RESEARCH PAPER

Skin Disease Classification and Early Detection Using Deep Learning

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Received: 20th Feb, 2026 | **Revised:** 4th Mar, 2026 | **Accepted:** 25th Mar, 2026 | **Available Online:** 10th Apr, 2026

ABSTRACT

Skin diseases affect more than 90 percent of people around the world, and doctors need to detect these conditions early to treat them successfully, especially for dangerous diseases like melanoma. The conventional diagnostic process needs dermatologists to use their specialized knowledge while they conduct physical assessments which results in lengthy and unreliable results. This study introduces an automated skin lesion classification system which uses deep learning technology to classify skin lesions through a Convolutional Neural Network (CNN) model that has been developed using the HAM10000 dermoscopic image dataset which includes seven different skin lesion types. The model uses image preprocessing methods together with data augmentation techniques to achieve better generalization results while solving the problem of dataset imbalance. The CNN system uses its architectural design to extract various levels of features from skin images while it simultaneously conducts multiple class identification tasks. The experimental results show that the proposed model reaches exceptional performance levels through its ability to achieve accurate results and through its evaluation metrics which include precision and recall and F1 score. The study results show that artificial intelligence technology has the ability to support dermatologists in achieving faster and more precise skin disease assessments.

Keywords: Skin Disease Classification, Deep Learning, Convolutional Neural Networks (CNN), Vision Transformers (ViT), Explainable AI (XAI), Grad-CAM, SHAP, LIME, Generative Adversarial Networks (GANs), Data Augmentation, Model Compression.

How to cite this article: Khanam S, Khatib MS. Skin Disease Classification and Early Detection Using Deep Learning. Int J Drug Deliv Technol. 2026;16(29s):615-621. DOI: 10.25258/ijddt.16.29s.78

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

I.INTRODUCTION

Skin diseases represent a common medical condition that affects people around the world because they include both mild conditions like acne eczema and dermatitis and severe diseases that can endanger life such as melanoma and basal cell carcinoma. Global health reports show that a considerable portion of the worldwide population experiences dermatological disorders at some point during their life. Skin disease requires early and precise diagnosis because its prolonged detection period results in disease advancement and higher death rates during critical skin cancer situations. Dermatologists use clinical examination together with dermoscopic image analysis to determine skin conditions. The methods prove effective yet their diagnostic effectiveness depends on medical professionals' expertise which leads to inconsistent results between different practitioners. The diagnostic expertise of experienced dermatologists remains out of reach for many remote and resource-constrained areas which creates challenges for both early diagnosis and adequate treatment. Healthcare professionals need automated diagnostic systems that work reliably to help them detect skin diseases without waste of time.

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II. LITERATURE SURVEY

Deep learning has brought major progress to medical image analysis through its application in dermatological skin lesion classification. The research by Esteva et al. [1] stands as a pivotal study because it proved that deep convolutional neural networks can reach dermatologist-level accuracy in skin cancer classification using extensive dermoscopic image data. The research demonstrated that deep learning models possess the ability to derive intricate visual attributes from images which lead to accurate identification of various skin lesion types. The HAM10000 dataset developed by Tschandl et al. [2] includes over 10,000 dermoscopic images which show seven different types of pigmented skin lesions. This dataset has emerged as a primary standard used by researchers to develop and test deep learning systems in dermatology studies.

Researchers in this field work to enhance classification accuracy and system strength through their application of deep learning methods. Codella et al. [3] studied how deep learning ensemble models work to identify melanoma in dermoscopic images through their research. The system used three convolutional neural networks as existing models for better accuracy and lower model bias. The research proved that automated skin lesion classification systems become more reliable through the application of ensemble learning methods. Researchers in other studies investigated deeper CNN architectures which include ResNet and EfficientNet to enable models to acquire more advanced hierarchical medical image representations.

The interpretability of deep learning models stands as a significant research area in this domain. The deep learning systems are commonly referred to as black-box systems because their operators fail to comprehend how the systems reach their conclusions. The researchers developed explainable artificial intelligence techniques which include LIME and SHAP and Grad-CAM to solve this particular problem. The methods show which parts of an image determine the model's prediction, which helps clinicians understand and trust the automatic diagnostic systems. Explainable AI serves as an essential component for healthcare systems that require transparent and trustworthy systems to gain acceptance in clinical environments.

