**AVE Trends in Intelligent Computer Letters**

# Skin Disease Classification Using a HFF-CNN Hybrid Feature Fusion Deep Learning Framework

**A. Muthukumaravel[1,*], S. Silvia Priscila[2], B. M. Praveen[3]**

[1]Institute of Engineering and Technology, Srinivas University, Dakshina Kannada, Karnataka, India.
[1]Faculty of Arts and Science, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
[2]Department of Computer Science, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India.
[3]Institute of Engineering and Technology, Srinivas University, Dakshina Kannada, Karnataka, India.
dean.arts@bharathuniv.ac.in[1], silviaprisila.cbcs.cs@bharathuniv.ac.in[2], bm.praveen@yahoo.co.in[3]

*Corresponding author

**Abstract:** In view of the increasing dermatological disease as well as the inevitable shortage of qualified experts, the automated skin syndrome classification based on DL (Deep Learning) has gained much significance recently. The research considers a CNN (Convolutional Neural Network) model for classifying multi-class skin diseases, compares its performance with existing DL models such as VGG16 and ResNet50, and Presents Results on InceptionV3. The International Skin Imaging Collaboration (ISIC) dataset is used to evaluate the proposed approach, which consists of dermoscopic images from multiple classes. In the preprocessing stage, the image is resized, and the CLAHE (Contrast Limited Adaptive Histogram Equalisation) technique is applied to enhance lesion visibility while reducing illumination variation. The proposed HFF-CNN uses a hybrid feature fusion technique that concatenates the features learned from the custom-designed CNN with the high-level TL (Transfer Learning) features extracted from the pre-trained ResNet50 model. Hybrid features capture local texture details via a custom CNN and global semantic representations via a pre-trained CNN. The classification process takes place in the fully connected layers, using a concatenated feature vector and drop-out regularisation. The suggested HFF-CNN model is tested using accuracy, precision, recall, F1 score, and ROC curve area. The hybrid model beats all DL methods in classification accuracy and robustness, according to trials. The HFF-CNN architecture appears useful for early, accurate clinical diagnosis of skin disease.

**Keywords:** Skin Disease; Framework and Classification; Feature Fusion; Image Preprocessing; Deep Learning; Transfer Learning; Hybrid Model; Clinical Setting; Precision Value.

**Cite as:** A. Muthukumaravel, S. S. Priscila, and B. M. Praveen, "Skin Disease Classification Using a HFF-CNN Hybrid Feature Fusion Deep Learning Framework," *AVE Trends in Intelligent Computer Letters*, vol. 2, no. 1, pp. 13–25, 2026.

**Journal Homepage:** https://www.avepubs.com/user/journals/details/ATICL

**Received on:** 23/11/2024, **Revised on:** 12/01/2025, **Accepted on:** 11/04/2025, **Published on:** 03/01/2026

**DOI:** https://doi.org/10.64091/ATICL.2026.000252

## 1. Introduction

There has been an uptick recently in the number of skin disorders observed in millions of people without any discrimination of age, and more pets and animals seem to be developing one. The skin disorder varies in severity, and the symptoms manifest clearly as the experts identify them [8]. This disease, which either hurts or doesn't, can cause skin cancer, eczema, psoriasis, acne, and seborrheic dermatitis in some individuals, and it can be temporary or permanent. Skin diseases lead to early embryonic death, infertility, altered behaviour, low milk yield, and skin problems in fetuses [11]. Many people are suffering from very common skin diseases. Every year, there are many cases of skin diseases. Millions of people worldwide suffer from skin diseases, and they are considered a serious public health problem. The skin's structure, function, and appearance are affected by many diseases. The process of identifying and predicting skin diseases is tedious. It is a procedure that includes a thorough physical examination, a review of the patient's medical history, and appropriate laboratory diagnostic testing [12]. Additionally, those with serious skin lesions need urgent diagnosis, which, if untreated, could prove life-threatening. This is very important to diagnose the skin correctly. The intelligent healthcare system is significantly benefiting from computer-aided diagnosis of skin diseases. Significantly, these intelligent systems can help doctors make accurate diagnoses. Besides this, they are intelligent automated machines as well. Doctors do not have to be involved a lot. On the contrary, the computer-aided diagnostic system interprets medical images. They also conduct analyses of clinical data that help diagnose illnesses. Skin diseases affect the skin and related structures.

### 1.1. Background Study

Skin cancer can be caused by the sun's dangerous ultraviolet (UV) rays and the use of UV tanning beds. Dermatologists have difficulty distinguishing melanoma from non-melanoma lesions because lesions can be poorly differentiated from the surrounding skin [15]. The rise in dermatological disorders and the urgency of prompt diagnosis have propelled skin disease categorisation to the forefront of research in medical image analysis. For a long time, skin diseases have been diagnosed through a combination of clinical examinations and dermoscopic analyses conducted by dermatologists. However, these manual approaches rely on the practitioner's experience and can yield variable outcomes, particularly in visually similar skin conditions. The rapid evolution of digital imaging and artificial intelligence has led to the development of automated skin disease classification systems that help dermatologists improve the accuracy and speed of skin disease diagnostics. The initial studies in this area focused primarily on traditional machine learning methodologies. In these methodologies, the first step involved preprocessing dermoscopic images to remove noise and improve image quality. Following this step, various feature-extraction approaches were employed, including analyses of colour, texture, and shape.

### 1.2. Importance of DL Methods in Skin Disease Classification

DL is a branch of ML algorithms used to enable learning in computational systems through experiential interactions and the conceptualisation of the surrounding world in a hierarchical structure of abstractions [17]. Clinically, early recognition and precise categorisation of skin disorders are critical, as delayed diagnosis increases patient risk, particularly when treatment is insufficient and visually related disorders necessitate distinct management. However, despite their significance, automated detection of skin-related issues remains difficult due to subtle differences within and between classes, as well as the need to consider the distinctive textures and patterns of lesions [16]. DL-based methods play a significant role in skin disease classification by enabling automated, precise analysis of dermoscopic images. Old diagnostic approaches often rely on dermatologists' manual visual inspection, which can be inefficient and subjective. DL models, especially CNNs, can automatically learn multifaceted patterns, such as colour variations, textures, lesion boundaries, and shape anomalies, directly from medical images. This removes the need for manual FE (Feature Extraction) and improves the efficiency of the diagnostic process. As a result, DL models can categorise various skin disease classes with high accuracy and consistency.

