International Journal of Applied Mathematics

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

STATE-OF-THE-ART IN SKIN DISEASE RECOGNITION AND CLASSIFICATION: AN IN-DEPTH ANALYSIS OF HYBRID DEEP LEARNING MODELS AND OPTIMIZATION TECHNIQUES

Namrata Gajare [1,2]*, Pranoti Mane [3]

[1] Department of Electronics & Telecommunication, Vishwakarma Institute of Technology

[2] Assistant Professor, Department of Electronics & Telecommunications, MES's Wadia College of Engineering, Pune. Email: namrata.gajare@gmail.com

[3] Associate Professor and HOD, Department of Electronics & Telecommunications, MES's Wadia College of Engineering, Pune. Email: ppranotimane@gmail.com

Corresponding Author Email: namrata.gajare@gmail.com

Abstract

Research on computer-aided systems for skin lesion diagnosis is expanding. Researchers' interest in creating computer-aided diagnosis systems has grown recently. A visual examination is a useful tool for detecting skin tumors, and dermoscopic research and other investigations can confirm the diagnosis. This is so that distinct skin pictures can be identified early on by eye inspection. In the realm of medical procedures, skin disorders are among the most prevalent, and when opposed to other condition kinds, they are more visibly represented. Thus, the application of deep learning strategies for skin conditions Investigators are interested in the identification of images because of their importance. The use of deep learning techniques for illness diagnosis has emerged as a new area of medical research interest. Skin diseases are among the most prevalent in the medical field, and when compared to other disease types, they are more visibly represented. At the early stages of a skin condition, it assists physicians and patients in determining the type of disease based on an image of the affected area. Thus, deep learning techniques are becoming increasingly important for the identification of skin diseases in images, and this has researchers interested. In this study, we examine the use of Hybrid deep learning technology to identify skin diseases, Hybrid deep learning framework, model performance, and model for image recognition of skin diseases. In addition, we assess the state of this field's development and forecast four potential future research areas. Our findings demonstrate that the deep learning-based approach to skin disease image recognition outperforms dermatologists' methods and other computer-aided treatment techniques in the diagnosis of skin diseases. Specifically, the multi-deep learning model fusion method exhibits the best recognition efficacy.

Received: July 20, 2025

***Keyword**:* skin disease, Hybrid Deep learning, Image Classification, image recognition, skin lesion classification, dermatology.

1. Introduction

The largest organ in the human body, the skin, serves as a crucial barrier. The primary roles of the skin are to shield the body from dangerous substances found in the environment and to stop different nutrients from leaving the body [1]. Numerous factors, including sun radiation, smoking, drinking, engaging in sports, viruses, and working conditions, can have an impact on an individual's skin health during their productive life [2]. These elements not only compromise the integrity of skin function but also harm skin in certain ways, negatively impact health, and in extreme circumstances even endanger life. As a result, skin conditions are now among the most prevalent illnesses in the world. Between 30% and 70% of individuals belong to high-risk categories [3]. Approximately 60% of British people have skin disease, according to the British Skin Foundation Report from 2018 [4]. In the US, 5.4 million new cases of skin cancer are reported each year, and one in five people will receive a diagnosis of a cutaneous malignancy at some point in their lives. In addition to having a serious negative influence on daily activities, interpersonal relationships, internal organ damage, and even death, skin disease also claims human lives. In addition to being a mental illness, this condition can cause loneliness, depression, and even suicidal thoughts [5]. As a result, one of the main issues in medicine today is skin disease. Early detection is essential for the treatment of skin diseases to cure the condition, effectively lessen its impact, and increase the survival rate. Consider melanoma, a skin condition. Malignant neoplasms in skin diseases have dramatically increased in the past few years. Malignant melanoma (the deadliest kind) accounts for 10,000 fatalities each year in the US alone [6]. Melanoma is an extremely deadly but not fatal illness. The survival rate is 96% if aberrant skin melanocyte proliferation is discovered early on; it drops to 5% if it is discovered later [7]. Thus, minimizing the damage caused by skin disease can be achieved through early diagnosis and treatment. However, because different skin diseases are similar to one another and there aren't enough dermatologists with advanced training, the accuracy of skin disease recognition isn't perfect. Skin disease diagnosis is becoming a major scientific challenge.

The most prevalent and the most dangerous kind of cancer is skin cancer. Melanoma and non-melanoma cancer are the two most prevalent forms of the disease. Lesions of melanoma have a greater death rate. However, 90% of patients can be cured by doctors if the illness is identified early enough. Because different types of lesions share a lot of characteristics, it is difficult and inaccurate to manually classify skin lesions, which might result in incorrect detection. Because of this, the type of lesion can be reliably detected with the help of deep learning, artificial intelligence, and image-processing algorithms for the automatic classification and identification of lesions. Although an odd consistency and/or color make an injury to the skin easy to identify, a variety of diseases might present with identical indicators, making an accurate diagnosis challenging. Red dots are occasionally scattered across the skin in cases of keratosis and measles. These parallels reduce the precision of diagnoses, especially

Received: July 20, 2025

International Journal of Applied Mathematics

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

for dermatologists with under two years of clinical training. It is crucial to accurately and promptly detect skin lesions to provide the right treatment. In most cases, a quick diagnosis improves the prognosis and raises the likelihood of a full recovery. A dermatologist must complete expensive schooling and multiple years of medical practice to be trained.

The skin, which shields the body from heat, light, and infection, is the largest organ in the body. It also aids in the regulation of body temperature and the storage of water and fat. The body's danger of skin infection is one of the most significant issues with skin [21].

To tackle the problem of diagnosing and treating skin diseases, computer-aided diagnosis was employed to automatically identify skin diseases based on previously taken skin disease images [5-6]. Deep learning has swiftly advanced computer vision due to the quick development of artificial intelligence technology. The intersection of image processing, machine science, and intelligent medicine has given significant attention to the medical image processing of skin diseases, making it a crucial component. The image recognition of skin diseases has attracted the attention of numerous specialists and academics. The most recent article is a useful place to start. This article provides a comprehensive list of pertinent research on deep learning-based melanoma diagnosis [8].

For the past thirty years, a large number of researchers have worked on the classification of skin diseases. The field has gained a lot of attention and is now a hot one for research. Despite the large number of research papers on the identification and categorization of skin diseases, there remains a vacuum in the field. The majority of earlier research is centered on a single illness [6,7], and what little research has been done is insufficient to classify various diseases [8]. Several classes present a very difficult classification task because the behaviour of the skin disease is more similar.

The diagnosis of skin lesions is difficult because benign and malignant melanomas come in a variety of forms. Melanoma, basal cell carcinoma (BSC), and squamous cell carcinoma (SCC) are the three main types of irregular skin cells that are encountered in clinical practice [9].

Additionally, Merkel cell carcinoma, actinic keratosis (AKIEC), and atypical moles are three less common types of abnormal cells that are distinguished by the Skin Cancer Foundation (SCF) [10], the six types of skin lesions are shown. Atypical moles rank second in terms of harm caused by cells, after cases of melanoma. SCF [4] states that abnormal tissues can be distinguished by the following characteristics:

Actinic Keratosis (AKIEC), also known as solar keratosis, is a type of keratosis that affects the skin. It is a skin growth that is scaly and crusty. It is categorized as pre-cancer because, if untreated, it could develop into skin cancer.

Atypical moles: These benign moles, also referred to as dysplastic nevi, have a strange appearance. They may have a melanoma-like appearance, and those who have them are more

Received: July 20, 2025

likely to get melanoma in a mole or any other part of the body. They own an increased risk of melanoma;

1. The most prevalent type of skin cancer is called basal cell carcinoma (BCC). It is rare for this type of skin cancer to spread. It frequently manifests as open sores, shiny bumps, red spots, pink growths, or scars;
2. The most deadly type of skin cancer is melanoma. Though it can also be pink, red, purple, blue, or white, it is typically black or brown. Carcinogenic tumors are caused by UV radiation from sunbeds and the sun itself. If melanoma is identified and treated promptly, it is often curable; otherwise, the disease may spread to other parts of the body, making treatment difficult or even fatal;
3. Merkel cell carcinoma: This is a rare, aggressive type of skin cancer with a significant risk of spreading. It is, nevertheless, 40 times less common than melanoma;
4. The second most common type of skin cancer is squamous cell carcinoma (SCC) Open sores raised growths with a central depression, scaly red spots, or frequent signs.
5. The automated lesion classification method was limited to dermoscopic images and did not apply to images from any other domain, including industrial, MRI, satellite, or CT images.
6. To improve performance, the segmentation-based classification model for skin lesions only used Inception v4; further deep learning models should be investigated.

UV radiation-induced skin tissue damage is the primary cause of these types of skin cancer [5-11]. One typical clinical procedure for diagnosing melanoma is a visual examination by a dermatologist [12]. The clinical diagnosis's accuracy can be a little misleading [13]. Dermoscopy is a non-invasive diagnostic technique that allows morphological traits not visible with the unaided eye to be displayed, bridging the gap between clinical and dermatological dermatology. A variety of techniques, including solar scans [14], microscopy of the epiluminescence (ELM), cross-polarization epiluminescence (XLM), and side transillumination [15-18], can greatly improve the morphological details visualized. As a result, the dermatologist gets additional diagnostic standards. Compared to a non-discrete eye, dermoscopy enhances diagnostic performance by 10% to 30% [19–22]. However, because dermoscopy requires a great deal of experience to identify lesions, [23–25] reported that the diagnostic accuracy of the procedure was decreased with novice dermatologists compared to expert dermatologists [26]. Professional dermatologists have achieved 90% sensitivity and 59% specificity in identifying skin lesions, according to ref. [27]. Simultaneously, data regarding physicians with lower qualifications showed a notable decrease in general practitioners of approximately 62–63%. The first step is for a dermatologist to visually inspect the suspicious skin area to identify a cancerous lesion. Because some lesion types are similar, a proper diagnosis is crucial. Dermatologists have a 65–80% accuracy rate when diagnosing melanoma without the use of technology [28]. To conclude the visual examination in cases

Received: July 20, 2025

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

that raise suspicions, a dermatoscopic image is captured with an extremely high-resolution camera. To see the deeper layers of skin during the recording, the lighting is adjusted and a filter is applied to minimize skin reflections. The diagnosis of skin lesions improved by 49% as a result of this technical support [31]. In the end, a visual examination plus dermoscopy images produced an absolute 75–84% melanoma detection accuracy [32, 35]. For a while now, the machine learning community has been working to classify skin lesions. Smartphone apps have been used outside of hospitals [38], and automated classification of lesions is used in clinical examination to assist physicians and allow quick and inexpensive access to life-saving diagnoses [40]. Before, the majority of studies used the conventional machine learning workflow, which consists of feature extraction, segmentation, preprocessing (enhancement), and classification [41–43].

