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SURVEY

Deep Learning-Based Dermatological Condition Detection: A Systematic Review With Recent Methods, Datasets, Challenges, and Future Directions

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ABSTRACT Dermatological conditions are a global health concern affecting all age groups. They encompass various skin issues such as rashes, moles, acne, blisters, hives, nodules, cysts, macules, and papules. Early diagnosis of dermatological conditions is crucial to prevent skin damage and chronic diseases. Recent advancements in artificial intelligence and medical image processing, particularly through deep learning, have significantly improved the precision and efficiency of dermatological disease detection by dermatologists. This paper thoroughly examines deep learning-based methods for detecting dermatological conditions from dermoscopic images. Specifically, it presents study of 22 methods that are used to detect dermatological conditions such as basal cell carcinoma, melanocytic nevus, seborrheic keratosis, psoriasis, benign keratosis, melanoma, acne, cold sore, warts, eczema, hives, shingles, scar, skin tag, inflammatory hyper pigment, cyst, dark circle, blackhead, burn and skin rash. It also covers clinical diagnostic methods for dermatological conditions and the need for computer-aided diagnosis. In this paper, we have also proposed the categorization of deep learning-based dermatological condition detection methods. Moreover, a comprehensive summary of these methods is presented. In addition, this paper summarizes the majority of the datasets available for computer-aided detection of dermatological conditions. Furthermore, it presents enormous challenges and potential future research directions. This survey informs researchers about the latest advancements in deep learning-based detection methods for dermatological conditions and allows dermatologists to stay updated on technological breakthroughs in this area.

INDEX TERMS Convolutional neural network, classification, dermatological condition, deep learning, dermoscopic image, feature extraction, image processing, medical imaging.

I. INTRODUCTION

Dermatological conditions are a rapidly growing health problem, affecting a significant portion of the population and causing emotional and psychological distress for patients. These conditions arise from various factors, including the presence of bacteria [1], [2], fungi [3], parasites [4], [5], microorganisms [6], [7], and viruses on the skin [8], [9], [10], as well as weakened immune systems, allergens, irritants, genetic factors, and contact with infected skin. Common

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dermatological conditions include acne, rash, mole, blister, papules, and vesicles. Early diagnosis is crucial for improving patients' quality of life. Clinical tests used for diagnosing these conditions include dermatological examination using a dermatoscope, skin biopsies (also known as whole slide imaging), gene mutation testing, and imaging tests like MRI, CT scan, and PET. However, these clinical tests have significant drawbacks: 1) manual diagnosis is subjective, and 2) the diagnostic process is time-consuming because dermatologists and dermatopathologists perform the procedures manually. The research community observed that automating the clinical tests will help the dermatologist and dermatopathologist to bring impartiality by providing a precise diagnosis. Furthermore, the automated tests would give speedier diagnosis results to dermatologists and an early medicinal aid to patients at an early stage. Hence, numerous machine learning-based and deep learning-based methods for detecting dermatological conditions have been proposed in the literature. To address the drawbacks, Machine Learning (ML) and Deep Learning (DL) approaches have been developed [11]. In recent years, Artificial Intelligence (AI) has made significant progress in the field of dermatology, particularly in image classification and predicting malignancy. However, the application of AI in clinical dermatology practice presents challenges due to the variability in models, image data, database characteristics, and outcome metrics. A comprehensive comprehension of the literature in dermatology that employs Convolutional Neural Networks (CNNs), a widely adopted deep learning architecture is surveyed [12].

An extensive analysis of deep learning-based techniques for detecting dermatological conditions by analyzing dermoscopic images is presented in the paper. It is a valuable resource, cataloging existing methods and enabling researchers and medical professionals to stay abreast of the latest technological advancements in this field. The key highlights of this survey include:

1. Original Contribution: This survey represents the comprehensive attempt to compile and analyze the 22 deep learning-based dermatological condition detection methods including the latest methods from the literature.
2. Taxonomy and Introduction: The survey concisely introduces common dermatological conditions in the literature. Additionally, a taxonomy is developed based on depicting various dermatological conditions using dermoscopic images.
3. Method Evaluation and Summary: An exhaustive evaluation of deep learning-based methods, considering identified parameters, is conducted. The survey then presents a detailed summary of each method individually.
4. Challenges and Future Directions: The survey concludes by highlighting the significant challenges faced in this field and outlining potential future research directions and possibilities.

Fig. 1 shows the organization of the paper.

Section II provides a comprehensive overview of the fundamental concepts related to dermatological conditions and the different types of such conditions. Section III focuses on the clinical tests commonly used for diagnosing dermatological conditions. In Section IV, we begin by introducing a classification of deep learning-based techniques categorized according to the conditions they detect. Furthermore, we summarize these methods, highlighting their key characteristics and outlining potential future research directions. We then perform a parametric evaluation of deep learning-based methods based on identified parameters. Finally, in Section V, we shed light on the open challenges and future research opportunities in deep learning-based methods for dermatological condition detection.

A. INTENDED AUDIENCE

The survey aims to help academic, industrial researchers, and dermatologists acquire comprehensive knowledge of deep learning-based methods to detect dermatological conditions. The contributions in this survey will benefit the technical experts and assist dermatologists and researchers from other interdisciplinary fields, such as biomedical engineering and medical imaging, to develop an effective deep learning-based method. The challenges along with the future research directions are highlighted in this paper that will motivate the prospective researchers to set goals and fill the current research gaps.

B. SURVEY METHODOLOGY

Over the past decade, several survey papers have focused on detecting dermatological conditions from images. However, several of them concentrated mainly on standard machine learning methods, with only a few deep learning-based methods. Furthermore, the most current deep learning-based methods for dermatological condition diagnosis were excluded. As a result, it is critical to include the most recent studies to assess the field's current state. Moreover, previous surveys exclusively examined a particular dermatological condition (e.g., acne) or specialized analysis tasks (e.g., skin lesion categorization) with no mention of non-melanoma disorders or general dermatological problems [13], [14], [15], [16]. Therefore, to address the abovementioned concerns, this paper thoroughly surveys computer-aided dermatological condition diagnosis based on deep learning. To assure the validity of the methodologies, most of the research in this survey is from peer-reviewed publications, including conference proceedings and journal papers. The papers included in this survey are published versions of recent papers from 2017 to 2023.

We have examined multiple research papers to address the following set of questions:

1. What is the current knowledge and understanding of dermatology and dermatological conditions?
   This question aims to understand dermatology and its associated conditions comprehensively. The correspond-

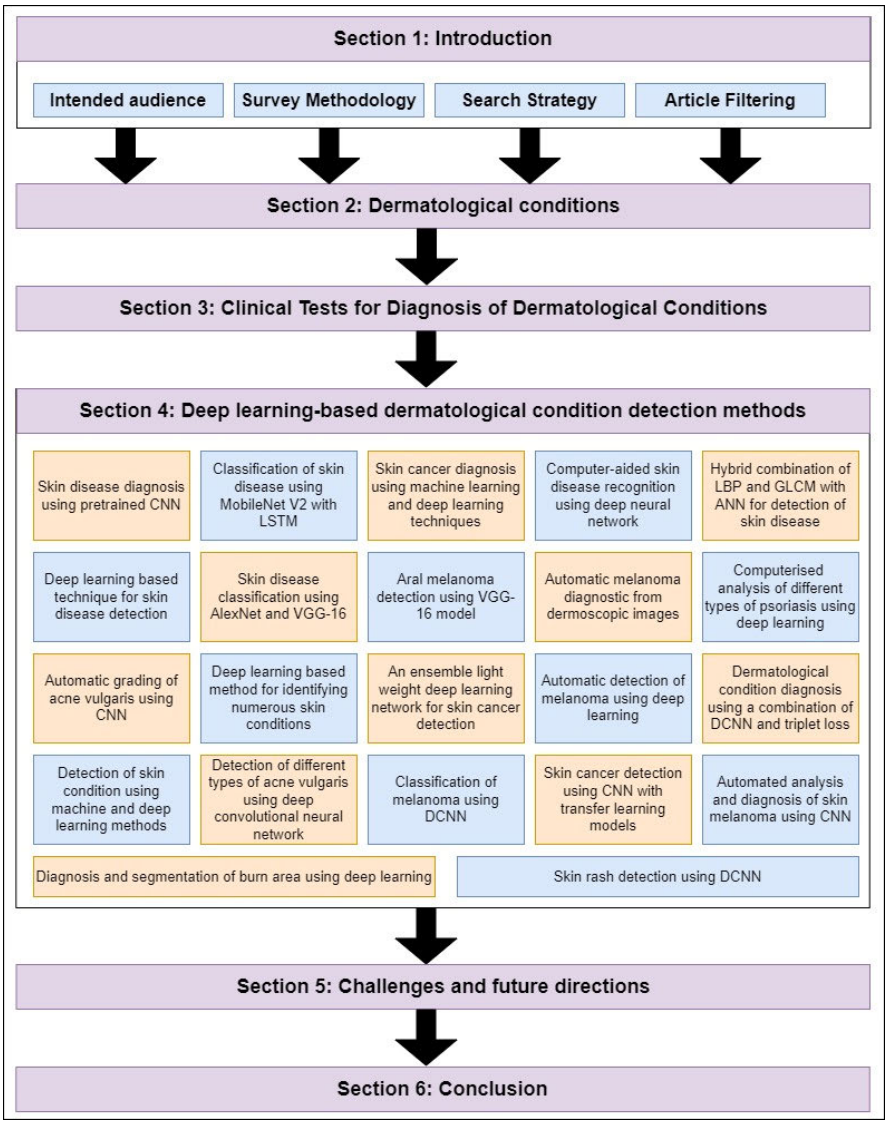

FIGURE 1. Paper organization.

ing section in the survey is titled "Dermatological conditions and their clinical tests."

2. Which dermatological conditions can be detected using deep learning-based methods with dermoscopic images?
   The survey aims to provide an extensive overview of the various types of dermatological conditions that can be detected using deep learning-based methods developed within the past five years.
3. What are the key advantages and potential limitations of deep learning-based methods for dermatological condition detection?
   This question complements the discussion on the benefits and limitations of deep learning-based methods in the section titled "Deep learning-based methods for detecting various dermatological conditions using dermoscopic images." The existing methods are summarized with their key characteristics and limitations in tabular form.
4. What indicators are used to evaluate the effectiveness of deep learning-based dermatological diagnosis methods? In the "Analysis and discussion" section, we present a technical evaluation of the methods using a set of identified parameters as indicators for their effectiveness.
5. What are the general limitations or research gaps in the literature regarding detecting dermatological conditions using deep learning-based methods?
   The survey addresses the limitations and research gaps in the field, which are highlighted in the "Analysis and discussion" section.

By addressing these questions, the survey provides a comprehensive understanding of the current state of deep learning-based methods for detecting dermatological conditions using dermoscopic images.