Another major benefit of DL techniques is their ability to support timely detection and clinical decision-making. Skin diseases require proper diagnosis to avoid serious complications. DL-based systems can quickly examine large volumes of dermoscopic images and identify suspicious lesions at an early stage. These systems also help decrease diagnostic errors and provide consistent outcomes, assisting dermatologists in making more informed decisions. DL models can be combined into telemedicine podiums and mobile healthcare applications, making skin disease screening more reachable, particularly in areas with limited access to dermatology experts. In general, the ML technique for classifying skin cancer involves manually extracting image features, feeding them into a learning algorithm, and generating classification results [18]; [19]; [20]. DL tools such as CNNs have become effective for automatically detecting skin diseases using computer vision and ML [13]. The proposed HFF-CNN uses features from the CNN and the ResNet50 model to accurately classify skin diseases. Using a standard dermoscopic image dataset, researchers will compare the proposed framework's performance with that of the most commonly used models. Such as VGG-16, ResNet-50, and InceptionV3. With high reliability, efficiency, and precision, the proposed approach can serve as a decision-support system for early diagnosis of skin diseases. In clinical dermatology and teledermatology, it can be an essential tool. So, this paper presents a new approach.

## 2. Related Works

Skin disease is a significant disorder that may be initially detected by visual observation, without tests, and later with dermoscopic or other tests. In the initial stage, visual observation enables us to use artificial intelligence to classify different skin images. Thus, many skin lesion classification methods use DL based on CNN. Also, annotated skin photos show better results and higher accuracy in skin lesion classification. Concerning this, Zahid et al. [1] described a reliable method for diagnosing skin malignancy using dermoscopy images, thereby improving healthcare practitioners' capabilities and visual perception in differentiating between benign and malignant lesions. The study employed swarm intelligence algorithms for segmenting skin lesion regions of interest from dermoscopy images. Feature extraction of the segments was performed using the speeded-up robust features. The Grasshopper Optimisation Algorithm, which emerged as the best algorithm, was reported to perform segmentation of dermoscopy images. CNN uses three data sets to classify skin lesions into two classes. A variety of classification metrics was applied to evaluate the proposed segmentation and classification methods. Skin disease is one of the most common diseases. Given the joint complexity of the skin disease types, the similarity of lesion samples at the early stage, and the extreme imbalance in the lesion samples, it is hard to classify them. Due to neural networks' poor generalisation and classification performance with limited training data, a basic ensemble model is proposed to improve CNN accuracy. Wei et al. [2] proposed a model for skin disease classification based on model fusion. The model's feature extraction ability is enhanced through model fusion, deep and shallow feature fusion, and the introduction of an attention module. The authors also performed a series of tasks, such as model pre-training, data augmentation, and parameter fine-tuning, to enhance the model's classification performance.

The results of the experiment demonstrate that the proposed model outperforms the two baseline models. The proposed honeypot model was evaluated in two phases: before and after the addition of honeypots. Quick and precise identification of skin malignancy is essential for successful treatment. In addition, variation in lesion colour is the most powerful indicator of malignancy. The efficacy of DL models may be hindered by the varying colour characteristics of lesions resulting from non-standardised image acquisition conditions. Prior literature often ignores this problem and relies on deep features from a single layer of a single DL model. Attallah et al. [3] described a new hybrid DL model that integrates the discrete cosine transform with multi-convolutional techniques for the classification of skin melanoma. Initially, the DCT is applied to the images to enhance and correct colour distortion. Following this, dermoscopic images and DCT images are utilised by separate CNNs. Next, extract deep features from the two deepest layers of each CNN. The hybrid model is planned to combine three deep feature fusions. The initial phase uses a discrete wavelet transform (DWT) to fuse the multidimensional features derived from the first layer of every CNN. The image is reduced in size, yielding a time-frequency representation. For each CNN, the second-layer deep features are concatenated. The following deep feature fusion process, performed on the first-layer integrated features and the second-layer features of each CNN, yields an efficient feature vector. In the third deep feature fusion stage, the bi-layer features of the different CNNs are fused. The three-way deep feature fusion involves training separate CNNs on the original dermoscopic images and the DCT-plus-image, extracting features from 2 distinct layers, and merging the features from the different CNNs. The trio-deep feature fusion showed 96.40% accuracy in experiments. The use of DCT-plus-image and dermoscopic image has a diagnostic impact. The inaugural hybrid trio-deep feature fusion model outperforms a singular CNN model and most recent peer research initiatives, thereby evidencing its optimal capabilities.

An accurate diagnosis is essential to treat skin diseases at an earlier stage. Zhao et al. [4] described a patch-based interpretable DL framework for disease recognition using wearable skin sensors and clinical data. They use a Fully Convolutional Residual Neural Network (FRCN) to extract local features from high-resolution skin images captured by a wearable skin sensor, using a patch-level training scheme. Pre-processing steps execute a variety of spatial and intensity corrections on each 2-dimensional image jointly. These include actions such as resampling that remove variations and noise, normalising images, and removing streak artefacts. Intensity sharpens the image and eliminates variations produced by the sensor. Resampling and normalising the images ensures they are consistent across different sensors. New residual modules have been added to the FCRN to enhance local feature learning in skin images. This module addresses vanishing gradients, improves learning, and enables ensemble learning across various recognition phases. These residual modules can learn better to distinguish several skin diseases from the original image. A visualised, interpretable disease probability map displays high-risk abnormal skin regions where the recognition of skin disease alters the monitoring system. The method for disease detection uses a CNN that combines image features with the patient’s clinical data and symptoms. The proposed CNN-based multimodal fusion surpassed other fusion schemes. Skin diseases commonly occur in clinical practice and constitute a major problem. Recognising skin injury early and promptly managing the disease are essential for early diagnosis and treatment. Nonetheless, a crisis is underway.

Skin cancer is a serious medical condition that affects many people worldwide and must be caught early. Skin EHDLF, introduced by Lilhore et al. [5], enhances skin cancer categorisation through an innovative DL approach. SkinEHDLF leverages the strengths of several existing methods and employs adaptive attention-based feature combination to enhance the fusion of extracted features. The hybrid method of SkinEHDLF leverages the remarkably efficient feature extraction capabilities of ConvNeXt, the scalable features of EfficientNetV2, and the long-range attention of Swin Transformer. Using the adaptive attention mechanism helps the model optimally fuse image segmentation and text segmentation features. This causes the SkinEHDLF to centralise only the relevant information. The SkinEHDLF is trained and tested on the ISIC 2024 dataset, which comprises 401059 images of skin lesions from 3D total-body photography. Moreover, the dataset comprises three groups, i.e., melanoma, benign lesions, and noncancerous skin lesions. Experimental findings indicate that SkinEHDLF outperforms the existing schemes. This model statistically outperformed the other models with fewer false detections than the best-performing benchmark models. As a result, SkinEHDLF is a better method for automatic skin cancer recognition. The primary challenge for a dermatologist is diagnosing skin disease early. Manual diagnosis of skin diseases by healthcare physicians and experts is subjective, expensive, and inconsistent. Furthermore, in this issue, traditional ML and DL models have shown promising results in the automated detection and classification of skin diseases. Uddin et al. [6] proposed a hybrid ensemble framework for skin disease detection and classification that leverages complementary strengths of two models via decision-level fusion (DLF) and feature-level fusion (FLF).