The following summarizes this research's primary contribution:

- To construct an image inpainting algorithm and Black-Hat Transformation model for hair removal.
- To create a robust segmentation model that recognizes the lesion while preserving information, thereby improving the images' suitability for additional processing, by utilizing the Grabcut technique.
- The goal is to create an accurate automatic skin disease classification model by utilizing a large enough number of pertinent features.

This study looks into the state of research on skin disease recognition in the last few years, provides an overview of the datasets that have been used, and analyzes data augmentation, image pre-processing, deep learning models, and framework performance indicators. On the one hand, dermatologists can use this study as a reference for deep learning techniques. Conversely, the literature on dermatological image recognition can be easily and rapidly retrieved by researchers thanks to this study. The rapidly advancing artificial intelligence-based diagnosis technology in the medical field, which is gaining popularity among researchers, is the basis of this survey. Artificial intelligence has shown tremendous promise in a variety of fields.

2. Systematic literature review

For the classification of skin diseases, numerous researchers put forth various methods. A variety of categories are applied to related works according to features, selection criteria, extraction methods, and models of classification. The tools and methods used in earlier studies were found and research gaps were identified by looking through several pertinent research articles in this section. The human body's largest organ, the skin is made up of the epidermis, dermis, and hypodermis. The three primary roles of the skin are thermoregulation, auspice, and sensation, which together offer the body a strong defense against environmental aggression.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The stratum corneum, an optically neutral protective layer of variable thickness, is the outermost layer of the epidermis. Keratinocytes, which produce keratin that benefits and protects the skin, make up the stratum corneum. The stratum corneum causes light to be scattered when it hits the skin. There are melanocytes in the basal layer of the epidermis. In particular, melanocytes cause the skin to produce the pigment known as melanin, which gives the skin its tan or brown tone [18-21]. Melanocytes produce more melanin, which serves as a filter to shield the skin from damaging UV rays from the sun. The concentration of melanocytes determines how much UV radiation is absorbed. Melanoma, on the other hand, is brought on by abnormal melanocyte growth. The dermis, which makes up collagen fibers, blood vessels, sensors, receptors, and nerve ends, is the middle layer of the skin. It gives the skin vigor and elasticity [32].

In [23,9] image processing-based skin disease detection was presented. Using the KNN and SVM classification algorithms in conjunction with wavelet analysis, they applied fuzzy clustering to fifty sample images. They demonstrated that, with an accuracy of 91.2%, the K-Nearest Neighbor classification algorithm outperforms the Support vector machine (SVM) classification technique. The algorithm also used classification methods to identify the type of skin disease. However, they had limited resources: 50 sample images totaling from two classes of basal and squamous disease.

A model for predicting skin cancer using support vector machines (SVMs) and image processing techniques [10, 15]. They separated a few highlights in the image using the GLCM method and a variety of pre-handling techniques for clamor evacuation and picture improvement. Ultimately, the images were categorized by the classifier as either harmful or harmless.

Machine learning (ML) and deep learning (DL) were combined in a model [16]. They used a Support Vector Machine, Decision Tree, Ensemble Boosting Adaboost classifier, and Googlenet, Resnet50, VGG16, and Alexnet deep neural networks for feature selection and classification, respectively. Lastly, they conducted a comparative analysis to determine which prediction model was the best.

A novel approach that integrates two distinct data mining techniques into one unit and an ensemble approach that combines both data mining techniques [17,28]. They classified skin disorders into seven categories by using the ensemble deep learning technique on an educational dataset of ISIC2019 images in dermatology that is publicly accessible. They found that skin diseases could be predicted more precisely and successfully by the ensemble technique.

A model for diagnosing skin diseases [40,35]. It can identify melanoma, psoriasis, acne, and cherry angiomas based on an image of the affected skin. To extract features from the Dermatnet NZ and Atlas Dermatological, they used Otsu's method for image segmentation and the Gabor, Entropy, and Sobel techniques. When it came to classification, they used

Received: July 20, 2025

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (K-NN) classifiers, and the results were 90.7%, 84.2%, and 67.1% accurate, respectively.

A system utilizing MobileNetV2 and LSTM for the classification of skin diseases [34,1]. Their primary goal was to improve the system's accuracy in predicting skin diseases and to guarantee that all necessary state data was stored with exceptional efficiency for precise forecasts. Additionally, they made comparisons with several other conventional models, including CNN and FTNN, and found that the suggested model performed better than the others in identifying skin conditions and assessing the advancement of tumor development utilizing texture-based data.

An automated method for classifying skin lesions. It involved the use of a deep learning network that had been trained and optimized. They compared the results using a range of transfer learning techniques and evaluated the performance using well-known quantitative criteria like specificity, sensitivity, precision, and accuracy.

A novel optimal probability-based deep neural network (OP-DNN) to accurately diagnose skin disease. Before extracting the features for the Optimal Probability-Based Deep Neural Networks (OP-DNN) training, they first eliminated the undesirable contents from the images. They also used an optimization technique, and the results showed 95% accuracy, 0.97 specificity, and 0.91 sensitivity.

A computer vision-based approach to identify four different kinds of skin diseases [27]. Convolutional neural networks, comprising approximately 11 layers the Convolution Layer, Activation Layer, Pooling Layer, Fully Connected Layer, and Soft-Max Classifier are the basis of the suggested methodology. Images from the DermNet database are used to verify the architecture. Although the database includes samples from every type of skin condition, it has been concentrated on four main categories: keratosis, eczema herpeticum, urticaria, and acne, each with between 30 and 60 samples. The suggested CNN Classifier has an accuracy range of 98.6% to 99.04%. However, they were limited to a small number of images with four classes. These represent the study's primary flaws.

The dermoscopic approach has improved melanoma diagnosis performance [21]. Through the use of invasive skin imaging technology called dermoscopy, skin lesions can be better visualized and made more visible. Eliminating the reflection from the skin's surface could enhance the deeper skin's effect [60]. Identification of automatically Taking dermoscopic pictures of melanoma is difficult for a variety of reasons: First, lesions' texture, scale, and color can vary within a class; second, there is a high degree of similarity between the non-melanoma and melanoma lesions; lastly, the surroundings, such as hair, veins, color calibration charts, and rule marks.

The AlexNet deep learning model and learning algorithms form the basis of the proposed skin lesion classification system. The suggested method was created and assessed using the open data set ISIC 2018 to compare it to the state-of-the-art developed model for the Alex-net,

Received: July 20, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ResNet101, and GoogleNet architectures using the principle of classification of cancer as melanoma or not using supervised learning [46].

The investigation examines the state of the field's recent research on skin disease recognition, provides an overview of the datasets researchers have used, and conducts analyses from the perspectives of deep learning models, framework performance indicators, image pre-processing, and data augmentation. Dermatologists can use this study as a reference for deep learning techniques, on the one hand. Conversely, this study makes it easier for researchers to locate literature on dermatological image recognition quickly and precisely. The rapidly evolving artificial intelligence-based medical diagnosis technology, which is gaining popularity among researchers, serves as the basis for this survey. Artificial intelligence has demonstrated its great potential through its application in other fields. The fact that deep learning has been applied in at least 45 studies to address problems with skin disease identification and has produced encouraging results motivates the authors to create the survey.

A. Needs for systematic literature review

To systematically investigate the integration of Skin Disease Recognition and Classification, this systematic literature review (SLR) closely adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Ensuring an organized and transparent review process is the goal. All articles published between 2018 and 2023 are included in the review, which was conducted using credible databases such as Google Scholar, IEEE Xplore, Scopus, and PubMed. Articles on process Skin Disease Recognition and Classification of hybrid deep learning are required to meet the inclusion criteria. After a rigorous selection procedure that followed the PRISMA guidelines for systematic reviews, a total of 75 articles were included. PRISMA guidelines were followed, and a thorough and methodical search strategy was used. Predefined search phrases like "Skin Disease Recognition and Classification, Hybrid deep learning Skin diseases, Skin disease of optimization techniques" were combined with relevant keywords to identify relevant articles. We searched reputable databases, such as Scopus, IEEE Xplore, Google Scholar, and PubMed. The first sources of the one thousand eight hundred articles were Google Scholar, IEEE Xplore, Scopus, and PubMed. Two hundred and eighty papers were deemed appropriate for further evaluation following a rigorous screening procedure that included eliminating duplicates and assessing their relevance. As shown in Figure 1, PRISMA principles were adhered to in the final selection process of 75 publications, ensuring a comprehensive and uniform evaluation based on preset inclusion criteria.