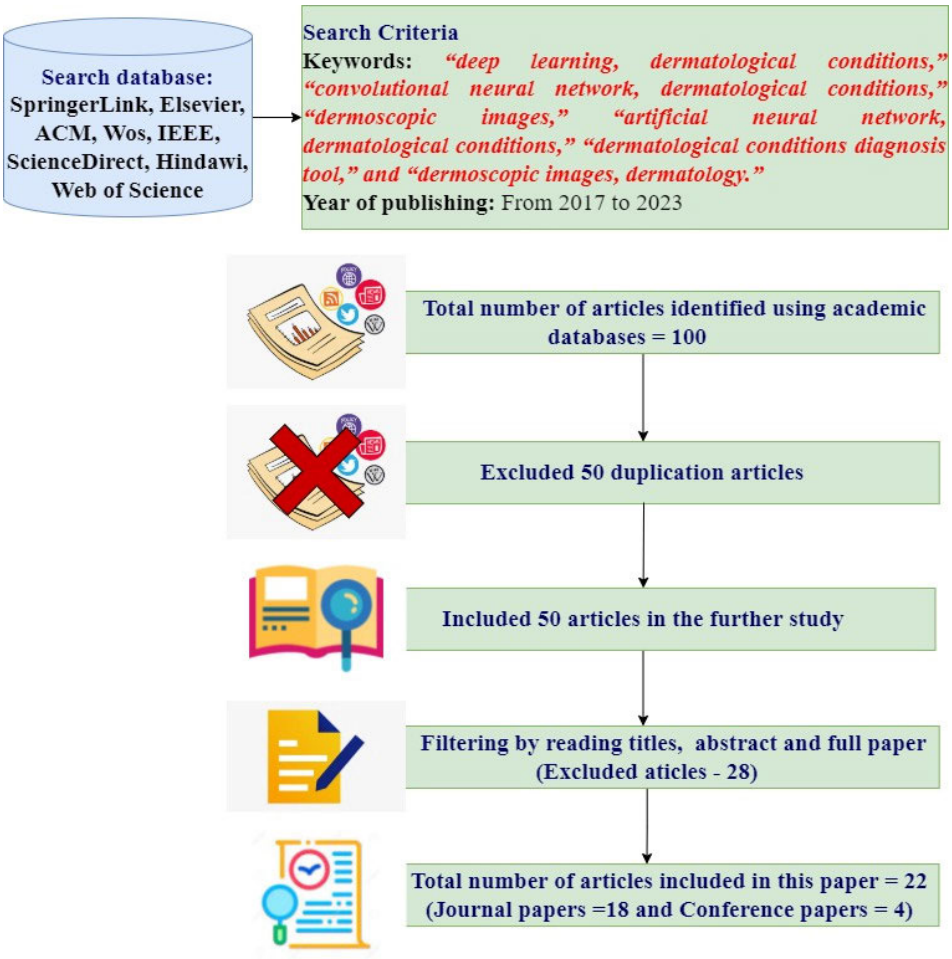

FIGURE 2. Process for selection of research papers.

C. SEARCH STRATEGY

The databases in Table 1 were used to find pertinent journal papers and conference papers published by top peer-reviewed journals.

TABLE 1. Academic databases.

Academic databases	Link
Web of science	https://apps.webofknowledge.com/
PubMed	https://pubmed.ncbi.nlm.nih.gov/
Scopus	https://www.scopus.com/home.uri
Elsevier	https://www.elsevier.com/en-in
ScienceDirect	https://www.sciencedirect.com/
SpringerLink	https://link.springer.com/
IEEE Explore	https://ieeexplore.ieee.org/Xplore/home.jsp
Hindawi	https://www.hindawi.com/

The initial search keywords were judiciously chosen following the research goal. Following a preliminary search, multiple words discovered in several related papers were used to generate several keywords. The keywords were eventually whittled down to fit the research goal. The keywords that were utilized in the survey include ''deep learning, dermatological conditions,'' ''convolutional neural network, dermatological conditions,'' ''dermoscopic images,'' ''artificial neural network, dermatological conditions,'' ''dermatological conditions diagnosis tool,'' and ''dermoscopic images, dermatology.''

D. ARTICLE FILTERING

The relevant studies in the above search results were filtered by gazing at the study's abstract, introduction, and conclusion sections. Papers matching the inclusion criteria were considered appropriate for the survey, whereas those not were eliminated. Fig. 2 graphically depicts the process for selecting the optimum set of research papers used for this survey. Moreover, the criteria implemented in the papers' selection process are provided in Table 2.

II. DERMATOLOGICAL CONDITIONS

This section gives an overview of numerous dermatological conditions. Before proceeding with the discussion, the abbreviations used throughout the paper are listed in Table 3. In dermatology, problems related to the hair [16], [17],

skin [18], [19], [20], [21], [22], [23], nails [24], [25], and mucous membranes [25] are prevalent throughout the world. Amongst these problems, the skin problem is the most common, and it is frequently associated with irritation [25], [26], [27], [28], clogged pores [29], or inflammation [30], [31], [32], [33] caused by an infection or immunological condition. Typical symptoms of the problems mentioned above include moles, acne, cellulitis, lupus, eczema, hives, redness, swelling, burn, rash, seborrheic dermatitis, redness, itchiness, and skin growth. These symptoms severely impact the quality of life and may affect the person's appearance. Fig. 3 (a) describes common dermatological conditions, and Fig. 3 (b) represents the dermoscopic images of the dermatological conditions.

Basal cell carcinoma [34], [35] develops in the basal cells, which are specialized skin cells that create new skin cells when old ones die. Basal cell carcinoma is most seen as a somewhat translucent lump on the skin, although it can also take different forms. Basal cell carcinoma is most common on sun-exposed parts of the skin, such as your head and neck. Long-term exposure to ultraviolet (UV) radiation from sunlight is considered to cause many basal cell carcinomas. Using sunscreen and avoiding the sun may help guard against basal cell carcinoma.

Melanocytic nevus/Mole [36], [37], [38] is medically known as nevi. A type of skin growth that is common is called a mole. Small, dark brown spots with clusters of pigmented cells can be seen on the skin. More children and adolescents experience moles than adults do. Most people have between 10 and 60 moles, which can change or vanish with time. Most moles are entirely safe to touch. They only occasionally progress to malignancy. Skin cancer, particularly malignant melanoma, can be detected by observing moles and other pigmented patches. The scalp, armpits, toes, between your fingers and toes, and other body parts may develop moles. Moles may darken and enlarge due to hormonal changes associated with puberty and pregnancy. Skin cancer is a highly dangerous form of cancer that can metastasize if not detected and treated early. In recent years, the integration of deep learning techniques into the field of skin cancer diagnosis has been a significant breakthrough in healthcare. The current state-of-the-art methods for automatically diagnosing skin cancer using deep learning algorithms are explored. The objective is to provide a comprehensive exploration of existing deep learning approaches and their application in analyzing dermoscopic images. Skin cancer is a highly prevalent form of cancer that requires clinical evaluation of skin lesions for accurate diagnosis. However, this process is time-consuming and subjective, leading to variations in interpretation. The use of deep learning and computer vision is done to improve the diagnosis of melanoma, a prevalent and deadly form of skin tumor and cancer by utilizing an approach using the Inception-V3 and InceptionResnet-V2 models for melanoma recognition. The ability to identify melanoma quickly and accurately can significantly decrease the chances of fatal outcomes for patients.

Seborrheic keratosis [38], [39] is a rash with flaky scales that develops on the skin. On light skin, it creates redness, while on duskier skin, it causes light spots. Cradle cap, hair dandruff, seborrhoea, eczema, and seborrheic psoriasis are their other names [39], [40]. It may resemble psoriasis, eczema, or allergic response in appearance. It mainly affects the scalp, although it can affect any body part. Symptoms and indications of seborrheic dermatitis include a flaky white crust on the scalp, hair, eyebrows, beard, mustache, sides of

TABLE 2. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
• The survey focuses on detecting dermatological conditions using deep learning-based methods from dermoscopic images.	• Nonindexed journals were eliminated from the survey. Without peer-reviewed manuscripts posted as preprint-to-preprint services like bioRxiv, medRxiv, arXiv, and others were omitted.
• Journal and conference papers published between 2017 to 2023 are considered.	• Papers published in journals or at conferences in languages other than English were not considered.
• Papers published in peer-reviewed journals and conferences that are well-known are indexed.	
• Journal conference papers written in English were taken into consideration.	

TABLE 3. List if abbreviations.

Abbreviation	Description
AD	Atopic Dermatitis
ANN	Artificial Neural Network
AUC	Area Under Curve
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Network
DNN	Dense Neural Network
DSLR	Digital Single-Lens Reflex
Ecz	Eczema
FPR	False Positive Rate
FTNN	Fine-Tuned Neural Networks
GAN	Generative Adversarial Networks
GLCM	Grey-Level Co-occurrence Matrix
HOG	Histogram of Oriented Gradients
IGA	Investigator's Global Assessment
KNN	K-Nearest Neighbor
LBP	Local Binary Patterns
LSTM	Long Short-Term Memory
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography Scan
Pso	Psoriasis
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristic
SD	Seborrheic Dermatitis
SVM	Support Vector Machine
SIFT	Scale Invariant Feature Transform
TNR	True Negative Rate
TPR	True Positive Rate
VGG	Visual Geometry Group

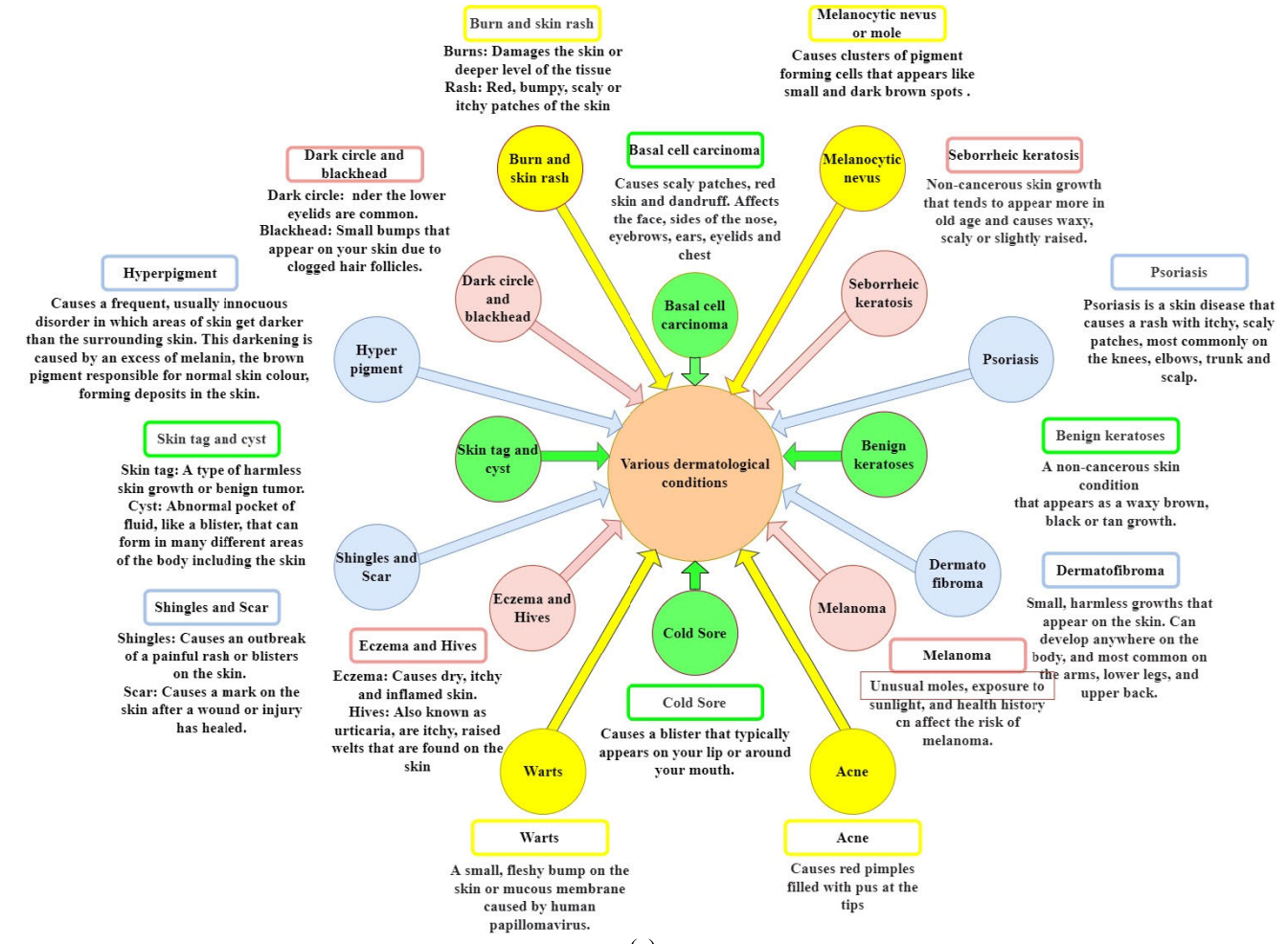

FIGURE 3. (a) Types of dermatological conditions, and (b) Dermoscopic images of dermatological conditions.

the nose, eyebrows, ears, under the eyes, chest, and under the breasts.