To detect and classify skin disorders, they employ a couple of CNN-based models. FLF sums the feature representations generated by various models on a point-wise basis. Next, they pass them through a shared classification head for final prediction. At DLF, collect the decisions made by the individual base models, and then make the final decision using a majority voting scheme. Further, the authors use GAN–based offline training data. Based on varying evaluations, they proposed the framework, which achieved the best results across various datasets. One of the most dangerous forms of cancer is skin cancer, which accounts for many deaths globally. The skin disorder occurs when the skin cells malfunction due to prolonged exposure to UV rays. The ultraviolet rays that cause the disease can come from the sun or from artificial tanning. Dermatologists may utilise visual clues and must identify suspicious lesions. Consequently, it has to be recognised as early as possible, which aids treatment and enhances the scope of recovery. Recently, different types of skin cancer have been predicted using machine learning and deep learning algorithms. These tools can forecast common and harmful dermatological issues. Soundarya and Poongodi [7] described a hybrid feature. The analysis of the dermoscopic image uses fused DL models. Images of skin lesions are taken from ISIC and several other sources. The images were processed even further. The feature is derived using the GLCM and the redundant discrete wavelet transform (RDWT) with a different pretrained model. They evaluated all the combinations and their results. The feature fusion model performed better compared to all the other models. The proposed feature fusion model consists of GLCM, RDWT, and DenseNet121 features. These features are estimated using different classifiers. The authors use a combination of feature extraction to improve the reliability of diagnosing skin tumours.

Zahid et al. [1] described a hybrid approach for skin lesion classification that combines features from DL methods and HOG, Gabor, SIFT, and LBP. Feature extraction is the process of extracting useful features from the tumour region using the proposed fusion techniques. They evaluated and contrasted features from various DL models and HOG-based features. To reduce dimensions and boost performance, employs PCA (principal component analysis), followed by SVM classification. Compared the approaches of interest on the reference database, skin illness: malignant vs benign. The results indicate that significant accuracy improvement may be achieved through the complementarity between the conventional and deep approaches. The findings indicate that performance improvement from fused feature extraction is much greater than from either of the individual approaches. In essence, it covers severe illnesses that may range from benign diseases to life-threatening cancerous tumours like melanoma. Research on computer vision for melanoma has been widely conducted due to the visual complexity and subjectivity involved in manual diagnosis. The research conducted by Fiaz et al. [9] described a hybrid DL model for skin lesion segmentation and multi-class classification using dermoscopic images. Furthermore, the resulting model is a combined U-Net and multi-class classification network using the EfficientNet-B0 backbone. The encoder is similar in both models. To emphasise the importance of each component of the lesion, they used Grad-CAM to generate heat maps, thereby increasing trust in new clinical trials. Evaluation of the proposed model was performed on the popular HAM10000 data set. The network's overall training losses saturate after a specific number of epochs: 77 for VGG and 144 for Inception. Dice and classification accuracies were over 0.85 and nearly 85%, respectively, for all lesion types despite class imbalance.

The proposed model effectively predicts multi-class skin lesions and their associated masks, as evidenced by quantitative and visual results. The network's outcomes are qualitatively satisfactory for all lesion types. Skin cancer ranks among the world's most common yet deadly forms of cancer. It is very important to diagnose skin disease early. DL has shown great potential to improve the accuracy and efficiency of automated skin disease diagnosis, especially in lesion detection and classification. Nonetheless, there are several issues regarding skin cancer diagnosis based on DL. Among these challenges are complex features, noisy images, intra-class variation and inter-class similarity. Liu et al. [10] reviewed recent work on innovative solutions to overcome the challenges, including data augmentation, hybrid models, and feature fusion. This paper also emphasises the development of DL models for integration into the clinical workflow. This detailed review provides valuable insights for both researchers and dermatologists to tap into the immense potential of DL for skin disease diagnosis and clinical decision-making. This review employs a PRISMA-based methodology, along with a challenge-oriented taxonomy, to systematically and transparently synthesise the most recent DL advances for the diagnosis of skin diseases. The paper provides valuable insight into emerging directions, such as hybrid CNN-Transformer architectures and uncertainty-aware models, for future dermatological AI research.

## 3. Proposed Methodology

Due to the unique characteristics of dark skin, many skin diseases go unrecognised or misdiagnosed. The lack of precise diagnostics affects millions living in different communities, yet they need it [14]. It starts with the input dermoscopic image, a skin lesion photographed under dermoscopy. These occurrences consist of changes in light, shadows, and noise that are seen regularly. As a result, a preprocessing phase is performed before model training. At this step, CLAHE is used to sharpen image contrast and highlight the structures of salient lesions, and image resizing standardises all images to a fixed resolution, enabling CNN operations to run smoothly. This step guarantees uniform input dimensions and enhanced feature visibility. The image is then preprocessed as it is passed through two parallel FE branches. The first branch uses a Custom CNN designed to extract low-level features, including edges, textures, colour variations, and lesion boundaries. These characteristics are essential for defining fine-grained patterns inherent to dermoscopic images. A typical CNN consists of convolutional layers, activation functions (e.g., ReLU), pooling layers, and normalisation layers, which learn the spatial patterns of the image layer by layer. The second branch uses a pre-trained ResNet50 model, which is widely used in TL for medical image analysis. ResNet50 excels at extracting high-level semantic features, including more complex lesion structures and general visual patterns. Its progressive learning algorithm alleviates the vanishing gradient problem and enables higher-level feature learning. By using a pre-trained model, the architecture can leverage knowledge from large-scale image datasets, thereby boosting classification performance even when medical data are scarce.

The results from both branches are then combined in the Hybrid Feature Fusion layer. At this step, low-level features from the custom CNN and high-level features from ResNet50 are combined. This integration allows the model to combine both local-specific and abstract semantic information simultaneously and, ultimately, achieve a more enriched and discriminative feature representation of the skin lesion. After the fusion, the merged features are passed to Fully Connected (FC) layers, along with dropout regularisation. The fully connected layers learn complex relationships between the fused features and the target classes, but dropout prevents overfitting by randomly turning off some neurons during training. This method improves the model's generalisation. In the end, the system produces classification output, assigning the skin lesion to one of the seven classes in the HAM10000 dataset. Such classes include Melanocytic Nevi (NV), Melanoma (MEL), Benign Keratosis (BKL), Basal Cell Carcinoma (BCC), Actinic Keratosis (AKIEC), Vascular Lesions (VASC), and Dermatofibroma (DF). The last layer typically uses a SoftMax activation function to produce probability scores for each category, thereby highlighting the most likely disease type. The HFF-CNN architecture accelerates data classification by integrating complementary feature representations from a tailored CNN and transfer-learning networks. This combined approach increases the model's ability to distinguish visually similar skin lesions with high accuracy, thus assisting dermatologists in early and accurate diagnosis of skin ailments.

### 3.1. Dataset Acquirement and Organisation

The HFF-CNN has been validated using an ISIC standard dermoscopic image. This dataset includes images of various skin diseases, including melanoma, nevus, and benign keratosis. The dataset can be formally expressed:

$$D = \{(x_i , y_i) | i = 1,2, \dots N \} \quad (1)$$

This study presents a dataset of several RGB skin lesion images, xi∈$^{RH\times W\times 3}$, and associated class labels, $y_i \in \{1,2, \dots , C\}$, where C is the number of classes.