Received: July 20, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

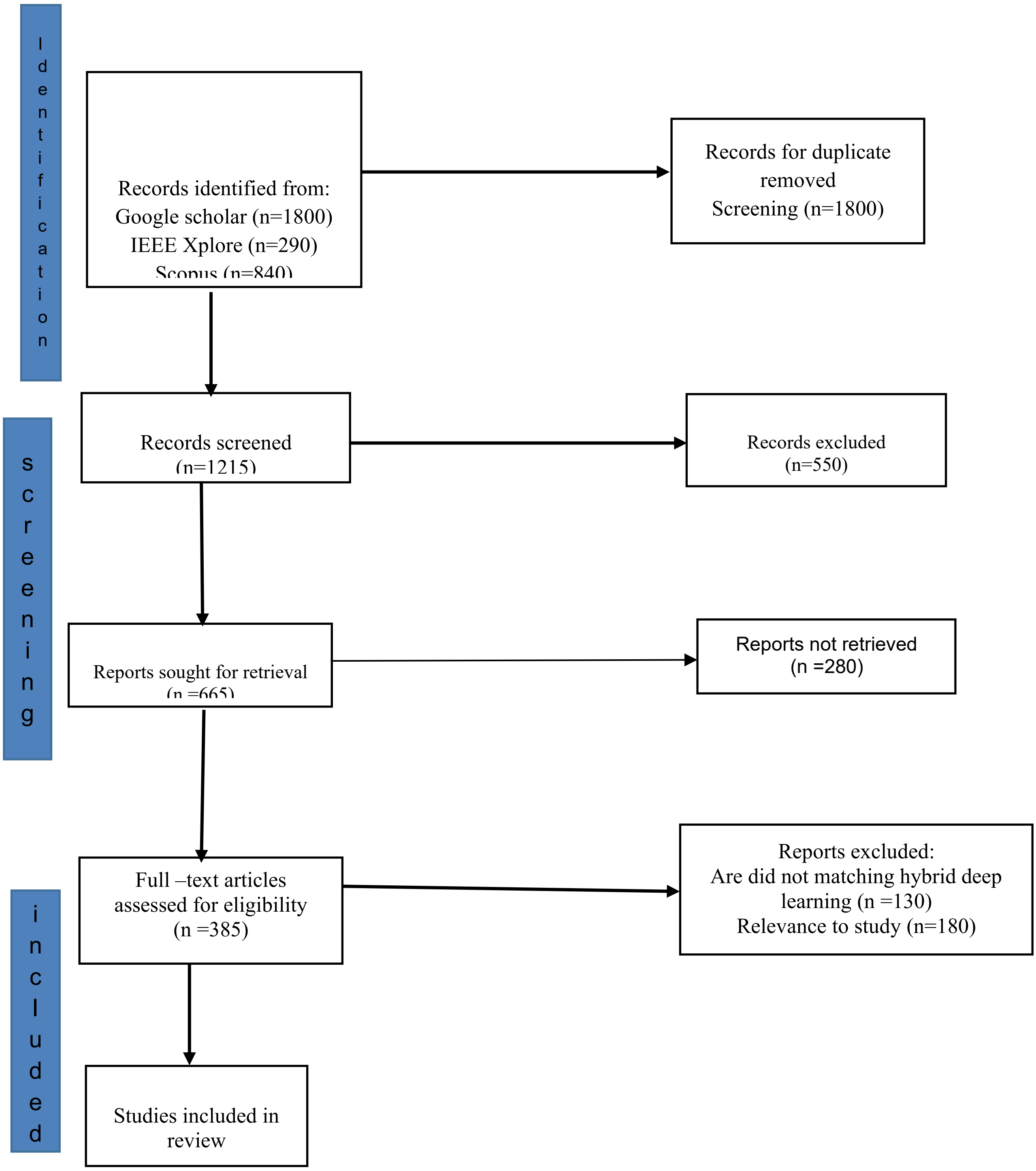

Figure 1. Prisma model

B. Research questions

1. RQ1. What are the different types of skin disease diagnosis methods?

- visual assessment of the skin.

Received: July 20, 2025

- Taking a tiny sample of skin for microscopic examination is called a biopsy. culturing, removing a sample of skin to check for viruses, fungi, or bacteria.
- Testing with a wood light (black light) Tzanck
- The patient's overall medical history is frequently pertinent to the diagnosis of skin conditions.

2. **RQ2. What are the most recent deep-learning techniques used for skin disease, and how can they be classified?**

To achieve high diagnostic accuracy, deep learning has been applied to the classification of skin diseases. A study that was published in the International Journal of Computer Science and Network Security suggested using dermoscopy images to develop an automated deep-learning model for early skin disease diagnosis. For classification accuracy on images from the skin dataset, the model was trained using four pre-trained transfer learning CNN models, including DenseNet121, ResNet50, VGG16, and ResNet18. Another study used multiple patient photographs to present a deep learning-based classification of 59 skin diseases2. In a third study, three specific skin conditions Benign keratosis, Actinic keratosis, and Dermatofibroma that, if correctly diagnosed, could cause disfigurement or progress to cancer were classified using a convolutional neural network approach built upon a tensor flow framework.

3. **RQ3. How can Deep learning improve Skin Disease Recognition?**

- To extract features related to the disease, obtain a lot of images.
- To increase a model's capacity for generalization, pre-process the images.
- Take features out of the images. Sort the skin conditions according to the features that were extracted.
- It is possible to identify skin diseases early on by combining deep learning and image processing techniques.

3. Development of skin disease diagnosis technology

a. Skin disease diagnosis using the conventional medical method

In traditional medicine, the diagnosis of skin disease is made by the physician based on his training, experience, and the features and guidelines provided by dermatoscopic images, which help to identify the condition of the patient's skin lesions. The following is a summary of the diagnostic procedure: dermoscopy and histopathological examination come first, followed by the doctor's visual observation, or visual diagnosis, which finds the relevant patient data. Dermoscopy is a high-definition, noninvasive skin imaging technique that studies the structure of the skin at the interface between the superficial dermis and the lower epidermis [23]. Medical professionals examined the makeup, arrangement, edge and boundary, color, shape, and appearance of skin lesions with pigmentation based on

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

dermatoscopy detection strategies including the ABCD rule [13], the seven-point checklist [12], 3-point checklists [14], cash, and chaos and clues [16] (hue, design, symmetry, and uniformity) [15]. However, the pathological features of pigmented skin diseases can only be correctly identified by skilled dermatologists because of the resemblance of skin lesions in terms of hue, texture, and border shape additionally, as well as the distinctions between pathological tissues between various patients. Still, this experience-based diagnosis approach falls well short of the patients' needs. requirements for medical supplies. Usually, it takes four to five days to go from a sample test to a doctor's diagnosis, a histopathological examination, and finally a patient report. This procedure takes a long time and has an impact on the patient's recovery.

In conclusion, the following drawbacks of the conventional dermatological diagnosis system exist: The dearth of medical resources comes first. There are few dermatologists with formal training in skin care. There are currently too few professional dermatologists for the number of patients due to the mismatch between the growth rate of dermatologists and the incidence rate of skin diseases. Second, there is a low level of diagnosis accuracy. Professional dermatologists may have different work histories and subjective opinions that lead to different diagnoses for the same patient. For the same skin disease picture, different diagnostic results are obtained by even the same doctor when they are influenced by light, fatigue, and other factors. Third, there are big gaps within categories as well as small gaps between them, making the images of skin diseases complex due to the characteristics of the diseases.

Dermoscopic images are more helpful for computer-aided diagnosis. Dermatologists utilize a device called a dermo scope [16] to create these images, which they employ to examine skin lesions. There is typically greater contrast and consistent lighting when using a Dermo scope. The lesions are sufficiently visible and distinguishable due to the device's high illumination. Additionally, because there is less noise in the images, processing dermoscopic images is made easier.

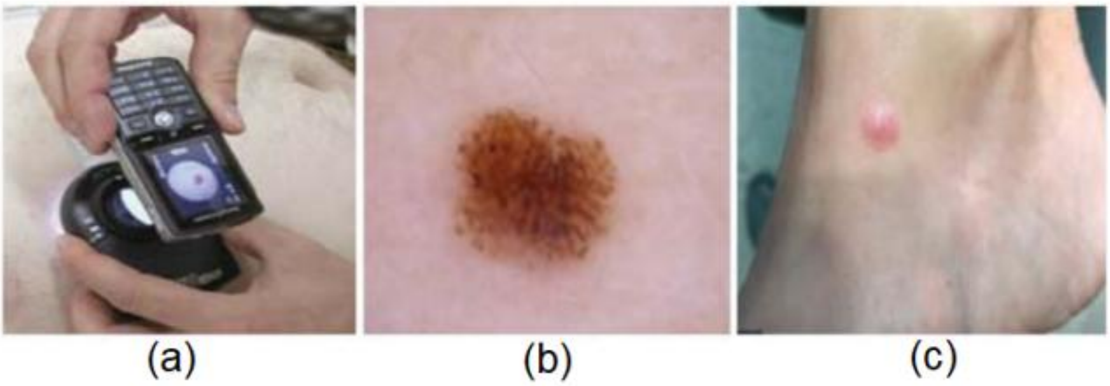

Figure 2. Skin disease image methods [4]

Received: July 20, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

b. Skin disease image recognition based on Machine learning.

The traditional skin disease diagnostic process's inadequacies were addressed with the advent of machine learning, which also led to the establishment of machine learning-based skin disease picture identification technology. Enabling the identification and diagnosis of skin diseases through feature engineering and machine learning classification algorithms, image recognition based on machine learning is an interdisciplinary field that combines computer technology, mathematical modeling, and medical skin disease imaging.