Researchers have studied dataset imbalance problems which occur in medical datasets because certain disease classes contain far fewer samples than others. The researchers used Generative Adversarial Networks (GANs) to create synthetic dermoscopic images which helped to increase minority class representation for better model training. Transfer learning techniques enable medical researchers to achieve better results with limited medical datasets through the use of pre-trained ImageNet models.

Researchers have started using transformer-based architectures for their medical image analysis work. Vision Transformers surpass traditional CNNs which only detect local image features because they use self-attention to analyze entire image data. Tang et al. [15] created the SkinSwinViT lightweight transformer-based model which performs multiclass skin lesion classification. Their research showed that their method achieved better generalization and classification results across different lesion types. The introduction of hybrid deep learning architectures which use CNNs for feature extraction with transformer-based global feature analysis shows increasing importance for automated dermatological diagnosis systems which require accurate and dependable performance.

III. PROBLEM DEFINITION

For serious skin diseases like melanoma and skin cancer correct skin disease diagnosis needs to happen early because it is vital for effective treatment. The traditional diagnostic process depends on doctors' professional skills because they must analyze dermoscopy images through their manual work which requires time and results in variable outcomes. The limited presence of skilled dermatologists in various areas results in both delayed medical assessments and incorrect diagnoses. The medical image datasets which training automatic systems use face multiple problems because they contain class imbalances and different image quality levels and various skin tone differences which decrease system performance. The development of an automated skin lesion classification system needs to create a reliable solution which will accurately process dermoscopic image data to decrease diagnostic mistakes while helping doctors with early diagnosis and clinical decisions through advanced deep learning methods.

IV.METHODOLOGY

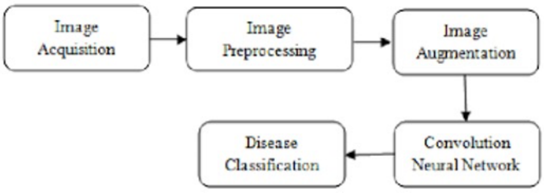


FIG 1: SYSTEM DESIGN

Fig 1: system design demonstrates its functioning through the structured pipeline which the diagram displays. The process begins with image acquisition which involves the collection of dermoscopic skin lesion images from the available dataset. The images undergo preprocessing through image processing techniques which include resizing and normalization and noise reduction to enhance image quality and prepare the data for model training. The preprocessing stage ends with the application of image augmentation techniques which include rotation and flipping and shifting to create additional dataset samples which help decrease overfitting. The processed images are input into a Convolutional Neural Network (CNN) which automatically identifies crucial visual elements including texture and color and shape within the images. The system uses learned features to perform disease classification which enables the model to identify skin lesion types from various categories for precise automated skin disease identification.

Researchers developed a skin disease classification method which uses deep learning technology to analyze dermoscopic images through various steps starting from image acquisition until the final classification. The research team starts their work by collecting dermoscopic images from the HAM10000 dataset which contains labeled images of seven different types of skin lesions. The deep learning model uses these images as its training and evaluation data. Preprocessing techniques help to standardize raw images which contain different size and lighting and quality attributes. The process requires images to undergo resizing until they reach their designated resolution while pixel values need to be normalized between 0 and 1 to create a neural network compatible format. This step helps maintain database consistency while improving model training effectiveness.

Researchers use image augmentation methods to create diverse datasets which help mitigate overfitting problems. The team used multiple augmentation methods which included rotation, horizontal and vertical flipping, width and height shifting, and shear transformation to produce new image variations from the original pictures. The model can learn stronger features through the augmented images which lead to better performance on previously unseen data. A Convolutional Neural Network (CNN) system processes the images to automatically extract hierarchical image features through its multiple convolutional and pooling layers. The convolutional layers identify crucial visual patterns which include edges and textures and shapes while the pooling layers decrease both spatial dimensions and the network's computational requirements.