Psoriasis [41], [40], and [42] is a skin condition in which skin cells proliferate up to ten times faster than usual. This causes rough patches of skin to form. On lighter skin, the patches can be red with white scales. The spots on darker skin might be purple, violet, or brown with grey scales. They can form everywhere, but most of the time they appear on the scalp, elbows, knees, and lower back. Psoriasis cannot be transferred from one person to the next. It does happen occa-

sionally among members of the same family. The symptoms of psoriasis vary based on the kind that someone possesses. Some of the most frequent symptoms of plaque psoriasis (the most prevalent kind) are Plaques. This appears red on lighter skin and is frequently coated with silver-colored scales. Plaques with deeper skin tones may be dark brown or purple with grey scales. These plaques can be itchy and unpleasant, and they can crack and bleed at times. In severe situations, the plaques will spread and combine, eventually covering enormous regions. Problems with your fingernails and toes. Your nails may change color or develop little pits. They may also crumble or get detached from the nail bed. Scalp. On the scalp, plaques, scales, or crust form.

Dermatofibroma [43] (superficial benign fibrous histiocytoma) is a common cutaneous lesion with an unknown cause that is more frequent in women. Dermatofibroma normally develops on the extremities (mainly the lower legs) and is asymptomatic, however, itching and discomfort can occur. It is the most frequent type of painful skin tumor. A variety of histologic subtypes of dermatofibroma have been identified. Unless there is diagnostic doubt or especially bothersome symptoms, removal of the tumor is usually not needed.

Melanoma, [44], [45] the worst kind of skin cancer, grows in the cells (melanocytes) that create melanin, the pigment that gives your skin its color. Melanoma can also develop in the eyes and, in rare cases, within the body, such as the nose or throat. Although the specific etiology of all melanomas is unknown, exposure to ultraviolet (UV) radiation from sunshine or tanning lights and beds raises your chance of acquiring melanoma. Limiting your exposure to UV light may help lower your chance of developing melanoma. Melanoma risk appears to be rising in those under the age of 40, particularly among women. Knowing the warning symptoms of skin cancer can aid in detecting and treating malignant changes before they spread.

Acne [46], [47] is a skin condition that occurs when oil and dead skin cells block the hair follicles. Pimples, whiteheads, and blackheads are all caused by it. Although it affects people of all ages, acne is most frequent among teens. Despite the availability of effective acne treatments, acne can be tough to control. It takes a long time for acne to heal, and as one disappears, another appears. Depending on the severity of acne, it can cause mental distress and skin scars. The symptoms of acne vary based on the severity of the illness. They are whiteheads (closed stopped pores), blackheads (open plugged pores), tiny red lumps (papules), pustules, tender lumps (nodules), and pus-filled tumors (cystic lesions).

A cold sore [48] is a collection of small, painful blisters caused by the herpes simplex virus (HSV). Fever blisters were commonly referred to as herpes simplex labialis. Around the world, up to 90% of people have at least one form of HSV. The first time you have cold sores, the symptoms are generally the most severe. A first cold sore may make a youngster quite sick. Cold sores are most found on the exterior of the mouth and lips, although they can also appear on the nose and cheeks.

Warts [49] is an infection of the skin caused by the human papillomavirus (HPV). The infection causes the skin to develop rough, skin-colored pimples. The virus is spreadable. Warts can be contracted by touching someone who has them. Warts are most frequent on the hands, although they can also occur on the feet, face, genitals, and knees.

Eczema [50], [51], [52], [53] describes a wide range of skin swellings. Eczema is a contagious skin disease which is also known as dermatitis. The etiology of eczema is uncertain. Although eczema is often chronic, it can improve or deteriorate with time. In people who have it, it can induce hay fever and asthma. Atopic dermatitis is the most prevalent kind of eczema. It primarily affects babies and children, although it can also affect adults. Atopic dermatitis in youngsters may improve or disappear as they become older. However, the skin may become dry and irritated at times.

Hives, [54] also known as urticaria, are skin welts that are itchy and swollen. On lighter skin, they are commonly red, pink, or flesh-colored; on brown or black skin, they may be flesh-colored or somewhat lighter or darker than your skin tone. They can sting or pain at times. Hives are typically caused by an allergic reaction to a drug or food, or by an irritant in the environment. Hives are often an acute (temporary) condition that can be treated with allergy medicines. The majority of rashes fade away on their own. Chronic (ongoing) instances, as well as hives followed by a strong allergic reaction, are more serious medical issues.

Shingles [54], [55] is a painful viral illness that develops a rash. Shingles may appear anywhere on the body. It usually appears as a single stripe of blisters that goes around the left or right side of your chest. Shingles are caused by the varicella-zoster virus, which is also responsible for chickenpox. The virus that causes chickenpox remains in your body for the rest of your life. The virus may return as shingles years later. Shingles is not a fatal disease. However, it can be excruciatingly unpleasant. Vaccinations can help reduce the risk of shingles. Early therapy may minimize the duration of a shingles infection and reduce the likelihood of complications. Postherpetic neuralgia is the most prevalent complication. This is a painful disorder that produces shingles agony over an extended period.

Scars [56] develop as an outcome of the skin's mending after it has been cut or injured. The skin heals itself by producing new tissue to close the incision and fill in any gaps left by the damage. Scar tissue is mostly composed of a protein known as collagen. Scars appear in a variety of forms and sizes. Some scars are big and terrible, while others are scarcely noticeable. People with dark complexion (particularly those of African, Asian, or Hispanic ancestry) and red hair are more susceptible to acquiring keloid scars. Keloids are elevated scars that expand and spread beyond the place of injury. Scars may be ugly and can make it difficult to walk depending on their size, nature, and placement.

FIGURE 4. Clinical tests for diagnosis of various dermatological conditions.

Skin tags [57], [58] are benign, noncancerous skin tumors. They are made up of fiber with duct cores, nerve cells, and fat cells. They can appear on the following areas: eyelids, armpits, beneath the breasts, groin, upper chest, and neck. They frequently go unnoticed unless they are in a conspicuous location or are continuously touched or scraped, such as by clothes, jewelry, or shaving. Some people may have skin tags and are completely unaware of them. In some circumstances, they just rub off or fall off. Large skin tags may explode when pressed. Skin tags' surfaces might be smooth or uneven in appearance. They are frequently elevated from the skin's surface on fleshy peduncles or stalks. They are often flesh-colored or somewhat brownish. Skin tags begin as little, flattened bumps, like a pinhead. Some remain little, while others become larger. They can be as little as 2 inches in diameter.

Dark circles [59] around your eyes might occur for a variety of causes. Aging is one of the most prevalent causes of dark circles. The skin behind your eyes continues to relax and shrink as you age, making the blood vessels beneath your skin more apparent. Hollowed regions known as tear troughs may also form. Tear troughs cast shadows, exaggerating the impression of swollen eyes.

Infections, heat, allergens, immune system abnormalities, and drugs are all possible causes of skin rashes [60], [61], [62]. Eczema, or atopic dermatitis, is considered the most prevailing skin rash. Atopic dermatitis is a long-term (chronic) rash characterized by swollen, itchy, and dry skin. The disorder can also develop tiny pimples near hair follicles that resemble goosebumps on brown and black skin. Atopic dermatitis patches commonly appear where the skin flexes, such as inside the knees and ankles.

Burns [63] are tissue injuries caused by heat, overexposure to sunlight or other radiation, or chemical or electrical contact. Burns can range from minor medical issues to life-threatening catastrophes. The severity of burn symptoms varies according to the depth of the skin injury. The signs and symptoms of a serious burn might take a day or two to appear. A first-degree burn is a mild burn that only affects the skin's surface layer (epidermis). It may result in redness and discomfort. Second-degree burn is a form of burn that affects both the epidermis and the dermis of the skin. It can produce swelling, as well as red, white, or splotchy skin. Blisters can form, and the discomfort can be excruciating. Scarring can result from deep second-degree burns. Lastly, a third-degree burn penetrates the fat layer just beneath the epidermis. Areas that have been burned may be black, brown, or white. The skin may seem leathery. Third-degree burns can cause nerve damage, resulting in numbness.

III. CLINICAL TESTS FOR DIAGNOSIS OF DERMATOLOGICAL CONDITIONS

Diagnosing the common dermatological condition [64], [65], [66], [67] has been essential for detecting various skin-related diseases and skin cancer. However, various visual and historical aspects of the skin are needed and considered the primary importance for recognizing the dermatological condition and its severity level. Therefore, a dermatologist needs to perform several clinical tests to develop a proper diagnostic conclusion. As shown in Fig. 4, various clinical tests are used in clinical practice like dermatological exams, gene mutation testing, skin biopsy, and imaging tests.

A. DERMATOLOGICAL EXAM [68], [69], [70]

This is the first step in diagnosing the dermatological condition. A dermatologist uses a dermatoscope to examine a person's skin, hair, or nails. In addition, the exam is meant to detect suspicious acne, rash, moles, growths, and other changes that appear on the skin. A dermatoscope uses light and magnification to allow a dermatologist to see a patient's skin in greater detail. A dermatoscope will enable doctors to see minute cells in the skin's outer layer that would otherwise be invisible to the human eye. If the dermatologist finds

something suspicious on the skin, they use a dermatoscope to examine the affected area closely.

B. SKIN BIOPSY [71]

In a skin biopsy, the dermatologist first examines the skin using a dermatoscope. A skin biopsy test is considered if the dermatologist suspects a spot may be cancerous. The skin cells are removed from the body and tested in a laboratory. A dermatopathologist uses the skin biopsy test to detect dermatological conditions and their severity level. The three most prevalent types of skin biopsies are as follows:

- Shave biopsy: A clinician uses an instrument that looks like a shaver to confiscate a tiny amount of the topmost layers of skin, the epidermis and dermis layer.
- Punch biopsy: A sort of biopsy in which the patient is anesthetized during the procedure. A dermatologist uses a spherical tool to eradicate a minor core of skin, including the epidermis, dermis, and superficial layers of the skin.
- Excisional biopsy: It is a process in which a piece of the skin is removed. A dermatologist uses a small knife to confiscate a lump of abnormal skin, including a segment of normal skin that passes the thickest layer of skin.

C. GENE MUTATION TESTING [36]

Any change to one or more genes results in a gene mutation. Certain mutations can result in genetic abnormalities or diseases. Gene mutation testing can help to determine a person's lifetime risk of developing cancer. It looks for specific alterations in the genes, chromosomes, and proteins. Genetic testing looks for transmutations or variations, which are variations in the DNA. In various instances, genetic testing can assist in receiving better medical treatment. There are a variety of genetic tests available. In this test, a person's spit or blood is collected and sent to the laboratory to test the gene alterations. The results of the test usually take a few weeks.