In 1987, the first research was conducted on the automatic classification of skin diseases [9]. retrieved the color features of melanomas, created color histograms, and categorized them in 2007 [10], [11]. generated texture using wavelet decomposition characteristics, derived boundary features by modeling and analyzing lesion boundary sequences, and relied on shape indications to obtain geometric characteristics. Ultimately, four classifiers are employed for classification: Random Forest, Hidden Naive Bayesian, Logical Model Tree, and Support Vector Machine [17]. The following classifiers are used for hierarchical combination and feature selection, which modifies each classifier's feature set to fit its purpose. This hierarchical K-NN classifier technique for melanoma skin disease is based on color and texture. More than 70% of the recognitions are accurate [18]. Ning et al. employed three distinct algorithms for feature extraction of their performance [21] in the same year: AdaBoost, classification and regression tree [20], and machine learning ID3 [19]. In these algorithms, AdaBoost performed admirably [22]. With 400 skin pictures obtained using laser confocal scanning microscopy, 94.75% of the images could be recognized, 93% were specific, and 96.5% were sensitive.

The machine learning-based approach to skin disease image recognition involves manually defining extractors and classifying the extracted features using conventional machine learning techniques. For this method to perform in-depth exploratory data analysis and minimize its dimension, a high level of professional medical knowledge is required [30,38]. Ultimately, the results can be output after a laborious and time-consuming process of adjusting complex parameters. Because of this method's limited portability, feature engineering is only useful within the same industry. These flaws restrict the advancement of machine learning in the identification of skin diseases. With its development, deep learning has produced promising results in image recognition. Unlike traditional image recognition techniques, the deep learning method can automatically mine the deeply ingrained nonlinear relationship in medical images and does not require feature engineering. Additionally, efficiency is the extraction efficiency. Deep learning is a flexible and easily transformable technology that can be applied to a wider range of fields and applications.

Machine learning is an Artificial Intelligence application that enables a structure to learn without requiring customization. The invention is the development of self-learning computer programs that take the material that is provided to them, incorporate it into their knowledge, and improve it [23]. Machine learning has numerous applications, including medical diagnosis, image processing, regression, prediction, classification, learning association, and so

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

forth. Machine learning approaches for picture recognition and classification are being applied in various domains. The machine may recognize the visual elements contained in an image using the image recognition technique, and it can map an instance to one of many classes by using a classification approach [11][45]. A large image database is employed for recognition, and it picks up new parameters and features of the images. We are upgrading the logistic regression, kernel SVM, Nave prejudice, random forest, and CNN machine learning algorithms for the categorization of skin diseases. An overview of the aforementioned algorithms may be seen below. One of the most important binary classifiers in supervised learning methods is logistic regression. Logistic regression uses a collection of predictors to assign a participant to one of the two classes [68]. In an issue of classification, the target variable can only accept discrete values for the given collection of attributes (or inputs). Classifiers in multiple logistic regressions are trained for each of the n classes present in the dataset. Every n class has a single classifier that has been trained. All other classes are considered negative samples while training the classifier for class 1, with the input data of class 1 labels serving as the positive values. In line with this, class 2's input data identifies the remaining samples as negative and the remaining samples as positive. Additionally, the same procedure is followed for various courses. Following the training of every class, the prediction function chooses the class for which the machine learning model provides the highest possibility.

4. Skin disease image recognition based on Hybrid deep learning

At application establishment, automatic pattern recognition of images can be achieved through the use of deep learning techniques. Important features can be automatically extracted from images by feeding them into a CNN with high fidelity. Therefore, this technique eliminates the need for information extraction from photos before the learning process. Shallow layers are where basic elements like picture edges are learned. Higher-order, more complicated features are learned at deep layers close to the output layer [56]. Various investigators, establishments, and obstacles are tackling the automated diagnosis of skin disorders. Diverse deep learning techniques have been established for the identification of dermatological diseases, and these have demonstrated efficacy across multiple domains [57]. The challenge's primary objective, which is also the primary objective in the field of dermatology [60], is to support research and the development of algorithms for the automated diagnosis of melanoma, including lesion segmentation, dermoscopy feature detection within a lesion, and melanoma classification [58, 59]. This approach is, in general, a modeling framework that can figure out how to transfer functionally from input images to output. The segmentation mask is the output picture, and the input image is preprocessed. The network architecture consists of a sequence of layers for compression and pooling, a fully linked layer, and a sequence of operations for unspooling and disconnec-tion [61].

a. Applied skin disease field

Hybrid Deep learning is primarily used in skin disease classification, or the quantitative feature extraction of lesion tissues from skin disease images, in the recognition of skin

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

diseases. The categorization is assessed and examined. The two primary categories of skin diseases are benign and malignant neoplasms. This direction is the mainstream application direction for skin disease recognition. Benign neoplasms are a kind of skin condition that has a low recognition rate, a tiny gap between lesions, and a gradually rising incidence. Commonly used benign neoplasms for research are seborrheic keratosis (17 articles) and nevus (23 articles).

Malignant neoplasms are another type of skin disease widely used in research. Malignant neoplasms are cellular dysplasia diseases that occur in the skin and are life-threatening through constant proliferation and metastasis. Malignant tumor identification in skin disease identification is exceptionally significant due to the high mortality rate of malignant neoplasms. The malignant neoplasms commonly used in research are basal cell carcinoma (13 articles), squamous cell carcinoma (seven articles), and malignant melanoma. Among the retrieved literature, the largest number of studies on melanoma recognition was 34. However, Non-neoplastic skin diseases are scarce, and only three articles on deep learning of eczema and psoriasis identification [46], [50], and [73] are collected in this study.

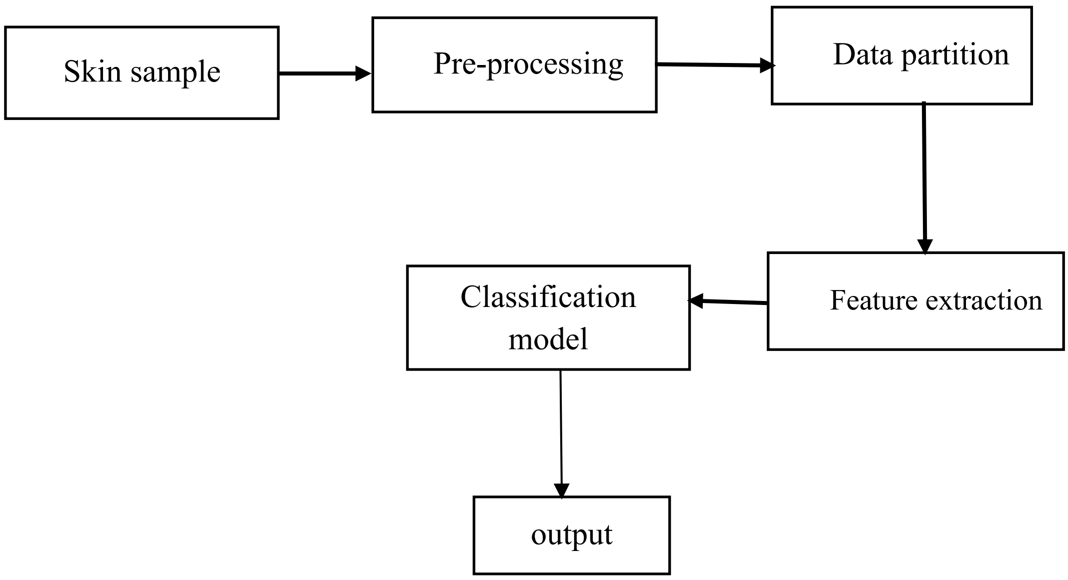

Figure 3. Flow chart of skin disease image recognition based on deep learning

Hybrid deep learning requires a large amount of data to extract features during training. Nevertheless, several issues, such as patient privacy, the variety of skin illnesses, and the occurrence of certain rare ailments, make gathering large-scale picture data on skin diseases difficult. Because diverse skin illnesses share similar lesion appearances, the quantity of publicly available skin disease datasets in academia is restricted by the requirement for specialists possessing the requisite medical knowledge to label skin disease photos. Currently, the majority of the datasets acquired for skin diseases are publicly available and self-collected. Self-collected datasets are now less accessible to the general public as illustrated in Figure 3. The majority of publicly available dermatological datasets consist of image data gathered from dermatological picture databases [40], [30], [32]–[34], [40]. Additionally, some

Received: July 20, 2025

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

datasets are gathered by universities working with well-known medical facilities [25], [26], [29], [37], [61]. The pathological sections of seborrheic keratosis and basal cell carcinoma that Meifeng et al. studied were obtained from Xi'an Jiaotong University's Second Affiliated Hospital [61]. The HAM10000 dataset is a collection of dermoscopic images gathered from Cliff Rosendahl's dermatological practice in Queensland, Australia, and the Dermatology Department of Vienna Medical University in Austria [29].

c. Image pre-processing

A deep learning model’s requirements for image quality are high in Hybrid deep learning image recognition because high-quality images can enhance the model's capacity for generalization [72]. Model training is preceded by image pre-processing. The main goals are to reduce the amount of unnecessary information in the picture, make the relevant and helpful information easier to find, and greatly simplify the data to increase the model's capacity for feature extraction and recognition accuracy. There are 28 image pre-processing studies in this work, broken down into data cleaning and data

1) Data cleaning

The primary purpose of data cleaning is to guarantee the accuracy of the data features of the skin disease photos. The most popular data-cleaning method for skin disease image recognition is to eliminate noise to lessen the impact of hair and shadow on the identification of skin diseases [58]. The type of skin, the surroundings, the tools, and the lighting all have an impact on the image's quality. A low-quality image will have an impact on the recognition effect, which will reduce computation cost and accuracy. Partial differential equation, transform domain, and spatial domain filtering are some of the frequently used denoising algorithms. Four studies in the chosen literature used the chosen datasets for noise reduction.

Improve the images by cleaning them up to improve our data for more accurate generalization [18-20]. The image processing toolbox in MATLAB was used to implement each of these procedures. In this case, the data is obtained, modified, and encoded so that the computer can understand it with simplicity.

