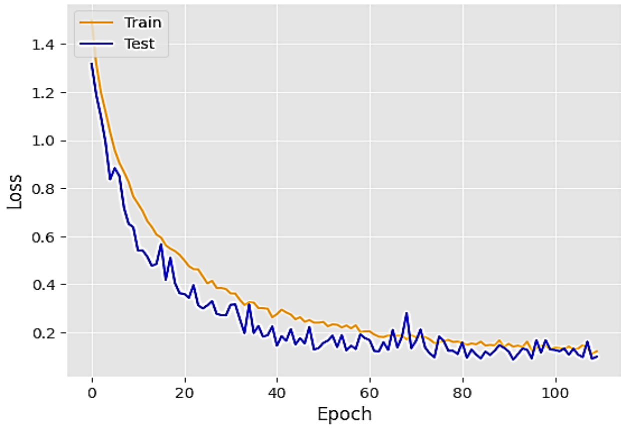

Figure 4. Loss vs Epoch

To further examine model behavior during training, accuracy and loss curves were charted, as presented in Figures 3 and 4. The accuracy curve represents a steady rise with a peak value of 99.23%, while the loss fell progressively to 0.0305 as training was continued over 150 epochs. The minimal gap between training and validation curves accounts for a good generalization ability, which implies that the model managed to avoid overfitting despite strong predictive ability.

Further, the confusion matrix shown in Figure 5 provides a more detailed interpretation of the results of classification. The diagonal entries indicate true positives for each type of skin lesion, and the off-diagonal entries indicate misclassifications. The matrix indicates that the majority of the samples were correctly labeled, with hardly any mislabeling in any of the six lesion classes, which further supports the robustness of the CNN architecture in performing challenging multiclass classification tasks

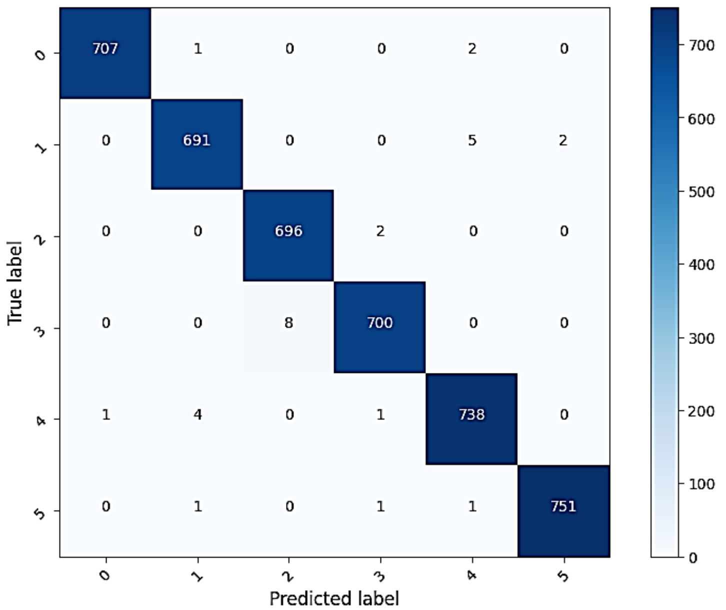

Figure 5. Confusion Matrix

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Table 4. suggested system and other previous studies that employed the collected dataset

Author/(s), Year	The obtained Accuracy
Allugunti (2022)	88.83%
Jaiyeoba et al. (2024)	95.5%
The proposed System	99.33%

A comparative analysis was also conducted with recent state-of-the-art studies utilizing the same dataset, as indicated by Table 4. Although Allugunti (2022) and Jaiyeoba et al. (2024) achieved classification accuracies of 88.83% and 95.5% respectively, the system proposed achieved significantly higher performance at 99.33%. This evident performance gain demonstrates the efficacy of the proposed CNN architecture and training approach in overcoming the complexities of multiclass skin lesion diagnosis.

In general, the performance results strongly suggest that the system proposed in this study offers highly accurate and efficient means of diagnosis, which can support dermatologists in clinical decision-making with nearly perfect reliability

4. Conclusions

This work introduced a strong three-layer CNN architecture for multiclass classification of skin lesions, trained and tested on a thoroughly prepared and enhanced dataset. The system proposed in this work performed superbly, with overall accuracy of 99.33%, precision of 0.99, recall of 0.99, and F1-score of 0.99, thus outperforming current state-of-the-art techniques. The almost perfect classification accuracy, corroborated again using accuracy/loss curves and a confusion matrix, shows the model's superb capacity to distinguish between different types of skin lesions, such as Nevus, Vitiligo, Baghdad boil, Tinea, Dermatitis, and Melanoma.

The excellence of this system over other techniques reported earlier is not only quantitative but also qualitative, as it indicates the capability of deep learning in diminishing misdiagnosis, improving decision-making speed, and assisting dermatologists with early and trustworthy identification of dermatoses. With the presentation of a standard, precise, and automatic diagnostic instrument, this paper makes a notable contribution to incorporating AI-powered solutions into healthcare, particularly in dermatology where prompt intervention can be lifesaving.

In the future, the platform can be extended to cover a broader range of skin conditions and modified for practical clinical use via mobile or web-based platforms. Additionally, incorporation of explainable AI (XAI) methods may improve trust and transparency, allowing clinicians to understand and interpret better model predictions. In summary, the suggested CNN-based system provides a new benchmark for multiclass skin lesion classification. Its outstanding performance, scalability, and clinical applicability make it a wonderful milestone toward

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AI-aided dermatological diagnosis, pushing the boundary between advanced machine learning studies and usable medical practice.

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