D. IMAGING TEST [20], [46], [47], [72]

Computer-aided diagnosis has emerged as a valuable alternative to overcome the limitations of clinical tests widely used for detecting human body illnesses. Clinical tests such as MRI, CT scan, X-ray, ultrasound, and PET are commonly employed, with each test serving a specific purpose. For instance, a CT scan, or CAT scan, is non-invasive and aids in diagnosing cancer by providing details about the shape and size of tumors. MRI is instrumental in locating cancer and identifying signs of metastasis, enabling doctors to plan appropriate treatments. Ultrasound, however, allows doctors to detect tumors in areas where X-rays are ineffective and are frequently used to guide biopsies. These tests are primarily utilized for identifying the spread of malignant cells within the skin layers. Despite the availability of these clinical tests, they come with certain limitations, including time-consuming procedures, high costs, and subjective manual diagnoses. Consequently, there has been a shift towards developing computer-aided diagnosis systems for dermatological conditions, aiming to mitigate these limitations and enhance diagnostic accuracy.

IV. DEEP LEARNING-BASED DERMATOLOGICAL CONDITION DETECTION METHODS

Over the years, numerous deep learning-based methods for diagnosing dermatological conditions have been suggested and published in the literature. This section presents twenty-one deep learning-based methods to detect dermatological conditions [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93]. We have introduced the categorization of deep learning models based on multiple dermatological conditions detected by them. Next, we present a comprehensive summary of the deep learning-based methods in the form of open research issues for the reference of the research community. In Fig. 5, we have depicted deep-learning models that detect various dermatological conditions. The input to all these methods is the dermoscopic image. The foremost steps involved in most of these methods are pre-processing, segmentation, feature extraction, and classification.

A. SKIN DISEASE DIAGNOSIS USING PRE-TRAINED CNN

In [73], a computerized technique utilizing VGG-16, Inception, Xception, Alexnet, VGG-19, and Googlenet has been proposed for diagnosing skin diseases. Fig. 6 illustrates the major steps involved in this technique. Firstly, the dermoscopic image undergoes preprocessing, which includes downsizing and image augmentation methods. Following preprocessing, the affected region is segmented using a hybrid watershed region-based image segmentation method. This segmentation aims to determine the watershed line within the dermoscopic image to identify prominent regions. The hybrid method combines both edge-based and region-based segmentation techniques. The segmented image is then used to train convolutional neural network (CNN) models to predict one of the four classes: basal cell carcinoma, melanocytic nevus, seborrheic keratosis, and psoriasis. The authors of the paper observed that among the various CNN models tested, GoogleNet demonstrates superior efficiency and accuracy while requiring minimal computational power. The performance evaluation of this technique encompasses metrics such as accuracy, precision, sensitivity, recall, and specificity.

B. CLASSIFICATION OF SKIN DISEASE USING MOBILENET V2 WITH LSTM

In reference [74], a technique for skin disease classification is proposed, leveraging the integration of MobileNet V2 with LSTM. The key advantage of this technique lies in the utilization of LSTM to enhance classification accuracy by preserving the state information of the features. The workflow of this technique is depicted in Fig. 7. Due to a slight class

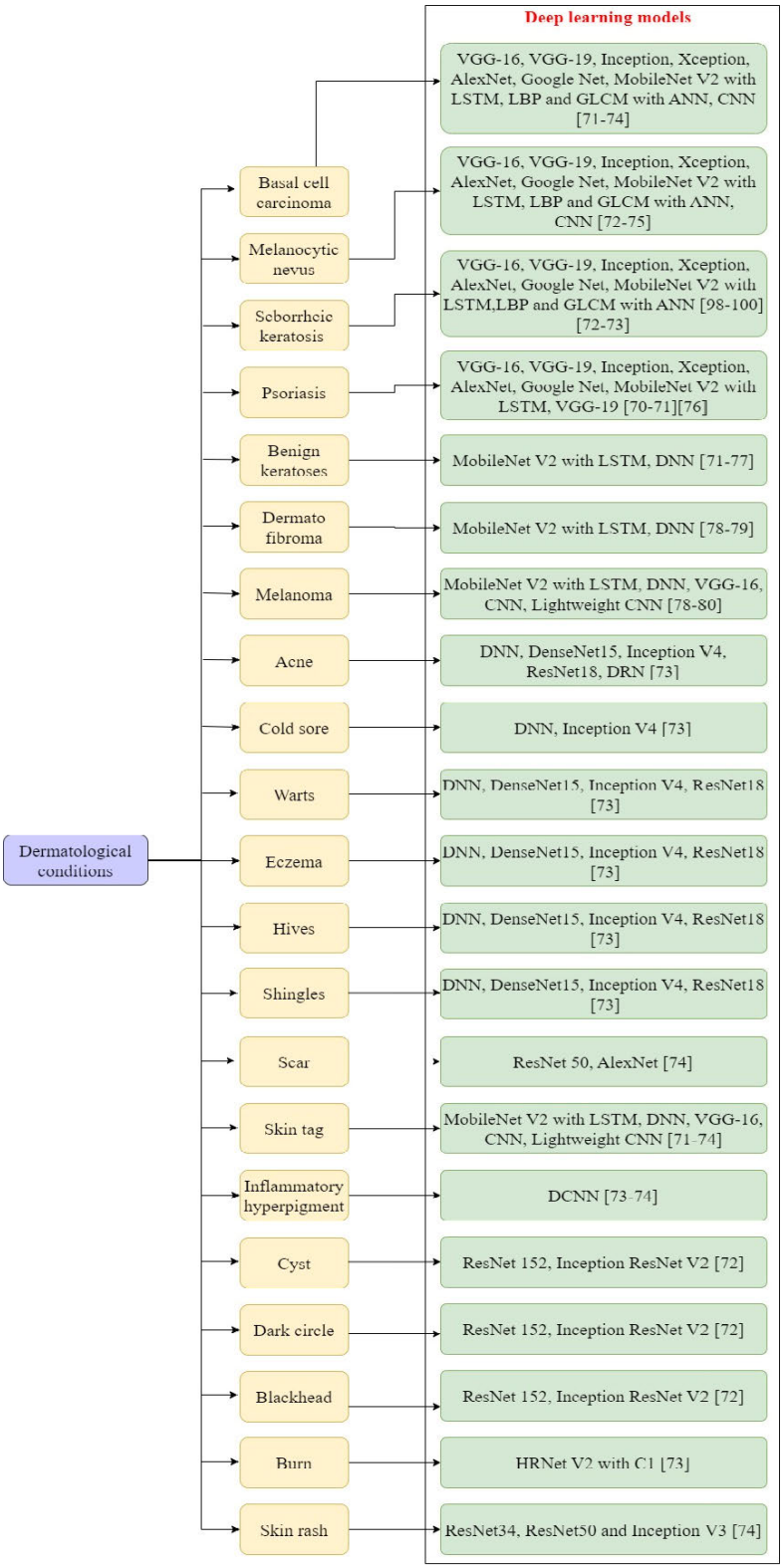

FIGURE 5. **Various dermatological conditions and deep learning models used to detect them.**

imbalance in the skin disease dataset, data augmentation techniques such as rotation and transformation are applied. MobileNet V2 is used to categorize the various skin diseases, and LSTM is utilized to improve the model's performance

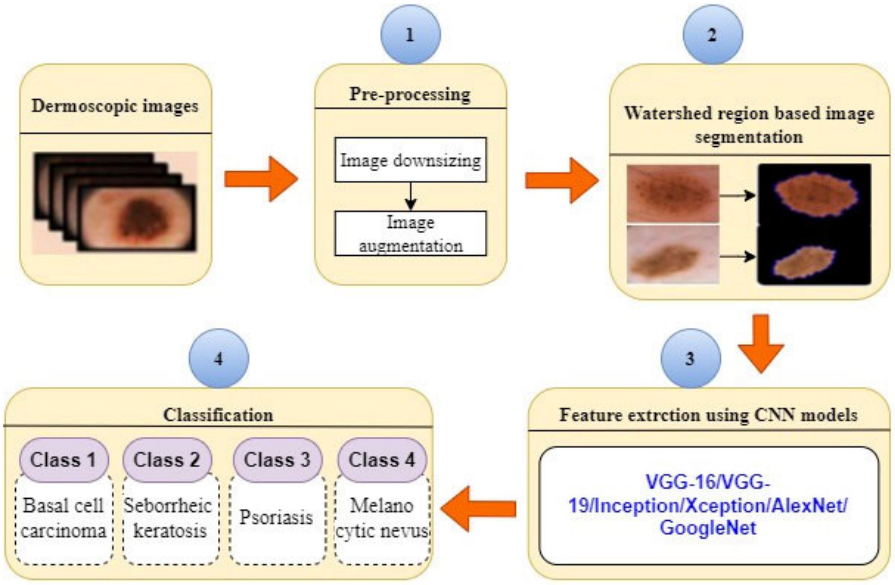

FIGURE 6. Major steps of skin disease diagnosis using CNN models.

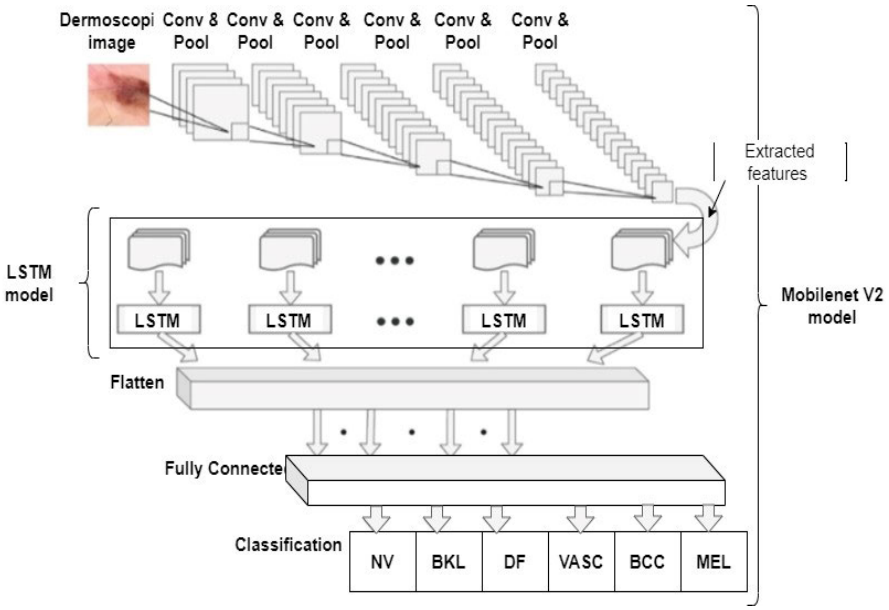

FIGURE 7. The working flow of MobileNet V2 combined with LST.

by retaining feature information encountered in the initial version of image classification. MobileNet V2 is employed for feature extraction, offering computational efficiency suitable for low-power computing devices. The core structure of MobileNet V2 is built on several abstraction layers, each of which is a component of a distinct convolution layer that appears to be the quantized configuration for thoroughly examining a problem's difficulty. The complexity of 1×1 is referred to as point-wise complexity. The general framework of the MobileNet V2 with the LSTM model is an assortment of multiple convolutions and max pooling layers including the LSTM element that is linked to the flattening layer of the model. The fully connected layer involves training to correlate the recognized characteristics with pre- existing data. Finally, there is the softmax layer, which calculates the probability of distinct skin disease categories. Following feature extraction, MobileNet V2 assesses the probability of skin disease, categorizing dermoscopic images into six classes: melanocytic nevus (nv), benign keratosis-like lesions (bkl), dermatofibroma (df), vascular lesions (vasc), basal cell carcinoma (bcc), and melanoma (mel). The technique is evaluated by configuring hyperparameters, including training and