2) Data conversion

Data transformation is the process of converting data from one format or structure to another to satisfy the demands of a deep learning model. Size adjustment (18 articles), normalization (10 articles), and graying (three articles) are the most often utilized data conversion techniques in the gathered literature.

Received: July 20, 2025

International Journal of Applied Mathematics

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

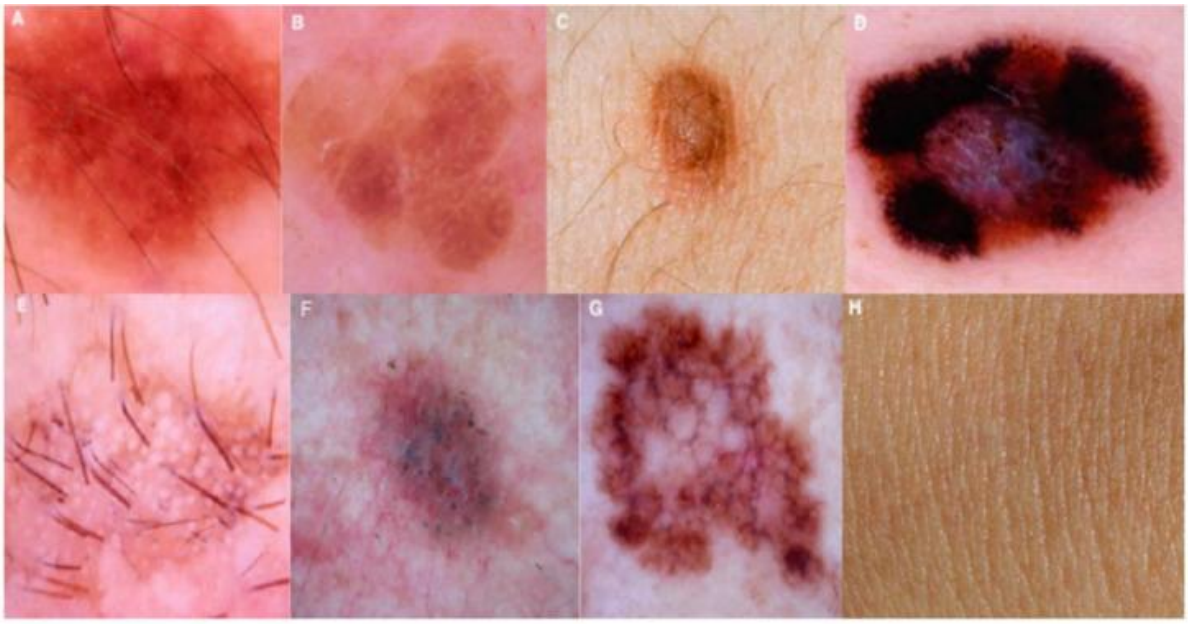

Fig. 4 sample images dataset

a. Size adjustment

The deep learning network model is constrained by its input size, and the majority of its input image's dimensions are fixed. The network model in deep learning primarily uses 224 × 224 or 227 × 227 fixed-size input because a small input will cause the picture information to be lost and the abstract level of information to not be able to meet the needs of the network, increasing the amount of calculation [47,49]. Size adjustment was done in seventeen papers, four of which did not disclose the size adjustment technique; the remaining literature, on the other hand, mostly used scaling (seven articles) and clipping (eight articles). Mahbod and Zhang used the bilinear interpolation method for scaling, whereas Mahbod used zooming and clipping [52].

Although the possibility of significantly large skin pictures, lesions often occupy a small area [75, 74]. The resolution of the original lesion photos is usually excessively enormous, which implies a high computation cost, therefore images for a deep learning network should be preprocessed before this task [73]. By adding a multiscale contextual information integration approach, accurate skin lesion segmentation improves its capability [62].

b. Normalization

Eleven papers normalized the images in the chosen literature. After the data is mapped to the interval of [0,1] or [−1,1], the extreme value of each variable only determines the data, and this process of normalization brings the samples' eigenvalues to the same dimension [50,42]. With this approach, the negative effects of the specific sample data are to be eliminated by restricting the pre-processing data to a certain range.

Received: July 20, 2025

International Journal of Applied Mathematics

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

c. Grayscale conversion

The main goals of gray conversion, which works on a single pixel in an image, are threshold processing and image contrast enhancement. The Grayscale transformation was applied by [69] in the collected literature to process images of skin diseases.

3) Image data augmentation

The challenges associated with personal privacy and the specialized equipment needed to gather medical skin disease datasets make gathering data on skin diseases challenging. As such, data on skin diseases have been scarcer. Because certain diseases are less common than others, there is an uneven distribution of the collected datasets due to the lack of data collection for these diseases. Small-scale datasets can easily result in overfitting and inadequate model learning in deep learning. Researchers employ data augmentation technology to increase the quantity of training data to address the issue of the small skin disease dataset and enhance the network model's capacity for generalization.

Data augmentation makes use of already-existing data to generate new data while adhering to task objectives. By adding geometric transformation and image operations to the original data without altering the data label, traditional image data augmentation increases the dataset. The most popular techniques are dimension reduction, rotation, mirror image, and noise addition. Based on the original data and by creating Gans' model, the new data amplification technology generates simulation data [62]. According to the internal distribution law of pictures, the generated confrontation network synthesizes pictures by utilizing information from different categories in addition to within-class information. In this study, 17 papers out of the 17 that were examined used data augmentation; 14 of those papers expanded the dataset using conventional data augmentation technology. Rotation was employed in eleven papers, with 90° rotation angles being the most frequently used 180°, 180°, and 270°I.e. Merely three papers were gathered for the generation of simulation data of skin disease image, considering that confrontation network generation is a relatively new technology among these studies generated data from the ISIC dataset using the generated countermeasure network.

The diversity of data has not increased even though traditional data amplification technology will produce more images because it does not learn the characteristics of the image; it is merely a simple copy transformation. Creating images by learning their features is the process of creating a model. When contrasted with conventional image amplification technology, the generated model exhibits strong feature learning and expression capabilities. The generated image has a higher quality and is distinct from the original image. The method has demonstrated significant improvement in the diversity of generated images and can effectively address the imbalanced data amount of different skin disease categories.

4) Model and framework

Hybrid Deep learning has an advantage over traditional machine learning in that it does not require traditional feature engineering because significant feature representations are

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

automatically learned from raw data, such as image pixels. Since convolution neural networks have translation, rotation, and scale invariances, they are currently the main tool used for skin disease image recognition in Hybrid deep learning, convolution, and pooling operations. When it comes to feature representation, CNN excels. Every piece of literature gathered for this analysis is predicated on the CNN model. The research work gathered for this study uses popular CNN architecture, including Inception, AlexNet, VGG, ResNet, and DensenNet [45].

A single Hybrid deep learning-based model method and a multimodel deep learning method are the two categories into which the gathered model methods can be divided based on the number of network models employed by researchers. Ten papers addressed the multimodel approach, and twenty-seven papers concentrated on a single model approach.

a. Skin disease image recognition based on a single model

Twenty-seven publications in the literature used a single model; of these, 15 articles optimized the model, and 10 papers ([38], [39], [43], [56], [58], [63], [72], [74], and [75]) did not improve the model. Changing the fully connected layer (five articles: [41], [44], [60], and 73]), applying a machine learning classifier (two articles: [64] and [80]), integrating the attention mechanism (two articles: [49] and [54]), introducing a self-building network model (two articles: [57] and [69]), and multilevel classification (three articles: [46], [55], and [73]) are the main optimization methods. Based on attention residual learning, a CNN (ARL-CNN) has been proposed. Attention residual learning (ARL-CNN) was proposed as the basis for a CNN. To build an ARL-CNN model with an arbitrary depth, the network stacks multiple ARL blocks, trains the model from start to finish, and integrates the residual and attention-learning mechanisms into each ARL module.

A global average pooling (GAP) layer, a classification layer, and several ARL blocks make up the suggested ARL-CNN model [38-43]. A novel attention strategy is created to increase the discriminative representation ability in each ARL block, while the degradation problem is addressed by the residual learning process.

Residual Learning Let us analyze a basic DCNN block made up of many convolution layers stacked on top of one another. H(x) is the underlying mapping that these layers have fitted. These are predicted stacks of layers.
to calculate H(x) directly.

$$y = F(x, W) \tag{1}$$

where F(·) is the underlying mapping function that these stacked layers learn using the parameter set W, and x and y indicate the block's input and output, respectively.

b. Skin disease image recognition based on multimodal fusion

Multimodal input has been used in an expanding variety of activities recently. Many prior studies [23–25] that classified skin diseases just employed photographs. This is mostly due to

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

the fact that few datasets have metadata, and when there is, it does not appear to be connected to skin conditions. But when a few studies [26, 27] showed how useful metadata is, additional researchers [28] started incorporating information into their models and saw excellent outcomes. Motivated by the aforementioned studies and the multimodal data present in the datasets, we regard the task as multimodal.

The main goal of multimodal fusion is to learn from multiple learners and combine their outputs using a set of rules. In the traditional multimodal fusion, the probability results of a specific type of output from each model are fused and recalculated using the average method, weighting method, linear regression method, simple majority voting (SMV) rule, and maximum probability rule. The result of the fusion process is the final output. An alternative method would be to combine the features extracted from various models, fuse the features, and then output the final product**.** The primary techniques include conventional multiple model fusion (four articles), fusion strategy blended with clinical information (four articles), multi-input model fusion (two articles), multimodel extraction feature SVM classification (two articles), and the combination of human and artificial intelligence (two articles). First, VGG, Inception, AlexNet, for fusion, and ResNet are frequently employed.

In the field of skin disease recognition, numerous experiments have demonstrated the superiority of the multimodel fusion method over the single model method [59], [61]. When solving problems, a model generalization bottleneck is frequently encountered because the objective factors limit a single model. By combining the best models and incorporating each one's advantages, multimodel fusion can overcome the limitation of a single model's capacity for generalization.