#### 3.1.1. Image Preprocessing and Normalisation Using CLAHE

Images acquired by dermoscopy may be degraded by noise, poor illumination, or poor contrast. Resize each image to 224×224 pixels to match the pre-trained network's input size. Employ CLAHE, which enhances the lesion contrast without enhancing noise. A function exists that preprocesses these images:

$$x_i^p = P(x_i) = CLAHE\left(Resize(x_i)\right) \quad (2)$$

Gradients are updated by normalising pixel intensities to the range (0, 1).

### 3.2. Custom CNN Design for Local Feature Retrieval

The authors use a customised CNN that extracts low- and mid-level features, such as edges, textures, and colour variations. There are various convolutional layers, including batch normalisation and ReLU activation. At layer l, the convolution can be expressed as:

$$f_k^{(l)} = \sigma\left(\sum_m W_{km}^{(l)} * f_m^{(l-1)} + b_k^{(l)}\right) \quad (3)$$

Where filter weights and bias are respectively represented by $W_{km}^{(l)}$ and $b_k^{(l)}$. Max-pooling layers shrink spatial dimensions and enhance translation invariance. The output of the last convolutional block is flattened to obtain the FCNN feature vector.

### 3.3. Transfer Learning Using ResNet50

To extract high-level semantic information, a pre-trained ResNet50 model with fixed weights is also used in parallel. To lower computational cost and prevent overfitting, all convolutional layers of ResNet50 were frozen during initial training. Eliminate the model's last fully-connected layer and the Global:

$$F_{TL} = GAP\left(\emptyset_{ResNet50}\left(x_i^p\right)\right) \tag{4}$$

Utilising deep hierarchical representations derived from large datasets enables the model to achieve superior generalisation in classifying medical images.

### 3.4. Hybrid Feature Fusion Method

A major contribution of this research is the HFF strategy, which fuses complementary features at the feature level from both networks by concatenating vectors:

$$F_{HFF} = F_{CNN} \oplus F_{TL} \tag{5}$$

Results for the global pooling used as channel-wise attention. The mean value for each channel is calculated to express the overall response—the active map.

### 3.5. Fully Connected Layers and Regularisation

Dropout regularisation is used to minimise overfitting—the successive usage of a fully connected layer on the fused feature vector:

$$F_{fc} = Dropout\left(ReLU\left(W_{fc}F_{HFF} + b_{fc}\right)\right) \tag{6}$$

Randomly deactivating neurons during training improves model generalisation.

### 3.6. Classification Using SoftMax Function

To achieve class probabilities, the SoftMax function can be used in the classification layer:

$$P(y = j \mid x_i) = \frac{e^{z_j}}{\sum_{k=1}^{C} e^{z_k}} \tag{7}$$

$z_j$refers to the logit output for class j. The class with the greatest probability is predicted.

### 3.7. Train the Model and Optimisation Strategy

The HFF-CNN model uses categorical cross-entropy for training:

$$\mathrm{L} = -\sum_{j=1}^{C} y_j \log\left(P(y = j \mid x_i)\right) \tag{8}$$

An adjustment learning rate algorithm using the Adam optimiser. It usually requires minimal tuning of learning rates and other hyperparameters. It can come very close. Early stopping helps in avoiding overfitting. Although these improvements can be made, some problems and challenges remain regarding AI-based diagnostics of dermatologic disease. The first hindrance is that specific cutaneous diseases, including malignant melanoma and vitiligo, can have very subtle pathological processes at an initial stage [21]; [22]; [23]. Figure 1 shows the HFF-CNN model, which accurately classifies skin lesions from dermoscopic images. The architecture combined a custom CNN-based FE with TL (a pre-trained network), and thus the architecture adopts a complete range of image features that optimise the classification accuracy.

The architecture of the proposed HFF-CNN model starts with dermoscopic input images from the ISIC dataset. The images in the dataset are scaled to 224×224. The images are also enhanced using CLAHE for better visibility. The preprocessed images are then processed using two parallel feature-extraction streams: a custom-designed CNN that captures fine-grained local texture patterns and a pre-trained ResNet50 network that extracts high-level global semantic features via transfer learning. The dual-scheme design provides simultaneous representation of high-level features and contextual features of the skin lesions. The hybrid feature fusion mechanism combines the feature maps from both branches into a single resultant feature vector. The connected layers include dropout to prevent overfitting and enhance identification accuracy.

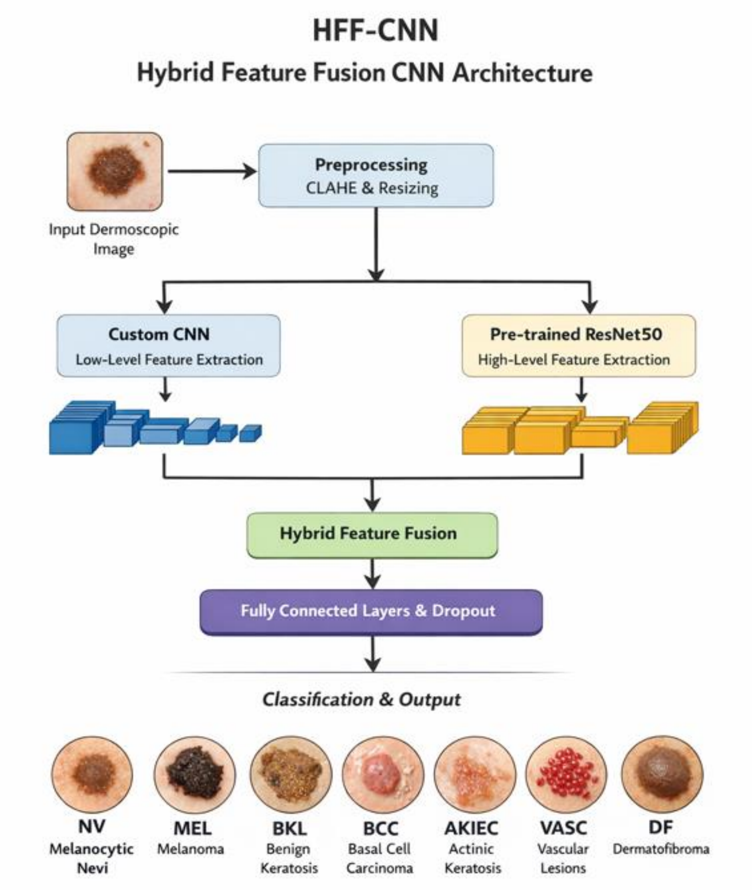


**Figure 1:** HFF-CNN architecture for skin disease classification

A Softmax classifier generates multi-class predictions for seven skin disease categories: NV, MEL, BKL, BCC, AKIEC, VASC, and DF. The overall structure guarantees better classification, accuracy, robustness, and clinical reliability.