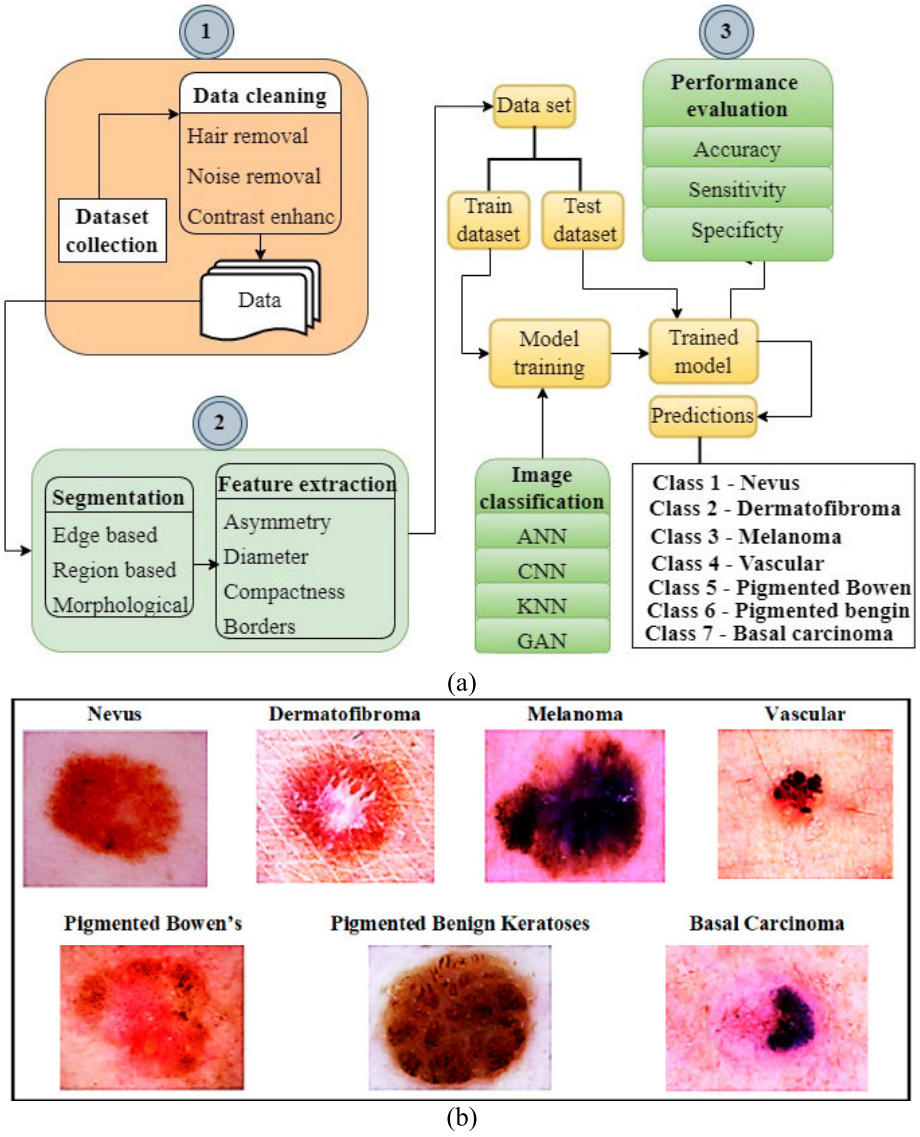

FIGURE 8. (A): Workflow of diagnosis of skin cancer using deep learning models [47], (B): Seven categories of skin cance.

validation loss. Performance evaluation measures encompass sensitivity, specificity, accuracy, Jaccard Similarity Index (JSI), and Mathew Coefficient Correlation (MCC).

C. SKIN CANCER DIAGNOSIS USING ANN, CNN, KNN AND GAN

A deep learning-based technique for diagnosing skin cancer has been presented in [75]. The workflow of this technique has been described in Fig. 8 (a). Fig. 8 (b) shows the seven different categories of skin cancer. In the first step, the dermoscopic image is cleaned using hair removal, noise removal, and contrast enhancement methods. Subsequently, the cleaned image is segmented using edge-based, region-based, and morphological-based segmentation methods. Next, the segmented images train the model to classify one of the dermoscopic images into seven skin cancer categories: nevus, dermatofibroma, melanoma, vascular, pigmented Bowens, pigmented benign keratoses, and basal carcinoma. The authors observed that among the deep learning models (ANN, CNN, KNN, and GAN), GAN gives better classification accuracy. The performance of this technique is assessed using accuracy, sensitivity, and specificity.

D. SKIN DISEASE RECOGNITION USING DEEP NEURAL NETWORKS

In [76], a computer-aided diagnostic technique based on Deep Neural Networks (DNN) is proposed for skin disease recognition. This technique leverages two publicly available skin image datasets: ISIC and DermNet. The major steps involved in this technique are illustrated in Fig. 9. The process begins with the preprocessing of dermoscopic images, which includes noise removal, hair removal, and

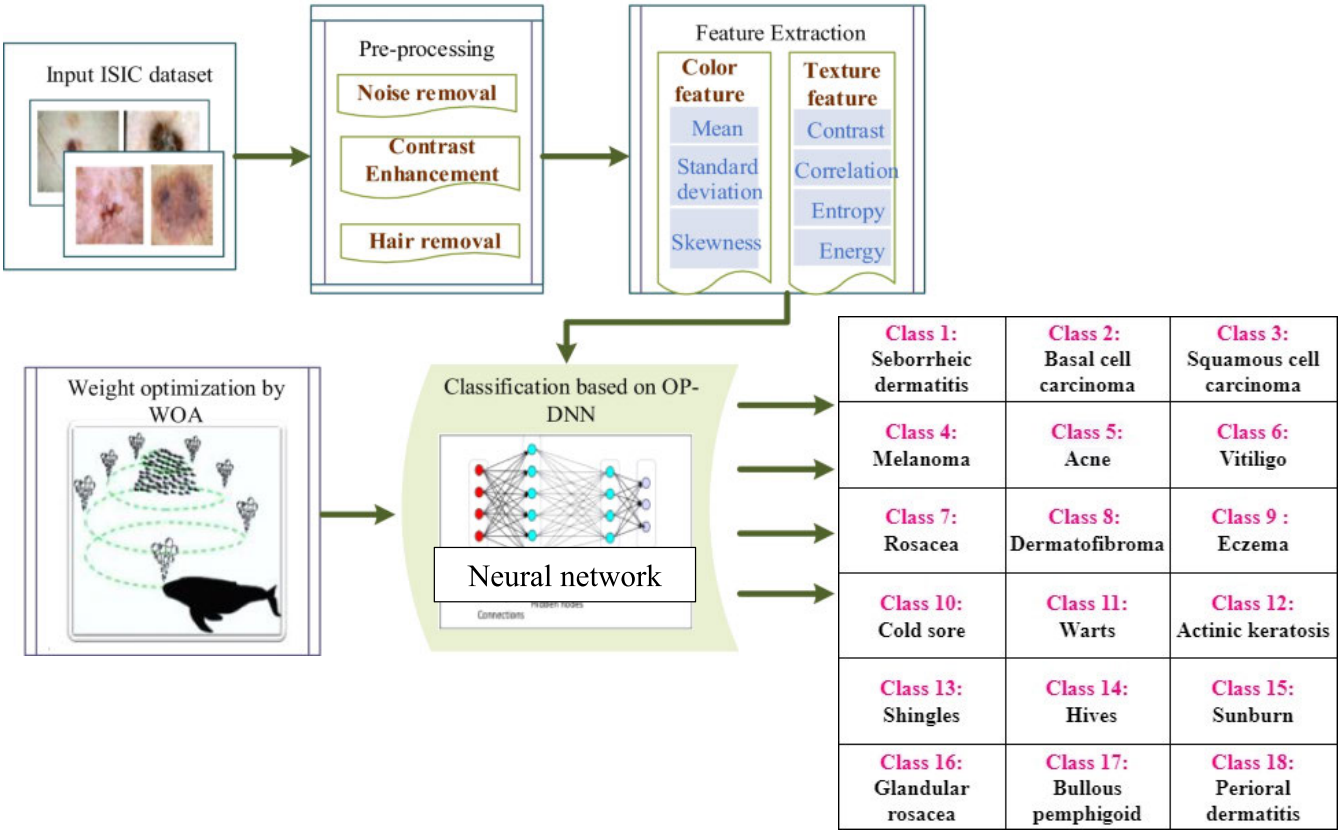

FIGURE 9. Steps of computer-aided skin disease recognition technique.

contrast enhancement methods. Subsequently, color and texture features are extracted from the preprocessed images. These extracted features are then utilized in the classification stage. During classification, the weight optimization method is employed with DNN to diagnose one of the 18 classes, including Seborrheic dermatitis, basal cell carcinoma, squamous cell carcinoma, melanoma, acne, vitiligo, rosacea, dermatofibroma, eczema, cold sore, warts, actinic keratosis, shingles, hives, sunburn, glandular rosacea, bullous pemphigoid, and perioral dermatitis. The weight optimization method offers the advantage of minimizing prediction errors and increasing classification accuracy. The performance evaluation of this technique includes sensitivity, specificity, accuracy, Positive Predicted Value (PPV), Negative Predicted Value (NPV), false positive rate, and false negative rate.

E. DETECTION OF SKIN DISEASE USING A HYBRID COMBINATION OF LBP, GLCM AND ANN

In [77], a skin disease detection method using a hybrid combination of LBP and GLCM with ANN has been offered. The process of this method is depicted in Fig. 10. In this method, the dermoscopic image is preprocessed using the Gaussian filter to filter unnecessary noise. After preprocessing, the active count segmentation method is used to identify the region of interest from the preprocessed image. Next, a hybrid combination of two methods with ANN is used to extract features from the segmented image. This feature extraction method extracts 216 texture features to classify skin diseases into one of the six classes viz. melanoma (mel), nevus (nv), dermatofibroma (df), vascular, basal cell carcinoma (bcc), actinic keratoses and intraepithelial carcinoma (akiec), and benign lesions of keratosis (bkl). The performance of this method is tested using accuracy, sensitivity, specificity, and recall.

F. SKIN DISEASE DETECTION USING DENSENET121, INCEPTIONRESNETV2, AND RESNET152V2

In [78], a technique for detecting skin diseases utilizing DenseNet121, InceptionResNetV2, and ResNet152 V2 is presented. The workflow of this technique is depicted in Fig. 11. Initially, the dataset exhibits imbalanced classes of skin diseases. Data augmentation techniques such as flipping, rotation, translation, color space augmentation, image mixing, kernel filters, and image space augmentation are applied to address the problem of imbalanced classes. Following augmentation, the images undergo preprocessing involving resizing, color normalization, and splitting techniques. Pretrained networks, including DenseNet121, InceptionResNetV2, and ResNet152V2, are employed to extract features and diagnose one of the five skin diseases: malignant melanoma, atypical nevus, dermal nevus, acral lentiginous melanoma, and nevus.

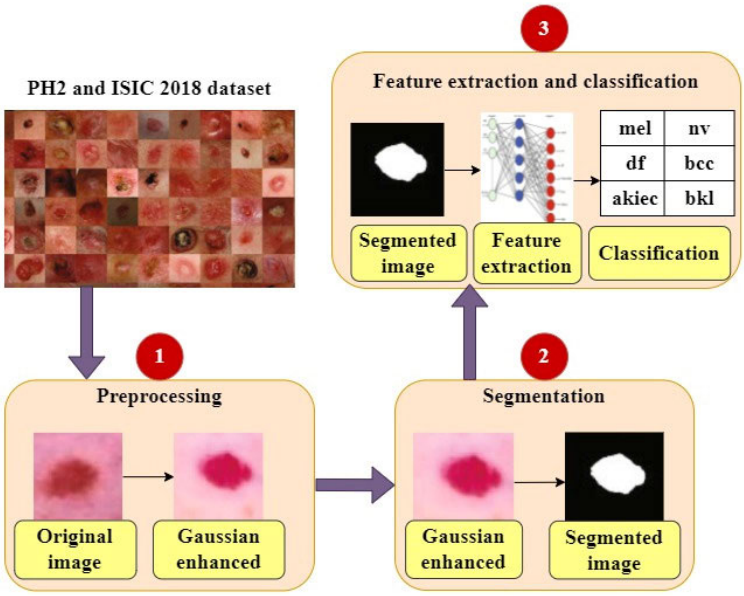

FIGURE 10. Process of a hybrid method for skin disease diagnosis [77].