ResNet-50: Training deep CNN models for skin cancer classification becomes a difficult endeavor, leading to lower accuracy in model estimations, because the skin cancer dataset has a much smaller number of labeled images than the ten million labeled images contained in ImageNet. However, by utilizing transfer learning's capabilities, we are able to achieve strong results with deep CNN models that were trained on ImageNet in the first place, even when compared to small datasets in a variety of domains, like automated medical image analysis, which includes the identification of skin cancer from dermoscopic images. For the purpose of classifying skin cancer, we actively use the ResNet-50 model [39], which was pre-trained on ImageNet. The assumption is that the feature extraction layers in ResNet-50 will perform exceptionally well when used for medical image classification because of its exceptional classification capabilities and capacity to extract reliable features from images. These methods successfully address the problem of disappearing gradients by improving training parameters during error backpropagation [28]. Consequently, this makes it easier to create deeper CNN structures, which in turn leads to better skin cancer performance. grouping. ReLU activation functions (BN), batch normalizations, several convolutional layers (Conv), and a single shortcut make up these residual blocks [32]. Assuming that f is a non-linear function in RB for the convolutional path, the following computation is made for the output:

$$y = f(x) + X \tag{2}$$

Received: July 20, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

c. *Hybrid Deep learning framework*

Only 16 papers including those from MATLAB [54], PyTorch [55], TensorFlow [63], and Keras [42] published the deep learning framework among the collected literature. Keras has gained popularity because of its clear and consistent API, which can greatly lessen users' workloads. The framework has been applied to six papers. Tensorflow and Keras are frequently combined. Without launching a Python interpreter or running a separate model decoder, the framework can deploy training models on a variety of servers and mobile devices. The deep learning framework Pytorch was made available by Facebook AI research. The flexibility, usability, and quick speed of this framework are its main advantages. In terms of deep learning frameworks, PyTorch is a novice. The framework is applied in five articles. The development of MATLAB has a lengthy history and provides benefits for the picture, video, and audio data precise annotation of values.

5) *Prospect*

The newly formed field of deep learning in machine learning offers new opportunities for medical image recognition and has promising applications in computer vision. As of right now, medical image recognition has seen empirical advancements thanks to deep learning [47]. Deep learning is still relatively new to the field of medical image recognition, though. In the future, there should be more advancements and thorough investigations made in the field of skin disease recognition. Four potential paths for the development of research are outlined below:

A. *Data generation of skin disease image*

Deep learning requires a large amount of data to learn, but it has good generalization ability in identifying skin diseases. Insufficient feature extraction due to a lack of data may impact lesion identification and diagnosis [30]. Obtaining a large number of data sets is a significant challenge in skin disease image recognition because of the intricacies involved in medical image collection and the uncommon occurrence of individual diseases. One great way to address this issue is to use an anti network to generate simulated images of skin diseases. A strategy like this also enhances the network's performance. This technology will have promising future developments in the skin future diagnosis of diseases.

The recognition of skin diseases and the network model's acceptable generalization capacity are predicated on a substantial amount of data. However, there are significant differences in the published datasets' image counts, disease types, image sizes, and shooting and processing techniques. This causes confusion between studies and makes it impossible to quantitatively describe different models [41-44]. In addition, gathering images of some rare diseases can be challenging. As was previously noted, there are many different types of skin disorders; yet, there are only about 20 datasets available, with fewer than 20 types of skin diseases included. To accurately reflect population forecasts, however, a publicly accessible database that permits the acquisition of a sufficient number of labeled datasets is probably required.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

B. Clinical identification of skin disease

In the field of skin disease recognition, there are currently only a few different kinds of images that are recognized. The majority of graphs are based on images produced by dermoscopic imaging technology. Pictures taken in real life or a clinical setting have not been the subject of many studies [23,54]. The lesion area only takes up a small portion of or is incomplete in images of clinical or real-world scenes, making it difficult to determine the lesion's location due to several issues, including low pixel count and the presence of shadows. This is an area that requires more research. To enhance the accuracy of clinical recognition models, lesion sites of skin diseases can be the focus of attention mechanisms or target detection techniques. This will facilitate the extraction of features from the lesion sites.

Astute identification and management of skin conditions Deep learning can help treat the growing number of skin disease patients and alleviate the workload for dermatologists who are in short supply. Given the widespread use of wearable technology, mobile computers, and smartphones, it is reasonable to anticipate that deep learning-based skin disease detection systems will be accessible to increasingly sophisticated devices [54,56]. Users can get the diagnosis results at any time by using the camera on their mobile device to upload their own images of the affected area to the cloud identification system. Simple communication with the "skin manager" may provide diagnosis recommendations and potential treatment options. In addition, the "skin manager" may keep track of the user's skin state and offer recommendations for treatments and real-time protection.

C. Interpretability study on skin disease identification

These days, researchers concentrate on models' indicators of success. However, a variety of environmental factors cause model concepts and performance to alter. To make certain decisions, one must comprehend the factors that influence the model [18]. There is currently a significant gap in this field that needs to be investigated regarding the interpretability of research on skin disease identification models. Deep learning models can be used to detect skin diseases to direct clinical automated medical diagnosis in the field of skin disease recognition. To make predictions based on input data, these algorithms are still a "black box." There isn't a clear explanation of which characteristics of skin diseases the deep learning model uses to make decisions. The advancement of deep learning ought to be dependable and comprehensible. Users will benefit from security and dependability if the algorithm's decision-making process is made public and transparent. Artificial intelligence-induced biases and auditing can be addressed by interpretability research on skin disease identification [68]. Artificial intelligence becomes transparent and open in philosophical, moral, and legal aspects when it is interpretable.

Advances in parameter adjustment technology and a highly nonlinear model are necessary for the advancement of deep learning in the recognition of skin diseases. But most neural network models are "black box" models, meaning it's hard to comprehend how they make decisions within. This "end-to-end" decision-making process results in deep learning's limited capacity

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

for explanation [61,72]. The diagnosis produced by the model is less compelling because the internal logic of deep learning is unclear. The system owner could be able to ascertain the dependability and safety of the system by having a clear understanding of the system's boundaries and behavior thanks to the interpretability research on skin disease classification. Additionally, it might keep an eye on the moral dilemma.

D. AI diagnosis and treatment of skin disease

Mobile gadgets like tablets, PDAs, and smartphones, are starting to become vital components of human existence [75]. Integrating artificial intelligence for skin disease diagnosis and treatment in the future, smart devices are going to be a big trend. Nonetheless, the majority of skin conditions are identified using graphics processors with great performance. The algorithm's complexity should be kept to a minimum when increasing the algorithm's capacity for recognition to guarantee Both wearable intelligent devices and mobile phones can easily be utilized [43]. The implications of this research for AI are enormous in the identification and management of skin conditions. Artificial intelligence (AI) assistants can take the role of dermatologists in intelligent questions and answers about skin diseases. They can ask patients about themselves and communicate with them about routine topics like diagnosis, prescriptions, and health promotion. In addition to technical difficulties with AI diagnosis and treatment, there are still some philosophical, legal, and ethical questions that need to be addressed.

In the section comparing the current and indicated models, we discovered that across all more algorithms DeMAL- SCNN_12, RDN, ResNet50, CNN, FCN, and DeneseNet. Hybrid deep learning the offered model has an approximate accuracy increase rate of 10% over the current model. If we further refine the result, we find that, of the more algorithms included in the recommended model, DT has the highest enhanced accuracy rate, coming in at about 98%. It is evident from the comparison table and graph above that DenseNet is superior to all the other algorithms included in the proposed model. We examined the offered framework on an alternative dataset to guarantee its dependability. Our conclusion that the hybrid deep learning model’s implementation algorithm was concise and produced an accurate result was validated by the data we discovered table 1 shows the comparison analysis. (fig 5)

Table 1. comparison table

Algorithm & Reference	**Accuracy**
DeMAL-CNN[66]	0.873
(SCNN_12) [59]	98.87%
RDN [53]	95%
ResNet50 [40]	0.897
CNN [49]	97.2%
FCN [47]	98.2%
DenseNet201[45]	99%

Received: July 20, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Deep metric attention learning convolutional neural networks(DeMAL-CNN)

shallow convolutional neural network(SCNN_12)

Residual Dense Network(RDN)

Residual Networks (ResNet50)

convolutional neural networks(CNN)

Fully Convolutional Network (FCN)