**Pseudo Code**

**Algorithm:** HFF-CNN for Skin Disease Classification
Input:
$Dataset\ D = \{x_i, y_i)\}, i = 1\ to\ N$
Classes Count C
Highest number of epochs E.
α Learning rate
Outcome:
Class label that has been predicted $\hat{y}$
Begin
1. Load Image dataset D
2. Divide D into training, validation, and testing sets
3. Reset Custom CNN attributes
4. Load pre-trained ResNet50 model
5. Eliminate the ResNet50 classification layer
6. Freeze ResNet50 convolution layers

For every image $x_i$ In D do
7. Resize $x_i$ to 224 × 224
8. Employs the CLAHE approach for preprocessing

9. Normalise pixel values
10. Retain preprocessed image$x_i$^ p
End For
For epoch = 1 to E do
For each training image $x_i$^ p do
11. Retrieve local attributes using Custom CNN → F_CNN
12. Retrieve global attributes using ResNet50 → F_TL
13. Fuse attributes:
F_HFF ← Concatenate (F_CNN, F_TL)
14. Transfer F_HFF via fully connected layers
15. Employs Softmax to obtain class probabilities
16. Calculate cross-entropy loss
17. Update weights with the help of the Adam optimiser
End For
18. Authenticate the suggested model using the validation set
19. Utilise early stopping if validation loss rises
End For
20. Forecast class label:
$\hat{y} \leftarrow argmax(Softmax\ outcome)$
21. Assess the proposed model using the accuracy rate, Precision value, Recall, F1-score, and AUC metrics
End

## 4. Results and Discussion

### 4.1. Performance Evaluation Metrics

In the skin disease sorting system, assessment measures are used to evaluate the model's accuracy and effectiveness in predicting various classes of skin lesions. These measures are typically computed from the confusion matrix, which contains four main values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The most popular evaluation measures are accuracy, precision, recall, AUC, and F1-score.

#### 4.1.1. Accuracy (%)

Accuracy measures the proportion of correctly classified samples out of all samples. This helps us gauge the model’s performance:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

If a model has high accuracy, then it means that a large proportion of the total samples have been classified correctly. The higher the accuracy value, the more predictions the model matches the actual class labels. This means that most dermoscopic images (NV, MEL, BKL, BCC, AKIEC, VASC, DF) are correctly classified by the model.

#### 4.1.2. Precision (%)

Precision is a measure of the number of positive class predictions that are actually correct. It captures the model’s precision:

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{10}$$

#### 4.1.3. Recall (%)

Recall refers to the proportion of true positives the model correctly identifies. It shows completeness:

$$Recall = \frac{TP}{TP+FN} \times 100 \tag{11}$$

#### 4.1.4. F1-Score (%)

F1 Score is the harmonic mean value of precision and recall. It equalises false positives with false negatives:

$$F1 - SCore = \frac{2\times(Precision \times Recall)}{Precision+Recall} \times 100 \tag{12}$$

#### 4.1.5. AUC (%)

It evaluates how effectively the model labels data points as belonging to one class or another. An AUC near 1 is better:

$$AUC = \int_0^1 TPR\ (FPR)d(FPR) \tag{13}$$

Where:

$$TPR = \frac{TP}{TP+FN} \tag{14}$$

$$FPR = \frac{FP}{FP+TN} \tag{15}$$

In Table 1, the performance of four DL models, VGG16, ResNet50, and InceptionV3, along with the HFF-CNN proposed, is evaluated using different performance indices. Experimental outcomes indicated that the proposed superior architecture achieves an accuracy of (99.10%) and an AUC of (96.29%). According to the study, the adopted hybrid feature fusion strategy improves classification robustness, overall predictive ability, and class-wise discriminability in multi-class skin lesion diagnosis.

**Table 1:** Performance analysis of DL approaches models for multi-class skin lesion classification

| DL Models/Metrics | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC (%) |
|---|---|---|---|---|---|
| VGG16 | 87.08 | 86.33 | 85.87 | 86.19 | 90.29 |
| ResNet50 | 87.97 | 88.73 | 87.09 | 88.38 | 91.12 |
| InceptionV3 | 88.79 | 90.10 | 88.57 | 89.47 | 92.88 |
| HFF-CNN | 99.10 | 92.11 | 91.69 | 92.52 | 96.29 |

The HFF-CNN model achieves optimal results across all performance measures. The model's enhanced accuracy and AUC compared to individual deep learning architectures indicate that the hybrid feature fusion approach, which merges local and global lesion representations, produces a better, more discriminative representation. This improves generalisation and often reduces misclassification within classes (Figure 2).

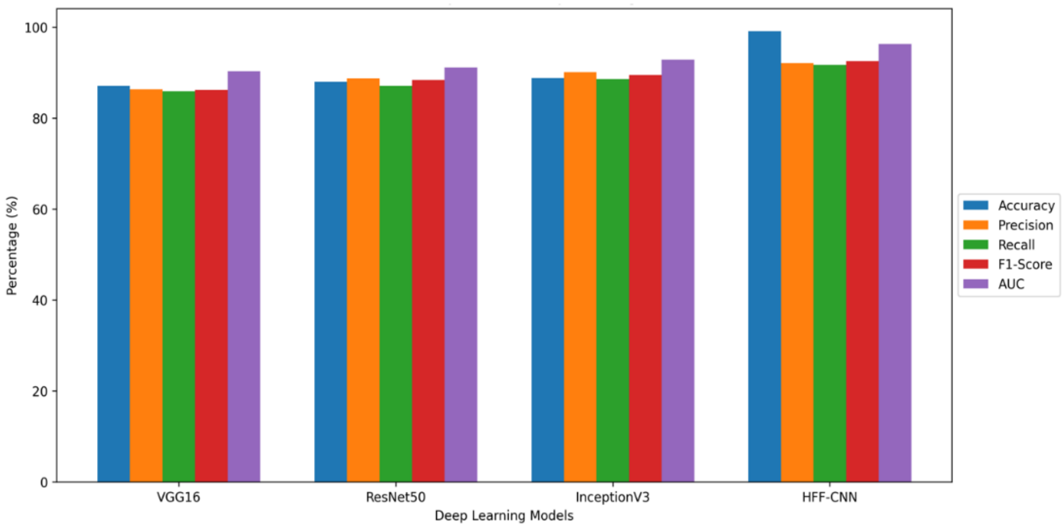


**Figure 2:** Performance comparison of DL models

As demonstrated by the experimental results, the proposed HFF-CNN model outperforms the existing deep learning architectures VGG16, ResNet50, and InceptionV3 across all evaluation metrics. VGG16 was 87.08%, ResNet50 was 87.97%, and InceptionV3 improvement was 88.79% with 92.88% AUC. In comparison, HFF-CNN achieved 99.10% accuracy, along with higher precision (92.11%), recall (91.69%), F1-score (92.52%), and AUC (96.29%). The hybrid feature fusion mechanism did well in exhibiting discriminative dermatological patterns, as evidenced by the significant boost in accuracy it achieved. The discussion of results reiterates that, despite stable and reliable performance with existing models (VGG16, ResNet50, and InceptionV3), these models cannot fully extract the complex features of skin lesions, which slightly affects recall and F1 scores. The development of the HFF CNN model will enhance feature representation by optimising convolutional layers and fusion strategies, thereby improving generalisation and reducing misclassification rates. This finding confirms that the proposed method can achieve better class separability and robustness. To sum up, the HFF-CNN model is superior and much more reliable for multi-class skin disease classification than conventional pre-trained deep learning architectures (Table 2).