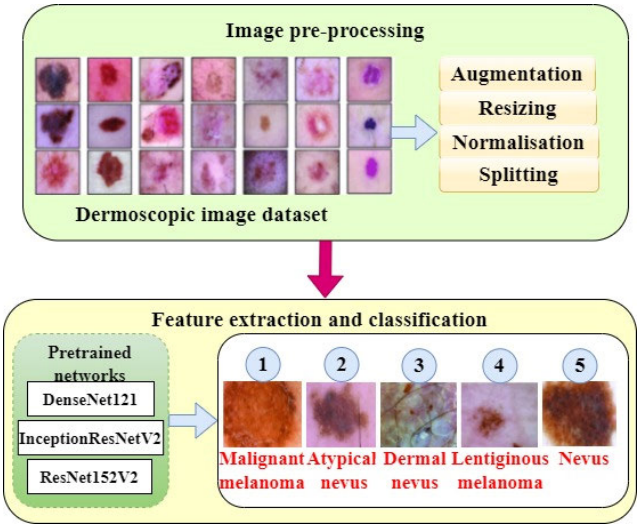

FIGURE 11. Workflow of skin disease diagnosis using pre-trained models.

The authors observed that ResNet152V2 outperforms the other pre-trained networks regarding efficiency and classification accuracy. Performance evaluation of this technique encompasses sensitivity, specificity, recall, precision, and f1-score as metrics.

G. SKIN DISEASE CLASSIFICATION USING ALEX NET AND VGG-16

In [79], a skin disease classification technique using AlexNet and VGG-16 has been proposed. Two datasets, ISIC 2019 and PH2 are used to evaluate this technique. These datasets include information on ten different skin diseases such as psoriasis, melanoma, melanocytic nevus, benign keratosis, basal cell carcinoma, squamous cell carcinoma, actinic keratosis, dermatofibroma, vascular lesion, and eczema. The main steps involved in this technique are depicted in Fig. 12. First, the image is pre-processed using illumination correction, contrast, and edge enhancement methods. These preprocessing methods remove artifacts such as hair, noise, and ink markers from the dermoscopic image. After the preprocessing step, the image is augmented using basic geometric transformation methods. The geometric transformation methods include zooming, cropping, scaling, rotation, and translation. Next, the features are extracted from the dermoscopic image using pre-trained CNN models: AlexNet and VGG-16. The extracted features classify the dermoscopic image in one of the ten skin diseases. The performance of this technique is assessed using accuracy, mean precision, true positive rate, false positive rate, true negative rate, AUC, and ROC.

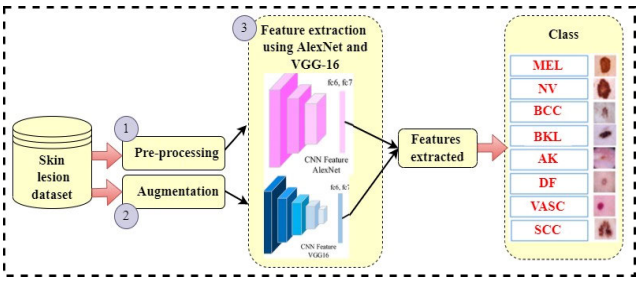

FIGURE 12. Steps for classification of skin disease using AlexNet and VGG-16.

H. ARAL MELANOMA DETECTION USING THE VGG-16 MODEL

In [80], a deep learning-based method is proposed for detecting acral melanoma, the most prevalent type among Asians,

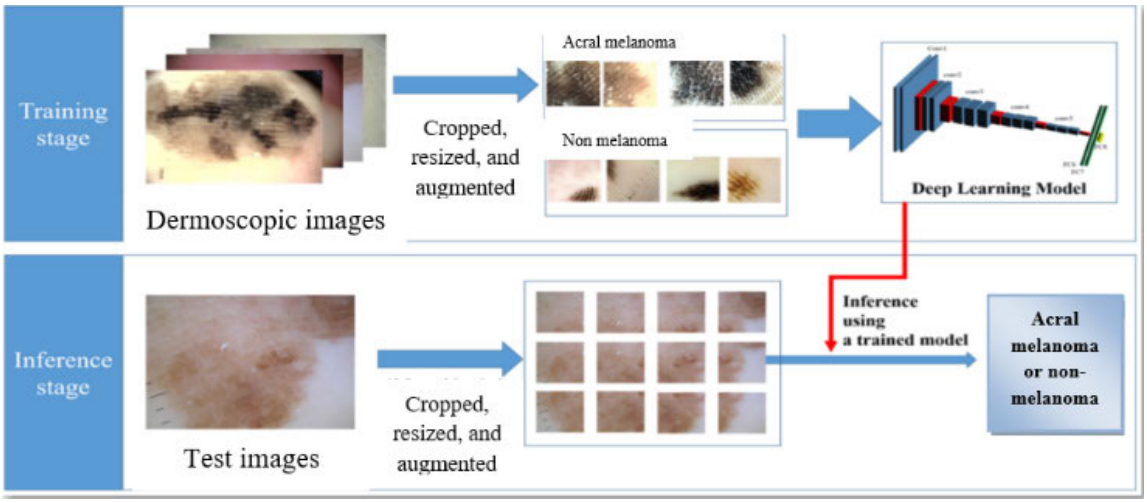

FIGURE 13. Schematic outline of skin disease diagnosis method [79].

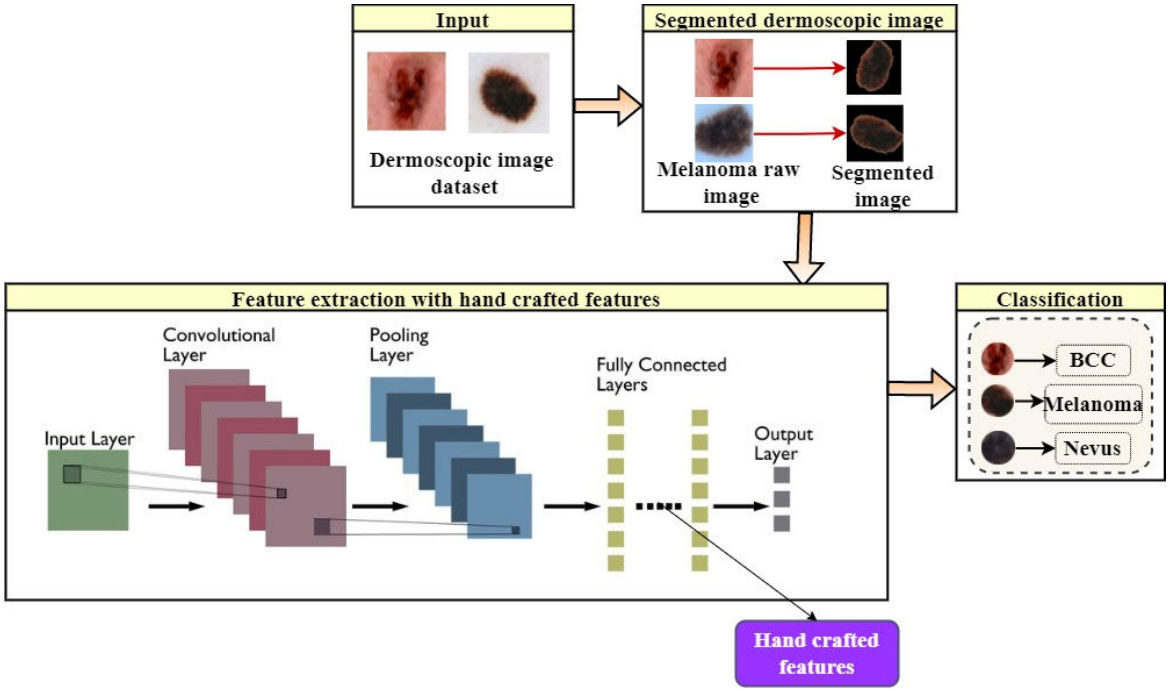

FIGURE 14. Functioning of diagnosis of melanoma from dermoscopic image.

and is often associated with a poor prognosis due to late detection. The methodology of this method is presented diagrammatically in Fig. 13, outlining two main stages: training and inference. Given the limited quantity of dermoscopic images available for training, the authors employed augmentation techniques such as cropping and resizing. The VGG-16 model was then trained for feature extraction using the augmented dermoscopic images. To enhance the model's performance, the authors fine-tuned the VGG-16 model by introducing sixteen additional layers, including thirteen convolutions and three fully connected layers. This fine-tuning process not only improved feature extraction but also mitigated overfitting. In the inference stage, the trained VGG-16 model was utilized to diagnose the two classes: non-melanoma and acral melanoma. The performance of the proposed technique was assessed using accuracy, sensitivity, specificity, AUC, and Youden's index values as evaluation metrics.

I. AUTOMATIC MELANOMA DIAGNOSIS FROM DERMOSCOPIC IMAGES USING HAND-CRAFTED FEATURES WITH CNN

A CNN-based method [81] has the advantage that it helps gain better classification accuracy compared to traditional

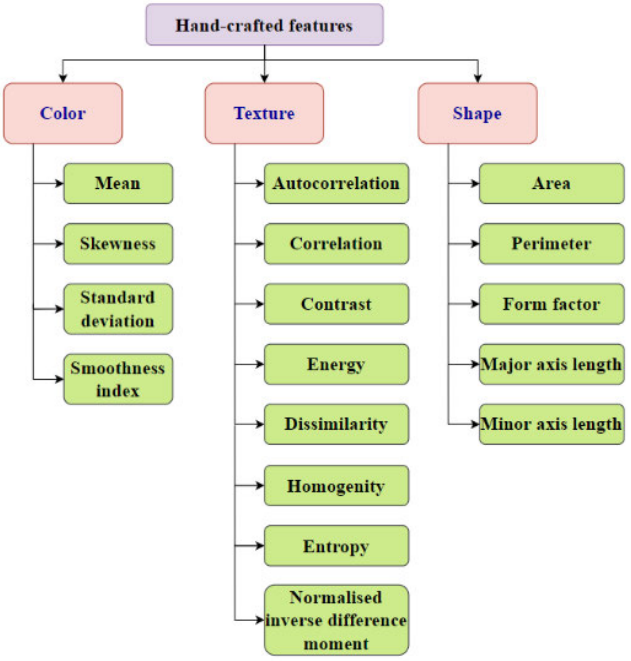

FIGURE 15. Extracted hand-crafted features to detect melanoma.

CNN. The method's functioning is depicted in Fig. 14. Firstly, the affected area is segmented by finding the relation between the pixels and neighborhood pixels using the region growing technique. Next, the hand-crafted features are extracted, as described in Fig. 15, from the segmented image using CNN combined with the scattered wavelet transform method. The extracted hand-crafted features are used to classify the dermoscopic image into one of the three classes of melanoma: basal cell carcinoma, melanoma, and nevus. The performance of this method is tested using accuracy, sensitivity, and specificity.