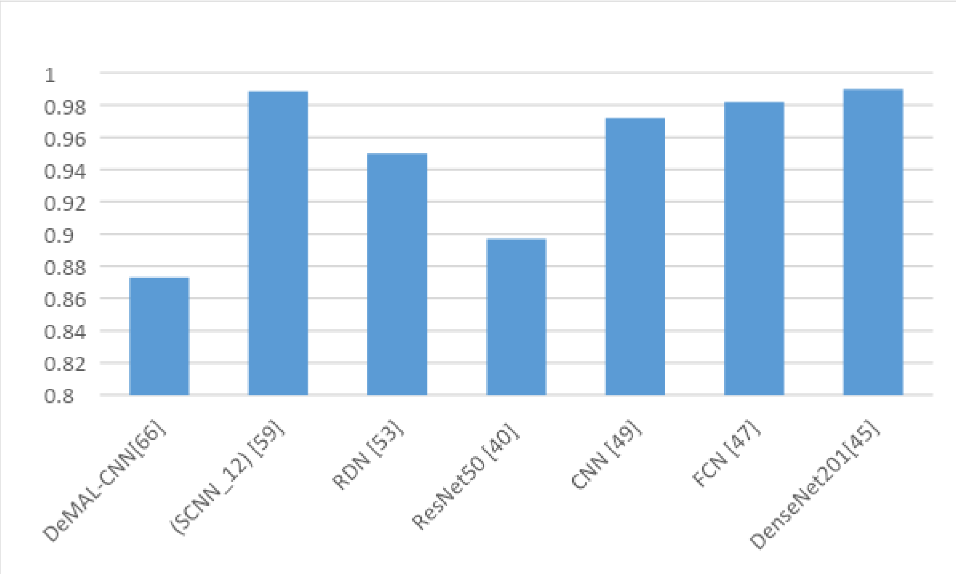

Figure 5. Different Methods comparison with performance metrics

5. Future directions and conclusion

The development of skin disease diagnostic technology, conventional medical diagnosis procedures, machine learning-based image recognition of skin disease, and the outcomes of deep learning-based research in the field of skin disease recognition are all covered in this article. 45 pertinent papers have been found to gather their concerns regarding the types and areas of skin diseases. The data source that was used, the preprocessing and data expansion methods, the technical specifications of the models, and the overall performance of the performance indicators are all studied using these papers as a foundation. Skin disease recognition uses deep learning models such as AlexNet, VGG, GoogleNet, and ResNet extensively. The multimodel fusion technology is frequently used by researchers to enhance model performance. We intend to use the deep learning principles and best practices covered in this survey in future work to address other medical specialties that have not yet made full use of this technology. With the help of this survey, more researchers should be inspired to carry out Hybrid deep learning experiments and use the deep learning model in the field of computer vision in medicine, which will lead to clever and practical advancements in the medical sector.

Received: July 20, 2025

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

References

[1] Li, L. F., Wang, X., Hu, W. J., Xiong, N. N., Du, Y. X., & Li, B. S. (2020).Automatic diagno?sis of skin diseases using convolution neural network,'' Microproces?sors Microsyst., vol. 76, Jul. 2020, Art. no. 103074, doi: 10.1016/j. micpro.2020.103074

[2] Nawar, A., Sabuz, N. K., Siddiquee, S. M. T., Rabbani, M., Biswas, A. A., & Majumder, A. (2021, March). Skin disease recognition: a machine vision based approach. In *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)* (Vol. 1, pp. 1029-1034). IEEE.

[3] Allugunti, V. R. (2022). A machine learning model for skin disease classification using convolutional neural networks. *International Journal of Computing, Programming and Database Management*, *3*(1), 141-147.

[4] Goswami, T., Dabhi, V. K., & Prajapati, H. B. (2020, March). Skin disease classification from image-a survey. In *2020 6th international conference on advanced computing and communication systems (ICACCS)* (pp. 599-605). IEEE.

[5] Wu, Z. H. E., Zhao, S., Peng, Y., He, X., Zhao, X., Huang, K., ... & Li, Y. (2019). Studies on different CNN algorithms for face skin disease classification based on clinical images. *IEEE Access*, *7*, 66505-66511.

[6] Khan, M. Q., Hussain, A., Rehman, S. U., Khan, U., Maqsood, M., Mehmood, K., & Khan, M. A. (2019). Classification of melanoma and nevus in digital images for diagnosis of skin cancer. *IEEE Access*, *7*, 90132-90144.

[7] Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. (2020). Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities. *Computers in biology and medicine*, *127*, 104065.

[8] Kadampur, M. A., & Al Riyaee, S. (2020). Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images. *Informatics in Medicine Unlocked*, *18*, 100282.

[9] Goceri, E. (2021). Diagnosis of skin diseases in the era of deep learning and mobile technology. *Computers in Biology and Medicine*, *134*, 104458.

[10] Mahbod, A., Schaefer, G., Wang, C., Ecker, R., & Ellinge, I. (2019, May). Skin lesion classification using hybrid deep neural networks. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 1229-1233). IEEE.

[11] Daghrir, J., Tlig, L., Bouchouicha, M., & Sayadi, M. (2020, September). Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. In *2020 5th international conference on advanced technologies for signal and image processing (ATSIP)* (pp. 1-5). IEEE.

[12] Hasan, M. K., Elahi, M. T. E., Alam, M. A., Jawad, M. T., & Martí, R. (2022). DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation. *Informatics in Medicine Unlocked*, *28*, 100819.

Received: July 20, 2025

[13] Li, H., Pan, Y., Zhao, J., & Zhang, L. (2021). Skin disease diagnosis with deep learning: A review. *Neurocomputing*, *464*, 364-393.

[14] Hasan, M. K., Elahi, M. T. E., Alam, M. A., Jawad, M. T., & Martí, R. (2022). DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation. *Informatics in Medicine Unlocked*, *28*, 100819.

[15] Ahmad, B., Usama, M., Huang, C. M., Hwang, K., Hossain, M. S., & Muhammad, G. (2020). Discriminative feature learning for skin disease classification using deep convolutional neural networks. *IEEE Access*, *8*, 39025-39033.

[16] Rodrigues, D. D. A., Ivo, R. F., Satapathy, S. C., Wang, S., Hemanth, J., & Reboucas Filho, P. P. (2020). A new approach for classification skin lesion based on transfer learning, deep learning, and IoT system. *Pattern Recognition Letters*, *136*, 8-15.

[17] Kaymak, S., Esmaili, P., & Serener, A. (2018, November). Deep learning for two-step classification of malignant pigmented skin lesions. In *2018 14th Symposium on Neural Networks and Applications (NEUREL)* (pp. 1-6). IEEE.

[18] Hameed, N., Shabut, A. M., Ghosh, M. K., & Hossain, M. A. (2020). Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques. *Expert Systems with Applications*, *141*, 112961.

[19] Tan, T. Y., Zhang, L., & Lim, C. P. (2019). Intelligent skin cancer diagnosis using improved particle swarm optimization and deep learning models. *Applied Soft Computing*, *84*, 105725.

[20] Goceri, E. (2021). Diagnosis of skin diseases in the era of deep learning and mobile technology. *Computers in Biology and Medicine*, *134*, 104458.

[21] Zhang, N., Cai, Y. X., Wang, Y. Y., Tian, Y. T., Wang, X. L., & Badami, B. (2020). Skin cancer diagnosis based on optimized convolutional neural network. *Artificial intelligence in medicine*, *102*, 101756.

[22] Haddad, A., & Hameed, S. A. (2018, September). Image analysis model for skin disease detection: framework. In *2018 7th International Conference on Computer and Communication Engineering (ICCCE)* (pp. 1-4). IEEE.

[23] Ai, P., Lei, S., Zhou, F., Chen, S., & Zhang, Y. (2020). Selenium levels and skin diseases: Systematic review and meta-analysis. *Journal of Trace Elements in Medicine and Biology*, *62*, 126548.

[24] Hsu, D. K., Fung, M. A., & Chen, H. L. (2020). Role of skin and gut microbiota in the pathogenesis of psoriasis, an inflammatory skin disease. *Medicine in Microecology*, *4*, 100016.

[25] Kassem, M. A., Hosny, K. M., & Fouad, M. M. (2020). Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning. *IEEE Access*, *8*, 114822-114832.

[26] Back, S., Lee, S., Shin, S., Yu, Y., Yuk, T., Jong, S., ... & Lee, K. (2021). Robust skin disease classification by distilling deep neural network ensemble for the mobile diagnosis of herpes zoster. *IEEE Access*, *9*, 20156-20169.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[27] Gheida, S. F., Neinaa, Y. M. E. H., & Mohammed, D. A. E. A. (2018). Caveolin-1 expression in hyperproliferative skin disorders: A potential predictive marker of disease severity and progression. *Dermatologica sinica*, *36*(4), 179-184.

[28] Ali, M. S., Miah, M. S., Haque, J., Rahman, M. M., & Islam, M. K. (2021). An enhanced technique of skin cancer classification using deep convolutional neural networks with transfer learning models. *Machine Learning with Applications*, *5*, 100036.

[29] Haenssle, H. A., Fink, C., Toberer, F., Winkler, J., Stolz, W., Deinlein, T., ... & Zukervar, P. (2020). Man against machine reloaded: performance of a market-approved convolutional neural network in classifying a broad spectrum of skin lesions in comparison with 96 dermatologists working under less artificial conditions. *Annals of Oncology*, *31*(1), 137-143.

[30] Qin, Z., Liu, Z., Zhu, P., & Xue, Y. (2020). A GAN-based image synthesis method for skin lesion classification. *Computer Methods and Programs in Biomedicine*, *195*, 105568.

[31] Hameed, N., Shabut, A. M., & Hossain, M. A. (2018, December). Multi-class skin diseases classification using deep convolutional neural networks and support vector machines. In *2018 12th International Conference on Software, Knowledge, Information Management & Applications (SKIMA)* (pp. 1-7). IEEE.

[32] Chen, M., Zhou, P., Wu, D., Hu, L., Hassan, M. M., & Alamri, A. (2020). AI-Skin: Skin disease recognition based on self-learning and wide data collection through a closed-loop framework. *Information Fusion*, *54*, 1-9.

[33] Goceri, E. (2019, November). Analysis of deep networks with residual blocks and different activation functions: classification of skin diseases. In *2019 Ninth international conference on image processing theory, tools and applications (IPTA)* (pp. 1-6). IEEE.

[34] Bhadula, S., Sharma, S., Juyal, P., & Kulshrestha, C. (2019). Machine learning algorithms based on skin disease detection. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, *9*(2), 4044-4049.

[35] Codella, N. C., Gutman, D., Celebi, M. E., Helba, B., Marchetti, M. A., Dusza, S. W., ... & Halpern, A. (2018, April). Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). In *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)* (pp. 168-172). IEEE.

[36] Urban, K., Chu, S., Giesey, R. L., Mehrmal, S., Uppal, P., Delost, M. E., & Delost, G. R. (2021). Burden of skin disease and associated socioeconomic status in Asia: A cross-sectional analysis from the Global Burden of Disease Study 1990-2017. *JAAD international*, *2*, 40-50.