V.PROPOSED SYSTEM

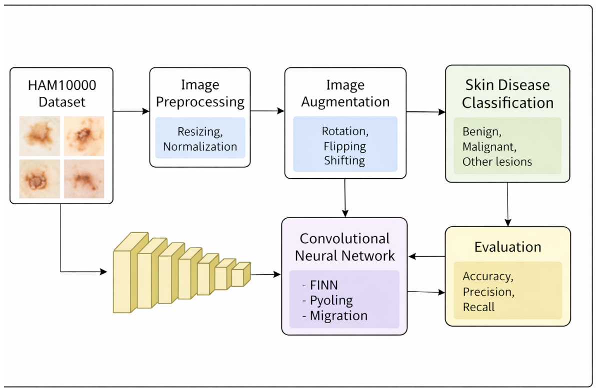


Fig. 2. Data flow diagram

Fig. 2. Data flow diagram illustrates the overall process of the proposed skin disease classification system. The process begins with the HAM10000 dataset, where dermoscopic images of skin lesions are collected as input data. The images undergo image preprocessing which combines resizing and normalization to create standardized input data that enhances model performance. After preprocessing, image augmentation techniques such as rotation, flipping, and shifting are applied to increase dataset diversity and reduce overfitting. The processed images are then fed into a Convolutional Neural Network (CNN), which automatically extracts important visual features that include texture, color, and lesion patterns. The system executes skin disease classification based on the acquired features which enable it to distinguish between various lesion types. The model performance evaluation uses accuracy precision and recall as metrics to confirm the proposed deep learning-based diagnostic system's reliability and effectiveness.

VI. MODULES

1. Image Acquisition Module

The module collects dermoscopic skin lesion images from the HAM10000 dataset. The dataset consists of various skin diseases' images, which include melanoma, basal cell carcinoma, melanocytic nevi, and others. The system uses the images as the major input to the system because they provide the required data to train the deep learning model.

2. Image Preprocessing and Augmentation Module

As part of this module, the collected images are prepared to train the model. Various operations are performed on the images to ensure that they are of a uniform size. Additionally, various data augmentation techniques are employed to ensure that there is diversity in the collected data. This is to prevent overfitting, which would impair the model's ability to generalize.

3. Feature Extraction using CNN Module

It uses a Convolutional Neural Network (CNN) that can automatically identify the main characteristics of the images of the skin lesions. The network has several layers that can identify the patterns in the image such as edges, texture, and changes in color that can be used for understanding various kinds of skin diseases.

4. Skin Disease Classification and Evaluation Module

In the last module, the extracted features are passed through fully connected layers to classify the skin lesions in various classes. The system predicts the probability of the diseases in each class with the softmax activation function. The performance of the system is measured with metrics such as accuracy, precision, recall, and confusion matrix to evaluate the effectiveness of the classification system.

VII.RESULT

The proposed Convolutional Neural Network (CNN) model was trained and evaluated using dermoscopic images from the HAM10000 dataset to classify different types of skin lesions. The dataset was divided into training and testing sets with an 80:20 ratio, and image preprocessing and augmentation techniques were applied to improve model performance and generalization. During training, the model effectively learned important visual features such as texture, color, and lesion patterns from the images. The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1-score, along with a confusion matrix to analyze classification performance across different classes. The results indicate that the CNN-based system successfully classifies skin lesion images with good accuracy and demonstrates its potential as an automated tool to assist dermatologists in early skin disease detection and diagnosis.