J. COMPUTERIZED ANALYSIS FOR DIFFERENT TYPES OF PSORIASIS USING VGG-19

Psoriasis [82], a chronic disease caused by immune system dysfunction, is recognized as the most common dermatological condition. Fig. 16 illustrates the distinct types of psoriasis. The workflow of the approach is depicted in Fig. 17. The approach begins with pre-processing the dermoscopic image to eliminate distortions using image enhancement techniques. Next, the prominent region is segmented by identifying the edges in the dermoscopic image through edge detection methods. Following segmentation, features are extracted utilizing the VGG-19 model, encompassing colon, texture, and shape attributes. These extracted features are subsequently employed to classify the dermoscopic image into one of six classes: plaque psoriasis, guttate psoriasis, inverse psoriasis, pustular psoriasis, erythrodermic psoriasis, and normal skin. On a dataset of 1838 photos, the suggested method's performance is assessed, and measures including accuracy, sensitivity, specificity, recall, and precision are used to gauge its efficacy.

K. AUTOMATED GRADING OF ACNE VULGARIS USING DENSENET15, INCEPTION V4, AND RESNET-18

The processing steps involved in this method [83] are illustrated in Fig. 18. Initially, the Region of Interest (ROI) is segmented using the adaptive growth cut method. Following segmentation, the segmented ROI is augmented using random combinations of right and left flipping, contrast adjustment, scaling, and shifting techniques. Subsequently, the dermoscopic images are utilized for training CNN models, specifically DenseNet15, Inception v4, and ResNet-18, for feature extraction. Based on the extracted features, the dermoscopic image is classified into two classes: acne and normal skin. Additionally, the dermoscopic image is further classified into three severity groups of acne: IGA Grades 0-1 (clear/almost clear skin), IGA Grade 2 (mild), and IGA Grades 3-4 (moderate to severe). The performance evaluation of this method involves 484 frontal facial images, each with a pixel size of 2000×3000, acquired from 420 individuals. The method's effectiveness is assessed using accuracy, sensitivity, specificity, Pearson correlation, recall, and precision metrics.

L. SKIN CONDITIONS IDENTIFICATION USING DENSENET15, INCEPTION V4 AND RESNET18

The functioning of this method [84] is depicted in Fig. 19. Along with the dermoscopic image, the metadata of the patient is considered. The features are extracted using the Inception V4 model to classify the dermoscopic image in one of the 27 classes of skin diseases. Actinic keratosis, allergic contact dermatitis, androgenetic alopecia, hidradenitis, basal cell carcinoma, lentigo, melanocytic nevus, post-inflammatory hyperpigmentation, psoriasis, squamous cell carcinoma, and seborrheic keratosis are among the conditions that fall into these categories. The performance of this method is evaluated using accuracy, sensitivity, and specificity. The results are compared with 360 specialized dermatologists who have annotated the dermoscopic images.

M. AN ENSEMBLE LIGHTWEIGHT COMBINATION OF MOBILENETV1 AND DENSENET-121 NETWORK FOR SKIN CANCER DETECTION

The method's workflow is illustrated in Fig. 20 [85]. The technique consists of three main steps: pre-processing, feature extraction, and classification. Initially, the dermoscopic image undergoes augmentation using an image augmentation method. Subsequently, features are extracted from the augmented image using a lightweight CNN architecture that combines MobileNet V1 and DenseNet-121 models. This combination offers the advantage of extracting highly discriminant features, improving accuracy. benign or The extracted features are then used to classify the image into melanoma classes. The technique's performance is evaluated using various indicators such as accuracy, Jaccard index, dice coefficient, specificity, and sensitivity.

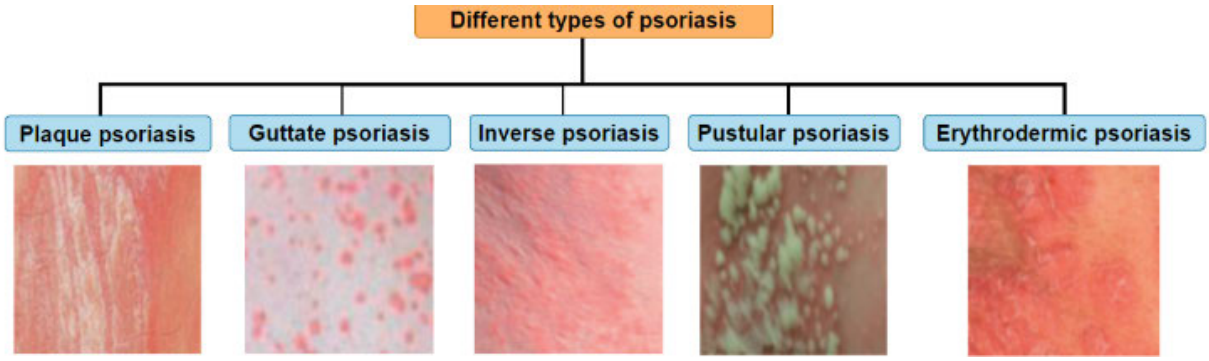

FIGURE 16. Different types of psoriasi.

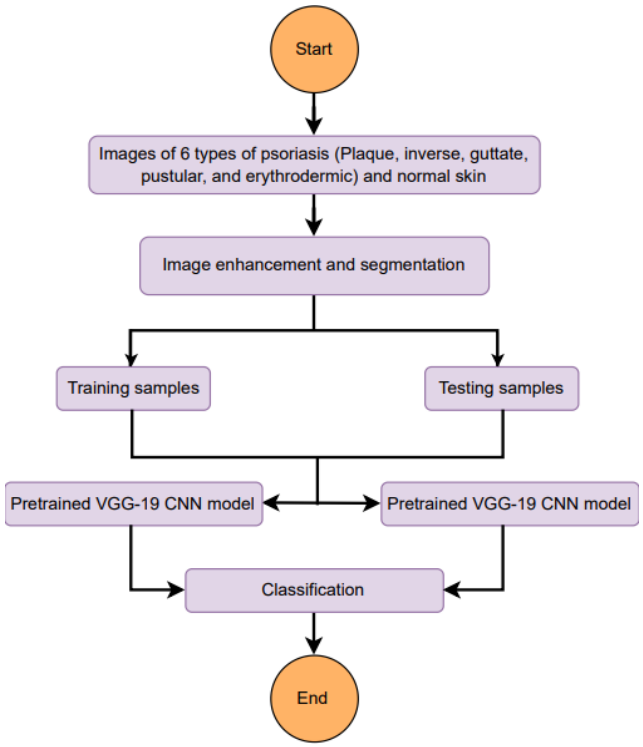

FIGURE 17. Flow of diagnosis of psoriasis using VGG-19 and LSTM.

N. AUTOMATED DETECTION OF MELANOMA USING FULLY CONVOLUTIONAL RESIDUAL NETWORK (FCRN)

The method's workflow is depicted in Fig. 21. The dermoscopic image undergoes preprocessing utilizing cropping and resizing techniques. Subsequently, the region of interest is segmented using the Fully Convolutional Residual Network (FCRN) [86]. FCRN offers significant advantages regarding segmentation accuracy, memory efficiency, and computing time. The segmented images are then employed to train the Deep Residual Network (DRN), distinguishing between benign and malignant melanoma. DRN is crucial in extracting representative and specific features from the dermoscopic image, enhancing classification accuracy. The performance of the proposed method is evaluated using multiple metrics, including sensitivity, specificity, accuracy, Jaccard index, and dice coefficient.

O. AUTOMATED DETECTION OF MELANOMA USING RESNET-152 AND INCEPTION RESNETV2

In [87], a deep learning-based technique to diagnose dermatological conditions has been proposed. The functioning of this technique is depicted in Fig. 22. The dermoscopic images collected by authors were insufficient in number to train the model. Hence, dermoscopic images have been augmented using rescaling, zooming, rotation, horizontal flipping, and resizing methods. Next, the images train the CNN models: ResNet-152 and Inception ResNetV2 for feature extraction. The authors have fine-tuned the CNN models by removing the last fully connected layer. The triplet loss function is added to extract more prominent features and reduce the vanishing gradient problem. After the feature extraction step, the model predicts one of the five dermatological conditions: dark circles, spots, blackheads, acne, and normal face. The performance of this technique is analyzed using parameters such as accuracy, sensitivity, specificity, Area Under Curve (AUC), True Positive Rate (TPR) and False Positive Rate (FPR).

P. DETECTION OF SKIN CONDITION USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

In [88], a hybrid technique has been proposed to detect skin conditions by combining machine learning and deep learning-based models. The working flow of this technique is depicted in Fig. 23. Firstly, the dermoscopic image is enhanced using the Gaussian filter method. The enhanced image is preprocessed using noise and hair removal methods. After preprocessing, the region of interest is segmented using the adopted region growth method. Next, the feature extraction is carried out in two different ways. First, the features are extracted using traditional machine learning methods such as LBP, GLCM, and DWT. A total of 220 features are extracted using these traditional methods. Second, the features are extracted using the deep learning architectures, ResNet-50

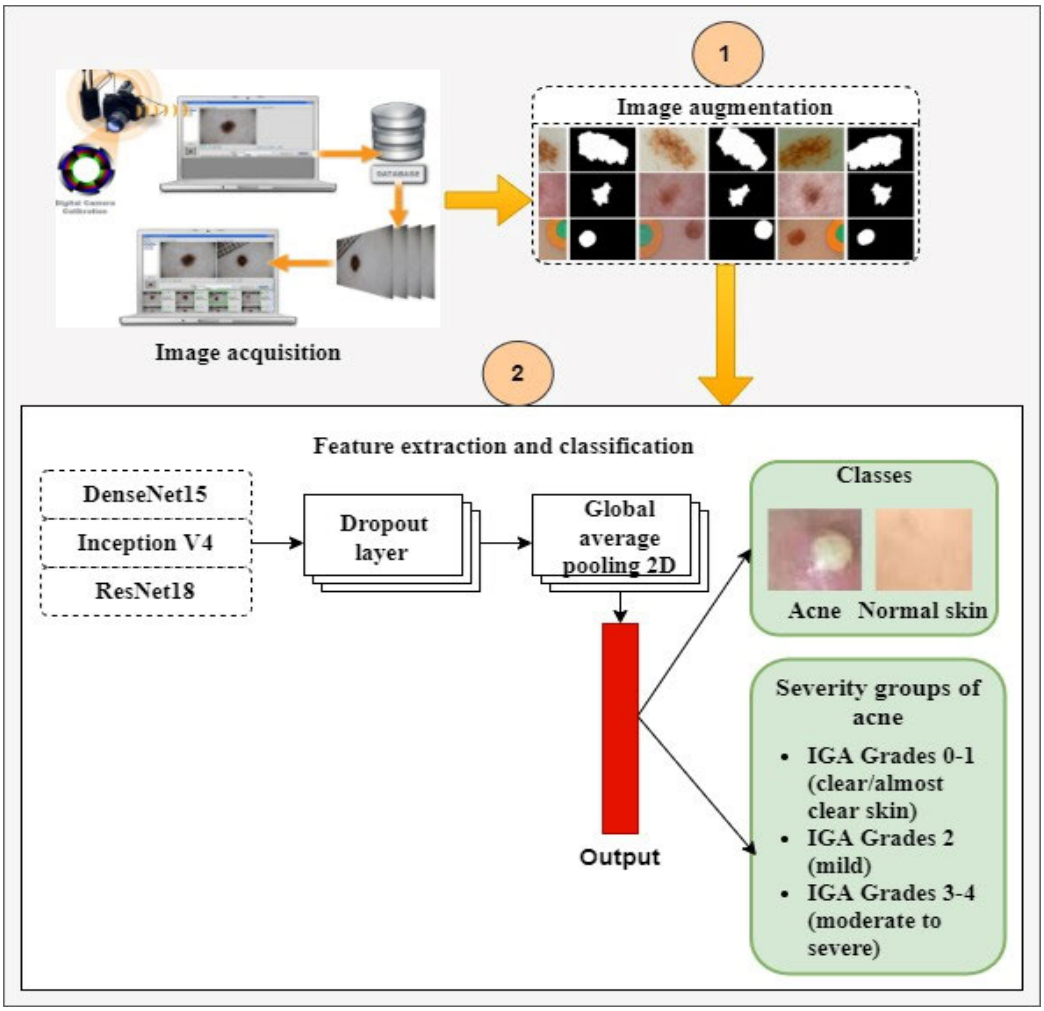

FIGURE 18. Processing steps of automated diagnosis of acne vulgaris and its severity level.

and AlexNet. Lastly, the extracted features are combined for classifying the dermoscopic image in one of the six different skin conditions: melanoma (mel), nevus (nv), basal cell carcinoma (bcc), actinic keratoses and intraepithelial carcinoma (akiec), and vascular (vasc). The performance of this technique is measured using accuracy, precision, sensitivity, specificity, and area under the curve.