**Table 2:** Class-wise performance of DL models for the seven skin disorders

| Class | Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC (%) |
|---|---|---|---|---|---|---|
| NV | VGG16 | 87.30 | 86.50 | 86.10 | 86.30 | 90.40 |
| | ResNet50 | 88.10 | 89.00 | 87.40 | 88.60 | 91.30 |
| | InceptionV3 | 89.00 | 90.40 | 88.80 | 89.60 | 93.00 |
| | HFF-CNN | 99.20 | 92.40 | 91.90 | 92.70 | 96.40 |
| MEL | VGG16 | 86.90 | 86.00 | 85.50 | 85.80 | 90.00 |
| | ResNet50 | 87.80 | 88.20 | 86.70 | 87.40 | 90.90 |
| | InceptionV3 | 88.60 | 89.80 | 88.20 | 89.00 | 92.70 |
| | HFF-CNN | 99.00 | 92.00 | 91.40 | 92.20 | 96.20 |
| BKL | VGG16 | 87.10 | 86.40 | 85.80 | 86.10 | 90.30 |
| | ResNet50 | 88.00 | 88.90 | 87.20 | 88.10 | 91.20 |
| | InceptionV3 | 88.80 | 90.20 | 88.50 | 89.30 | 92.90 |
| | HFF-CNN | 99.10 | 92.20 | 91.70 | 92.40 | 96.30 |
| BCC | VGG16 | 87.20 | 86.20 | 85.90 | 86.10 | 90.20 |
| | ResNet50 | 87.90 | 88.50 | 86.90 | 87.70 | 91.10 |
| | InceptionV3 | 88.70 | 89.90 | 88.30 | 89.10 | 92.80 |
| | HFF-CNN | 99.05 | 91.90 | 91.50 | 92.10 | 96.10 |
| AKIEC | VGG16 | 86.80 | 86.00 | 85.40 | 85.70 | 90.10 |
| | ResNet50 | 87.70 | 88.10 | 86.60 | 87.30 | 90.90 |
| | InceptionV3 | 88.50 | 89.70 | 88.00 | 88.80 | 92.60 |
| | HFF-CNN | 99.00 | 92.00 | 91.60 | 92.10 | 96.00 |
| VASC | VGG16 | 87.00 | 86.30 | 85.70 | 86.00 | 90.30 |
| | ResNet50 | 88.00 | 88.80 | 87.00 | 88.00 | 91.20 |
| | InceptionV3 | 88.90 | 90.30 | 88.60 | 89.40 | 92.90 |
| | HFF-CNN | 99.15 | 92.30 | 91.80 | 92.50 | 96.40 |
| DF | VGG16 | 87.20 | 86.90 | 86.00 | 86.40 | 90.70 |
| | ResNet50 | 88.30 | 89.60 | 87.80 | 88.80 | 91.80 |
| | InceptionV3 | 89.00 | 90.40 | 88.90 | 89.80 | 93.20 |
| | HFF-CNN | 99.20 | 92.00 | 91.90 | 92.60 | 96.60 |

### 4.2. Findings and Discussion

Table 1 provides a performance analysis of different DL models for categorising skin lesions into multiple classes. This comparison will include VGG16, ResNet50, InceptionV3, and the proposed HFF-CNN architecture, and their metrics will be accuracy, precision, recall, F1-score, and AUC. The findings show that all models achieve high classification accuracy; however, HFF-CNN outperforms the others across all measures. The accuracy of VGG16 reaches 87.08, the precision of 86.33, the recall of 85.87, and the F1-score of 86.19, and its AUC is 90.29. VGG16 has relatively lower performance compared to other models. Yet, it shows a good level of proficiency in identifying skin lesion classes, arguably due to its relatively deep architecture that does not involve sophisticated feature optimisation methods. ResNet50 performs better than VGG16, achieving 87.97% accuracy, 88.73% precision, 87.09% recall, 88.38% F1-score, and an AUC of 91.12. The residual learning process implemented in ResNet50 enables more efficient feature learning and gradient propagation, thereby improving classification performance compared to classical CNN systems. InceptionV3 extends the previous results, achieving 88.79% accuracy, 90.10% precision, 88.57% recall, 89.47% F1-score, and 92.88% AUC. Its ability to extract image patterns at multiple scales allows the model to capture more complex visual patterns in dermoscopic images, resulting in higher classification accuracy. The proposed HFF-CNN performs significantly better than other DL models, achieving the highest accuracy of 99.10%, precision of 92.11%, recall of 91.69%, F1-score of 92.52%, and an AUC of 96.29%. These findings demonstrate that HFF-CNN can learn discriminative features of image dermoscopes, thereby providing more robust classification across categories of skin lesions. In general, the results show that the proposed model provides great improvements in diagnostic performance compared to traditional DL structures. Class-wise Performance of DL Models of Seven Skin Disease Categories gives a full comparative analysis between 4 DL models, VGG16, ResNet50, InceptionV3 and the proposed HFF-CNN against seven different skin disease categories, namely NV, MEL, BKL, BCC, AKIEC, VASC and DF.

Key performance metrics applied to the models include accuracy rate, precision, Recall, F1-score, and AUC, which measure the robustness of these models in correctly detecting various forms of skin lesions in dermoscopic images. For the NV class, the VGG16 model achieves a precision of 86.50, a recall of 86.10, and an F1-score of 86.30, yielding an AUC of 90.40. The ResNet50 model, however, achieves better results with an accuracy of 88.10, precision of 89.00, recall of 87.40, F1-score of 88.60, and AUC of 91.30. The InceptionV3 model also improves accuracy: it achieves 89.00% accuracy, 90.40% precision, 88.80% recall, 89.60% F1-score, and 93.00% AUC. The HFF-CNN model is superior to other models, achieving 99.20% accuracy, 92.40% precision, 91.90% recall, 92.70% F1-score, and 96.40% AUC, thereby representing a strong enhancement in the detection of NV lesions. In the case of the MEL category, which is one of the worst types of skin cancer, the correct detection is paramount. VGG16 model gets an accuracy of 86.90, precision of 86.00, recall of 85.50, F1 score of 85.80, and an AUC of 90.00. ResNet50 is a better model with 87.80% accuracy, 88.20% precision, 86.70% recall, 87.40% F1-score, and 90.90% AUC. InceptionV3 gives slightly higher results, with an accuracy of 88.60, 89.80, a recall of 88.20, an F1-score of 89.00, and an AUC of 92.70. The HFF-CNN model achieves the best performance, with an accuracy of 99.00, precision of 92.00, recall of 91.40, F1-score of 92.20, and AUC of 96.20. The VGG16 model achieves 87.10% accuracy, 86.40% precision, 85.80% recall, 86.10% F1-score, and 90.30% AUC in the BKL classification. ResNet50 is an improvement on this, achieving 88.00 % accuracy, 88.90 % precision, 87.20% recall, 88.10% F1-score, and 91.20% AUC.