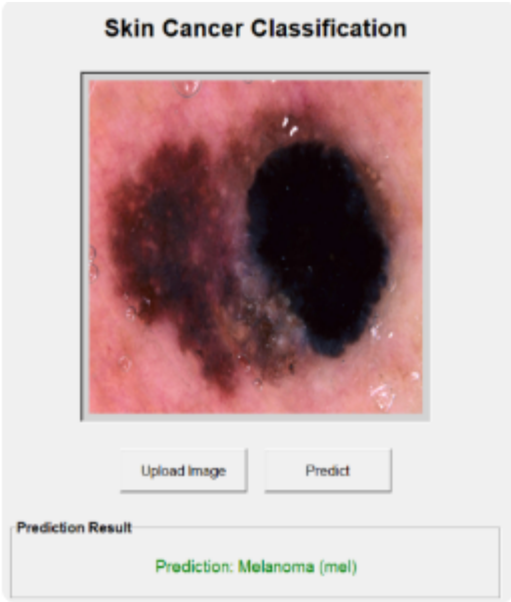


Fig 3:- Melanoma Detection Result

Fig 3 Melanoma Detection Result The system analyzes the uploaded skin lesion image using a trained deep learning model and predicts the type of skin cancer. In this case, the model classifies the lesion as Melanoma (mel), which is one of the most serious types of skin cancer. The prediction result is displayed after the user uploads an image and clicks the Predict button, helping in early identification and supporting medical diagnosis.

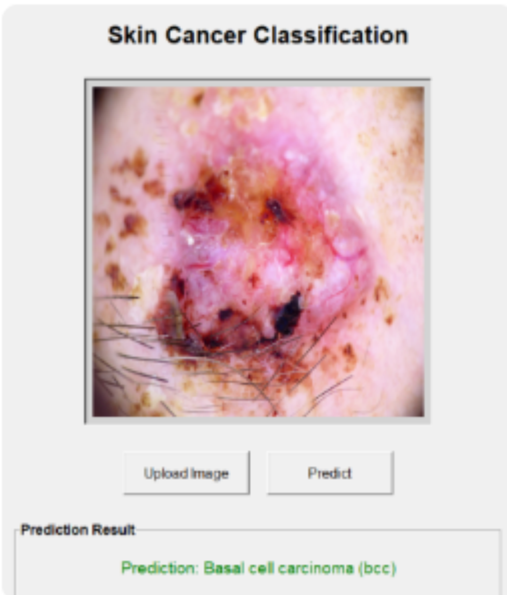


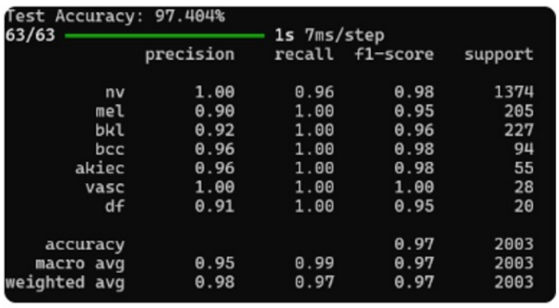
Fig 4 :-Basal Cell Carcinoma Detection

Fig 4 Basal Cell Carcinoma Detection The system processes the uploaded skin lesion image using a trained deep learning model and predicts the type of skin cancer. In this case, the model classifies the lesion as Basal Cell Carcinoma (bcc), a common form of skin cancer that usually grows slowly. The result appears after the user uploads an image and clicks the Predict button, assisting in early detection and supporting medical evaluation.

FIG 5:-Benign Keratosis-like Lesion Detection

Fig 5 Benign Keratosis-like Lesion Detection The system analyzes the uploaded skin image using a trained deep learning model to identify the type of skin lesion. In this case, the model predicts Benign Keratosis-like Lesions (bkl), which are non-cancerous skin growths. The prediction appears after the user uploads an image and clicks the Predict button, helping support early screening and assisting medical professionals in diagnosis.

Fig 6: Model Performance Evaluation



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Test Accuracy: 97.404%
63/63 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
              precision    recall  f1-score   support

          nv       1.00      0.96      0.98      1374
         mel       0.90      1.00      0.95       205
         bkl       0.92      1.00      0.96       227
         bcc       0.96      1.00      0.98        94
       akiec       0.96      1.00      0.98        55
        vasc       1.00      1.00      1.00        28
          df       0.91      1.00      0.95        20