[37] Yang, W., Han, W., Gao, H., Zhang, L., Wang, S., Xing, L., ... & Xue, X. (2018). Self-powered implantable electronic-skin for in situ analysis of urea/uric-acid in body fluids

Received: July 20, 2025

Volume 38 No. 3s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

and the potential applications in real-time kidney-disease diagnosis. *Nanoscale*, *10*(4), 2099-2107.

[38] Wilson, B. N., Sun, M., Ashbaugh, A. G., Ohri, S., Yeh, C., Murrell, D. F., & Murase, J. E. (2021). Assessment of skin of color and diversity and inclusion content of dermatologic published literature: an analysis and call to action. *International Journal of Women's Dermatology*, *7*(4), 391-397.

[39] He, H., Suryawanshi, H., Morozov, P., Gay-Mimbrera, J., Del Duca, E., Kim, H. J., ... & Guttman-Yassky, E. (2020). Single-cell transcriptome analysis of human skin identifies novel fibroblast subpopulation and enrichment of immune subsets in atopic dermatitis. *Journal of Allergy and Clinical Immunology*, *145*(6), 1615-1628.

[40] Janoria, H., Minj, J., & Patre, P. (2020, November). Classification of skin disease from skin images using transfer learning technique. In *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 888-895). IEEE.

[41] Balaji, V. R., Suganthi, S. T., Rajadevi, R., Kumar, V. K., Balaji, B. S., & Pandiyan, S. (2020). Skin disease detection and segmentation using dynamic graph cut algorithm and classification through Naive Bayes classifier. *Measurement*, *163*, 107922.

[42] Purnama, I. K. E., Hernanda, A. K., Ratna, A. A. P., Nurtanio, I., Hidayati, A. N., Purnomo, M. H., ... & Rachmadi, R. F. (2019, November). Disease classification based on dermoscopic skin images using convolutional neural networks in teledermatology systems. In *2019 international conference on computer engineering, network, and intelligent multimedia (CENIM)* (pp. 1-5). IEEE.

[43] Lin, J., Guo, Z., Li, D., Hu, X., & Zhang, Y. (2019, July). Automatic classification of clinical skin disease images with additional high-level position information. In *2019 Chinese Control Conference (CCC)* (pp. 8606-8610). IEEE.

[44] ALEnezi, N. S. A. (2019). A method of skin disease detection using image processing and machine learning. *Procedia Computer Science*, *163*, 85-92.

[45] Akmalia, N., & Sihombing, P. (2019, September). Skin diseases classification using local binary pattern and convolutional neural network. In *2019 3rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM)* (pp. 168-173). IEEE.

[46] Gupta, S., Panwar, A., & Mishra, K. (2021, July). Skin disease classification using dermoscopy images through deep feature learning models and machine learning classifiers. In *IEEE EUROCON 2021-19th International Conference on Smart Technologies* (pp. 170-174). IEEE.

[47] Gouda, N., & Amudha, J. (2020, October). Skin cancer classification using ResNet. In *2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA)* (pp. 536-541). IEEE.

[48] Petrellis, N. (2018, May). Using color signatures for the classification of skin disorders. In *2018 7th International Conference on Modern Circuits and Systems Technologies (MOCAST)* (pp. 1-4). IEEE.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[49] Rathod, J., Waghmode, V., Sodha, A., & Bhavathankar, P. (2018, March). Diagnosis of skin diseases using Convolutional Neural Networks. In *2018 second international conference on electronics, communication and aerospace technology (ICECA)* (pp. 1048-1051). IEEE.

[50] Adegun, A. A., & Viriri, S. (2020). FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images. *IEEE Access*, *8*, 150377-150396.

[51] Widiyaningtyas, T., Wirawan, I. M., & Mahmud, S. H. (2020, November). Diagnosis of Feline Skin Disease Using C4. 5 Algorithm. In *2020 Fifth International Conference on Informatics and Computing (ICIC)* (pp. 1-5). IEEE.

[52] Rimi, T. A., Sultana, N., & Foysal, M. F. A. (2020, May). Derm-NN: skin diseases detection using convolutional neural networks. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1205-1209). IEEE.

[53] Akyeramfo-Sam, S., Philip, A. A., Yeboah, D., Nartey, N. C., & Nti, I. K. (2019). A web-based skin disease diagnosis using convolutional neural networks. *International Journal of Information Technology and Computer Science*, *11*(11), 54-60.

[54] Hossen, M. N., Panneerselvam, V., Koundal, D., Ahmed, K., Bui, F. M., & Ibrahim, S. M. (2022). Federated machine learning for detection of skin diseases and enhancement of internet of medical things (IoMT) security. *IEEE journal of biomedical and health informatics*, *27*(2), 835-841.

[55] Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. (2020). Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities. *Computers in biology and medicine*, *127*, 104065.

[56] Hekler, A., Utikal, J. S., Enk, A. H., Hauschild, A., Weichenthal, M., Maron, R. C., ... & Thiem, A. (2019). Superior skin cancer classification by the combination of human and artificial intelligence. *European Journal of Cancer*, *120*, 114-121.

[57] Dietze, K., Moritz, T., Alexandrov, T., Krstevski, K., Schlottau, K., Milovanovic, M., ... & Hoffmann, B. (2018). Suitability of group-level oral fluid sampling in ruminant populations for lumpy skin disease virus detection. *Veterinary microbiology*, *221*, 44-48.

[58] Pathan, S., Prabhu, K. G., & Siddalingaswamy, P. C. (2018). Techniques and algorithms for computer aided diagnosis of pigmented skin lesions—A review. *Biomedical Signal Processing and Control*, *39*, 237-262.

[59] Wilke, A., Brans, R., Nordheider, K., Braumann, A., Hübner, A., Sonsmann, F. K., ... & Wulfhorst, B. (2018). Skin protection seminars to prevent occupational skin diseases: results of a prospective longitudinal study in apprentices of high-risk professions. *Safety and Health at Work*, *9*(4), 398-407.

[60] Hosny, K. M., Kassem, M. A., & Foaud, M. M. (2018, December). Skin cancer classification using deep learning and transfer learning. In *2018 9th Cairo international biomedical engineering conference (CIBEC)* (pp. 90-93). IEEE.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[61] Nahata, H., & Singh, S. P. (2020). Deep learning solutions for skin cancer detection and diagnosis. *Machine Learning with Health Care Perspective: Machine Learning and Healthcare*, 159-182.

[62] Han, S. S., Park, I., Chang, S. E., Lim, W., Kim, M. S., Park, G. H., ... & Na, J. I. (2020). Augmented intelligence dermatology: deep neural networks empower medical professionals in diagnosing skin cancer and predicting treatment options for 134 skin disorders. *Journal of Investigative Dermatology*, *140*(9), 1753-1761.

[63] Tschandl, P., Codella, N., Akay, B. N., Argenziano, G., Braun, R. P., Cabo, H., ... & Kittler, H. (2019). Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study. *The lancet oncology*, *20*(7), 938-947.

[64] Zhang, J., Xie, Y., Xia, Y., & Shen, C. (2019). Attention residual learning for skin lesion classification. *IEEE transactions on medical imaging*, *38*(9), 2092-2103.

[65] Maron, R. C., Weichenthal, M., Utikal, J. S., Hekler, A., Berking, C., Hauschild, A., ... & Thiem, A. (2019). Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks. *European Journal of Cancer*, *119*, 57-65.

[66] Gessert, N., Nielsen, M., Shaikh, M., Werner, R., & Schlaefer, A. (2020). Skin lesion classification using ensembles of multi-resolution EfficientNets with metadata. *MethodsX*, *7*, 100864.

[67] Verma, A. K., Pal, S., & Kumar, S. (2019). Comparison of skin disease prediction by feature selection using ensemble data mining techniques. *Informatics in Medicine Unlocked*, *16*, 100202.

[68] Rahaman, M. M., Li, C., Yao, Y., Kulwa, F., Wu, X., Li, X., & Wang, Q. (2021). DeepCervix: A deep learning-based framework for the classification of cervical cells using hybrid deep feature fusion techniques. *Computers in Biology and Medicine*, *136*, 104649.

[69] Adegun, A. A., & Viriri, S. (2020). FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images. *IEEE Access*, *8*, 150377-150396.

[70] Gu, Y., Ge, Z., Bonnington, C. P., & Zhou, J. (2019). Progressive transfer learning and adversarial domain adaptation for cross-domain skin disease classification. *IEEE journal of biomedical and health informatics*, *24*(5), 1379-1393.

[71] Hameed, N., Shabut, A., & Hossain, M. A. (2018, September). A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning. In *2018 10th computer science and electronic engineering (CEEC)* (pp. 186-191). IEEE.

[72] Hosny, K. M., Kassem, M. A., & Foaud, M. M. (2018, December). Skin cancer classification using deep learning and transfer learning. In *2018 9th Cairo international biomedical engineering conference (CIBEC)* (pp. 90-93). IEEE.

[73] Shanthi, T., Sabeenian, R. S., & Anand, R. (2020). Automatic diagnosis of skin diseases using convolution neural networks. *Microprocessors and Microsystems*, *76*, 103074.

Received: July 20, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[74] Yan, R., Ren, F., Wang, Z., Wang, L., Zhang, T., Liu, Y., ... & Zhang, F. (2020). Breast cancer histopathological image classification using a hybrid deep neural network. *Methods*, *173*, 52-60.

[75] Vesal, S., Ravikumar, N., & Maier, A. (2018, November). SkinNet: A deep learning framework for skin lesion segmentation. In *2018 IEEE Nuclear Science Symposium and Medical Imaging Conference Proceedings (NSS/MIC)* (pp. 1-3). IEEE.

Received: July 20, 2025