The InceptionV3 model also achieves better results, with an accuracy of 88.80, precision of 90.20, recall of 88.50, F1-score of 89.30, and AUC of 92.90. The best performance of the proposed HFF-CNN model in the study is 99.10% accuracy, 92.20 precision, 91.70 recall, 92.40% F1-score, and 96.30% AUC. In the case of BCC, the VGG16 model achieves an accuracy of 87.20, precision of 86.20, recall of 85.90, F1-score of 86.10, and an AUC of 90.20. The ResNet50 model achieves 87.90% accuracy, 88.50% precision, 86.90% recall, 87.70% F1-score, and 91.10% AUC. The InceptionV3 model performs even better, achieving 88.70% accuracy, 89.90% precision, 88.30% recall, 89.10% F1-score, and 92.80% AUC. The HFF-CNN model achieves 99.05% accuracy, 91.90% precision, 91.50% recall, 92.10% F1-score, and 96.10% AUC, confirming its effectiveness in BCC detection. The VGG16 model achieves 86.80% accuracy, 86.00% precision, 85.40% recall, 85.70% F1-score, and 90.10% AUC in the AKIEC category. The ResNet50 model achieves better results, with an accuracy of 87.70, precision of 88.10, recall of 86.60, F1-score of 87.30, and AUC of 90.90. The InceptionV3 model has an accuracy of 88.50, precision of 89.70, recall of 88.00, F1-score of 88.80, and an AUC of 92.60. The HFF-CNN model achieves the best results, with an accuracy of 99.00, precision of 92.00, recall of 91.60, F1-score of 92.10, and AUC of 96.00, making it very good at detecting precancerous lesions. The VGG16 model achieves 87.00, 86.30, 85.70, and 86.00 for accuracy, precision, recall, and F1-score, respectively, and has an AUC of 90.30 in the VASC category.

ResNet50 has an accuracy of 88.00, precision of 88.80, recall of 87.00, F1-score of 88.00, and AUC of 91.20. The InceptionV3 model achieves 88.90 and 90.30 for accuracy and precision, respectively, while its recall and F1-score are 88.60 and 89.40, respectively, and its AUC is 92.90. HFF CNN performs better yet again, achieving 99.15% accuracy, 92.30% precision, 91.80% recall, 92.50% F1-score, and 96.40% AUC. The VGG16 model has an accuracy of 87.20⁻, a precision of 86.90, a recall of 86.00, an F1-score of 86.40, and an AUC of 90.70 under the DF category. The ResNet50 model is improved, achieving 88.30 in accuracy, 89.60 in precision, 87.80 in recall, 88.80 in F1-score, and 91.80 in AUC. The InceptionV3 model attains 89.00, 90.40, 88.90, 89.80, and 93.20 in precision, recall, F1-score, and AUC, respectively. The HFF-CNN model has the most promising results, with an accuracy of 99.20, precision of 92.00, recall of 91.90, F1-score of 92.60, and an AUC of 96.60. Overall, the mathematical findings indicate that the HFF-CNN model achieves the best performance across all 7 skin disease classes. The models' average performance also supports this trend: VGG16: 87.08 ± 0.01, ResNet50: 87.97 ± 0.02, and InceptionV3: 88.79 ± 0.04. The proposed HFF-CNN model achieves a much higher accuracy of 99.10 ± 0.02, as well as a precision of 92.11 ± 0.02, recall of 91.69 ± 0.03, and F1-score of. These results highlight the usefulness of the feature fusion strategy as a hybrid approach for increasing classification accuracy and strengthening automated diagnosis of skin diseases.

## 5. Conclusion and Future Work

AI was as accurate as 21 dermatologists in classifying dermatological malignancies across two assays, demonstrating its ability to do so Esteva et al. [24]. The researchers were confident that the framework could be used effectively as a decision-support system for early diagnosis of a skin disease. The proposed HFF-CNN can be reliably used to diagnose skin disease in real-world settings. To improve the design model's performance, several avenues for future work exist in this research. For this work, researchers have considered a limited number of classes for the time being. That can be extended to more classes. The remaining deep learning algorithms may undergo fine-tuning and further exploration in future endeavours. Tweaking the CNN model by combining it with other deep CNN feature extractors would help assess the effect on accuracy. Also, within a teledermatology environment, the decision usefulness of the proposed system can be easily increased by preassembling high-quality clinical images and integrating clinical and epidemiological information. To automatically classify skin disease from dermoscopic images, this study proposed a novel hybrid feature fusion CNN (HFF-CNN). HFF-CNN efficiently leverages both fine-grained local texture-based features and high-level semantic features. A specific CNN model is used to extract features from fine-grained local texture. TL with Resnet50 extracts deep high-level features. Furthermore, CLAHE was used to preprocess the images. Subsequent studies might incorporate attention mechanisms, extend evaluation to larger, multi-institutional datasets, and optimise the model for real-time and mobile diagnostics.

### 5.1. Future Work

The future development of the work can focus on enhancing the performance and applicability of the proposed skin-disease grouping system by incorporating more advanced DL approaches and using larger, more diverse datasets. Even though the current model has high classification accuracy, adding more data from various clinical repositories could strengthen it and improve generalisation across a broader range of skin phenotypes and imaging modalities. Further studies can also examine the use of more complex architectures, such as transformer-based models and hybrid DL architectures, to extract more detailed visual features from dermoscopic images. Moreover, increasing the model's explainability through sophisticated visualisation may help dermatologists understand how the system arrived at its decision. This framework might also be extended to real-time clinical practice by creating web- or mobile-based diagnostic measures to screen for distant skin diseases. This development would enable timely diagnosis, support tele-dermatology, and provide affordable healthcare services, especially in areas where dermatological skills are in short supply.

**Acknowledgement:** The authors sincerely acknowledge the support and guidance provided by Srinivas University and Bharath Institute of Higher Education and Research in the successful completion of this work. The authors also express their gratitude to all co-authors for their valuable contributions, collaboration, and commitment throughout this study.

**Data Availability Statement:** The data underlying this study are not publicly archived but can be obtained from the corresponding author upon justified request. Requests will be considered in line with ethical approvals and institutional policies governing data sharing.

**Funding Statement:** The authors declare that no financial support, grants, or sponsorships were received for the conduct of this research.