    accuracy                           0.97      2003
   macro avg       0.95      0.99      0.97      2003
weighted avg       0.98      0.97      0.97      2003
```

Fig 6: Model Performance Evaluation The classification report shows the performance of the trained skin cancer classification model on the test dataset. The model achieved an overall test accuracy of 97.40%, indicating very high prediction performance. Metrics such as precision, recall, and F1-score are calculated for each skin lesion class including nv, mel, bkl, bcc, akiec, vasc, and df. The high scores across most classes demonstrate that the model can accurately identify different types of skin lesions and effectively support automated skin cancer detection.

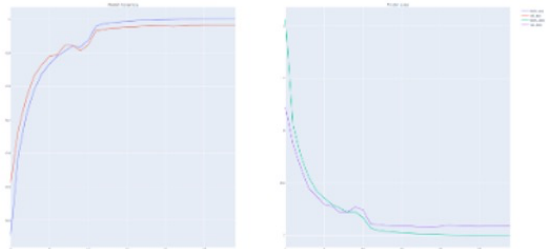
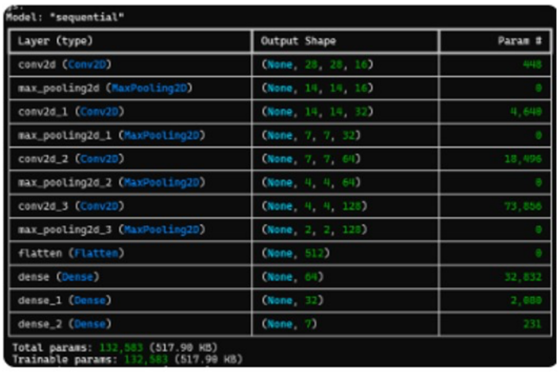


Fig 7 :Training and Validation Performance

Fig 7 Training and Validation PerformanceThe graphs show the training and validation accuracy and loss of the skin cancer classification model during the training process. The accuracy graph demonstrates that both training and validation accuracy steadily increase and reach nearly 98–100%, indicating strong learning performance. At the same time, the loss graph shows a significant decrease in both training and validation loss over epochs, suggesting that the model is effectively minimizing errors and improving prediction capability. These results indicate that the model has learned meaningful features for accurate skin lesion classification.



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 16)	448
max_pooling2d (MaxPooling2D)	(None, 14, 14, 16)	0
conv2d_1 (Conv2D)	(None, 14, 14, 32)	4,640
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 32)	0
conv2d_2 (Conv2D)	(None, 7, 7, 64)	18,496
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 64)	0
conv2d_3 (Conv2D)	(None, 4, 4, 128)	73,856
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 128)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 64)	32,832
dense_1 (Dense)	(None, 32)	2,080
dense_2 (Dense)	(None, 7)	231

Total params: 132,583 (517.90 KB)
Trainable params: 132,583 (517.90 KB)

Fig 8: CNN Model Architecture

Fig 8 CNN Model Architecture The table shows the architecture of the Convolutional Neural Network (CNN) used for skin cancer classification. The model contains multiple Conv2D and MaxPooling layers that extract important image features, followed by a Flatten layer and several Dense layers for final classification. The network processes the image step-by-step to learn patterns in skin lesions and finally predicts one of the seven skin disease classes. In total, the model contains 132,583 trainable parameters, enabling effective feature learning and accurate prediction.

VIII.CONCLUSION

This study presents a deep learning–based approach for skin cancer classification using a Convolutional Neural Network (CNN) to analyze dermoscopic images of skin lesions. The proposed model was designed with multiple convolutional and pooling layers to effectively extract important visual features such as color variations, texture, and irregular lesion patterns. These features help the model differentiate between several types of skin diseases including melanoma, basal cell carcinoma, benign keratosis-like lesions, melanocytic nevi, vascular lesions, dermatofibroma, and actinic keratoses. After training on the dataset, the model achieved a high test accuracy of 97.40%, along with strong precision, recall, and F1-scores, demonstrating its ability to accurately classify different categories of skin lesions. The training and validation results also show that the model successfully learns meaningful patterns from the data, as the accuracy increases and loss decreases during the training process. Additionally, a simple user interface was developed that allows users to upload a skin image and receive an instant prediction of the detected skin condition. This system demonstrates how artificial intelligence can assist medical professionals by providing quick and reliable preliminary analysis. Overall, the results indicate that deep learning techniques have strong potential in automated skin disease detection, which can support dermatologists in early diagnosis, improve healthcare efficiency, and contribute to better patient outcomes.

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