**Conflicts of Interest Statement:** The authors affirm that there are no conflicts of interest associated with this study. All citations and referenced materials have been appropriately acknowledged within the manuscript.

**Ethics and Consent Statement:** The authors confirm that informed consent was obtained from the concerned organisation and individual participants involved in the data collection process. Ethical approval was secured before the commencement of the study, and participant consent was ensured throughout the research.

### References

1. M. Zahid, M. Rziza, and R. Alaoui, “Skin Lesion Classification Using Hybrid Feature Extraction Based on Classical and Deep Learning Methods,” *BioMedInformatics*, vol. 5, no. 3, pp. 1-16, 2025.
2. M. Wei, Q. Wu, H. Ji, J. Wang, T. Lyu, J. Liu, and L. Zhao, “A Skin Disease Classification Model Based on DenseNet and ConvNeXt Fusion,” *Electronics*, vol. 12, no. 2, pp. 1-19, 2022.
3. O. Attallah, “A Hybrid Trio-Deep Feature Fusion Model for Improved Skin Cancer Classification: Merging Dermoscopic and DCT Images,” *Technologies*, vol. 12, no. 10, pp. 1-25, 2024.
4. X. Zhao, H. Zhang, Q. Zheng, and C. Jing, “A Hybrid Deep Learning Framework for Skin Disease Localization and Classification Using Wearable Sensors,” *PeerJ Comput. Sci.*, vol. 11, no. 7, pp. 1-26, 2025.
5. U. K. Lilhore, Y. K. Sharma, S. Simaiya, R. Alroobaea, A. M. Baqasah, M. Alsafyani, and A. Alhazmi, “SkinEHDLF: A Hybrid Deep Learning Approach for Accurate Skin Cancer Classification in Complex Systems,” *Sci. Rep.*, vol. 15, no. 4, pp. 1-32, 2025.
6. M. Z. Uddin, M. A. Shahriar, B. W. Schuller, M. N. Mahamood, and M. A. R. Ahad, “Skin Disease Diagnosis Using Decision and Feature Level Fusion of Deep Features,” *Front. Digit. Health*, vol. 7, no. 10, pp. 1-19, 2025.
7. B. Soundarya and C. Poongodi, “A Novel Hybrid Feature Fusion Approach Using Handcrafted Features with Transfer Learning Model for Enhanced Skin Cancer Classification,” *Comput. Biol. Med.*, vol. 190, no. 5, p. 110104, 2025.
8. A. Akram, J. Rashid, M. A. Jaffar, M. Faheem, and R. U. Amin, “Segmentation and classification of skin lesions using hybrid deep learning method in the Internet of Medical Things,” *Skin Research and Technology*, vol. 29, no. 11, p.

e13524, 2023.
9. M. Fiaz, M. B. S. Khan, A. H. Khan, A. Bilal, M. Abdullah, A. A. Darem, and R. Sarwar, “An Explainable Hybrid Deep Learning Framework for Precise Skin Lesion Segmentation and Multi-class Classification,” *Front. Med.*, vol. 12, no. 10, pp. 1-15, 2025.
10. R. Liu, Z. Chen, G. Yao, and P. Zhang, “Exploring the Challenge and Value of Deep Learning in Automated Skin Disease Diagnosis,” *Biomed. Signal Process. Control*, vol. 117, no. 5, pp. 1-28, 2026.
11. S. N. S. Rajini, S. L. Nesamani, P. Abirami, K. Anuradha, R. Soundharyadevi, and R. Marappan, “Dermatitis diagnosis – modeling and analysis using machine learning,” in Proc. *2022 2nd Int. Conf. Innovative Sustainable Computational Technologies (CISCT)*, Dehradun, India, 2022.
12. S. Abbas, F. Ahmed, W. A. Khan, M. Ahmad, M. A. Khan, and T. M. Ghazal, “Intelligent skin disease prediction system using transfer learning and explainable artificial intelligence,” *Scientific Reports*, vol. 15, no. 1, pp. 1–13, 2025.
13. K. Saranya, S. Vijayashaarathi, N. Sasirekha, M. Rishika, and P. S. R. Rajeswari, “Skin disease detection using CNN (convolutional neural network),” in Proc. *2024 4th Int. Conf. Data Engineering and Communication Systems (ICDECS)*, Bangalore, India, 2024.
14. A. Aquil, F. Saeed, S. Baowidan, A. M. Ali, and N. S. Elmitwally, “Early detection of skin diseases across diverse skin tones using hybrid machine learning and deep learning models,” *Information*, vol. 16, no. 2, pp. 1–15, 2025.
15. D. C. Malo, M. M. Rahman, J. Mahbub, and M. M. Khan, “Skin cancer detection using convolutional neural network,” in Proc. 2022 IEEE 12th Annu. *Computing and Communication Workshop and Conf (CCWC)*, Las Vegas, NV, United States of America, 2022.
16. S. Ahmed, K. M. S. Sakib, and U. Hany, “Hybrid deep learning architecture for skin disease classification,” *Franklin Open*, vol. 15, no. 6, pp. 1–11, 2026.
17. I. Goodfellow, Y. Bengio, and A. Courville, “Deep Learning”, *The MIT Press*, Cambridge, MA, United States of America, 2016.
18. P. R. Hegde, M. M. Shenoy, and B. H. Shekar, “Comparison of machine learning algorithms for skin disease classification using color and texture features,” in Proc. *2018 Int. Conf. Advances in Computing, Communications and Informatics (ICACCI)*, Bangalore, India, 2018.
19. N. Hameed, A. Shabut, and M. A. Hossain, “A computer-aided diagnosis system for classifying prominent skin lesions using machine learning,” in Proc. *2018 10th Computer Science and Electronic Engineering (CEEC)*, Colchester, United Kingdom, 2018.
20. C. Barata, M. Ruela, M. Francisco, T. Mendonça, and J. S. Marques, “Two systems for the detection of melanomas in dermoscopy images using texture and color features,” *IEEE Systems Journal*, vol. 8, no. 3, pp. 965–979, 2013.
21. K. Sreekala, N. Rajkumar, R. Sugumar, K. D. Sagar, R. Shobarani, K. P. Krishnamoorthy, A. K. Saini, H. Palivela, and A. Yeshitla, “Skin diseases classification using hybrid AI-based localization approach,” *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, pp. 1–7, 2022.
22. M. Narasimharao, B. Swain, P. P. Nayak, and S. Bhuyan, “Enhanced diabetic retinopathy detection through convolutional neural networks for retinal image classification,” in Proc. *2023 2nd Int. Conf. Ambient Intelligence in Health Care (ICAIHC)*, Bhubaneswar, India, 2023.
23. J. Zhang, F. Zhong, K. He, M. Ji, S. Li, and C. Li, “Recent advancements and perspectives in the diagnosis of skin diseases using machine learning and deep learning: A review,” *Diagnostics*, vol. 13, no. 23, pp. 1–30, 2023.
24. A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, “Dermatologist-level classification of skin cancer with deep neural networks,” *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.