Q. DETECTION OF DIFFERENT TYPES OF ACNE VULGARIS USING A DEEP CONVOLUTIONAL NEURAL NETWORK

An automated computer-aided method for acne vulgaris detection is presented in [89]. The key steps of this method are illustrated in Fig. 24 (a), while Fig. 24 (b) showcases the seven distinct categories of acne vulgaris. Initially, the dermoscopic image undergoes augmentation using random rotation, shifting, shearing, scaling, and horizontal flipping techniques. Subsequently, the region of interest is identified within the augmented image. The VGG-16 model is employed to extract features, offering the advantage of efficient feature extraction with minimal training time. The trained VGG-16 model classifies the dermoscopic image into one of the seven categories of acne vulgaris: papule, cyst, blackhead, pustule, whitehead, nodule, and normal skin. The performance evaluation of this method encompasses various metrics such as Receiver Operating Characteristic Curve (ROCC), Area Under Curve (AUC), Youden's index, best threshold, accuracy, sensitivity, and specificity.

R. CLASSIFICATION OF MELANOMA USING DCN

The main objective of an automated approach for efficient melanoma detection using a Deep Convolutional Neural Network (DCNN) is to achieve an accurate classification of melanoma while utilizing a less complex DCNN architecture [90]. The functioning of this method is demonstrated in Fig. 25. A data normalization technique is employed to eliminate redundancy and address the issue of non-normalized dermoscopic images in the dataset. Subsequently, a noise removal technique is applied during preprocessing to ensure that the DCNN model operates effectively on artifact-free raw images. This technique helps remove unwanted elements

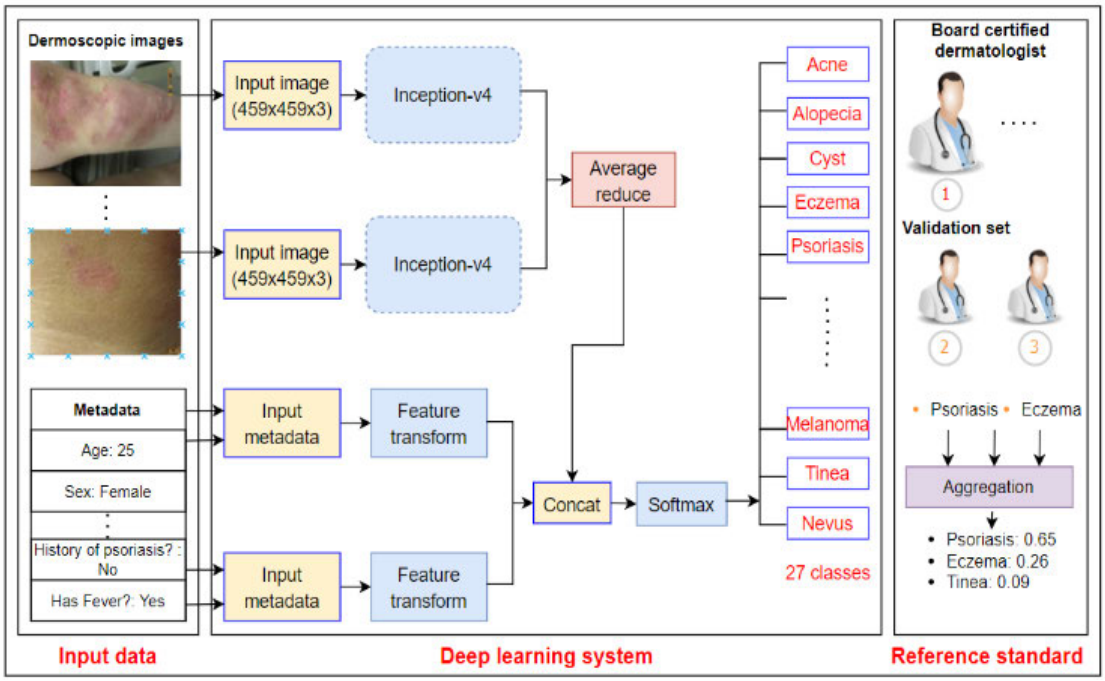

FIGURE 19. Functioning of an automated method to diagnose multiple skin diseases [83].

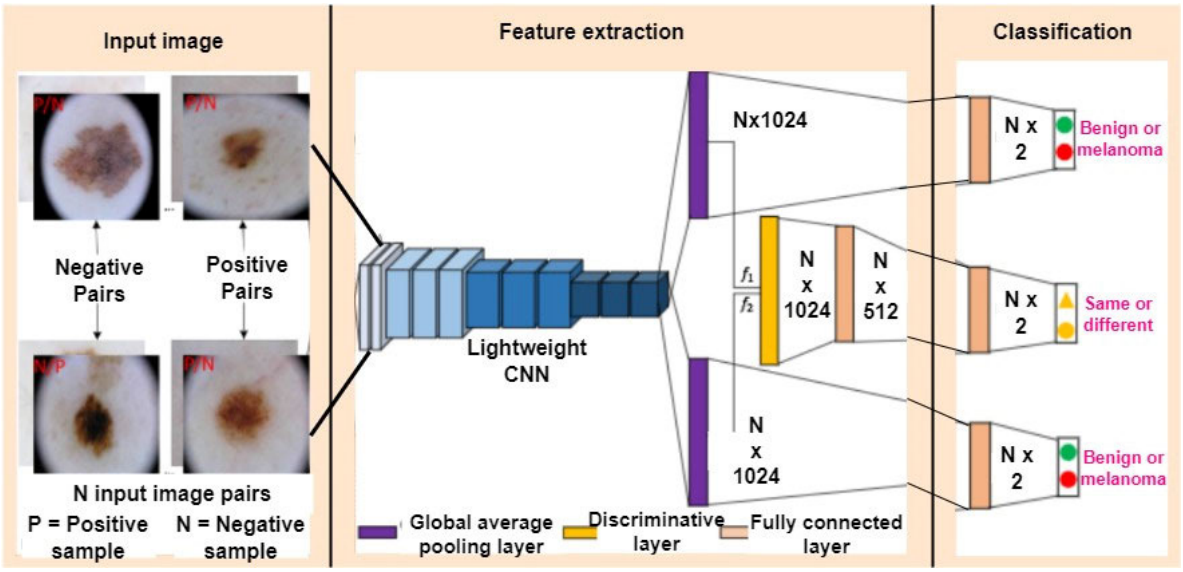

FIGURE 20. Working flow to detect skin cancer using ensemble lightweight deep learning network [84].

such as hairlines, gel bubbles, ruler markings, and ink markers. The preprocessed image is then augmented using rotation, scaling, and translation methods to enhance the dataset diversity. The augmented images are utilized for training the DCNN model, enabling the classification into two classes: melanoma and benign. The methodology involves experimentation with hyperparameters such as learning rate, mini-batch size, epoch, activation function, momentum, and regularization. The performance evaluation of this method is conducted using metrics such as accuracy, precision, recall, specificity, and F1-score.

S. SKIN CANCER DETECTION USING CNN WITH TRANSFER LEARNING MODELS

An automated technique has been proposed to detect skin cancer using CNN with transfer learning [91]. Input to this method is the dermoscopic image. The initial stage in this process is pre-processing, where the median filter is

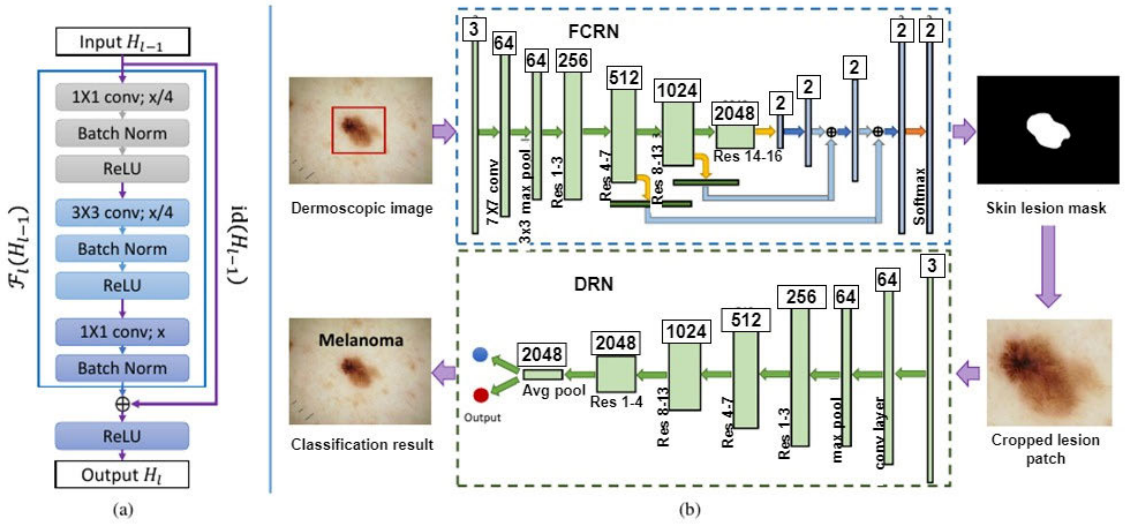

FIGURE 21. Process of the melanoma detection technique [85].

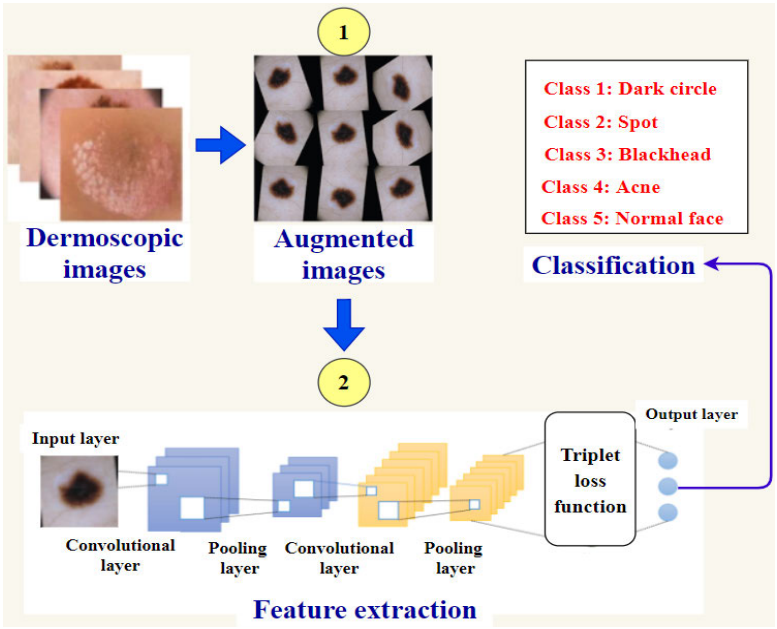

FIGURE 22. Functioning of the dermatological condition diagnosis method.

applied for noise removal. Next, the pre-processed image is augmented using rotation and flipping methods. The dermoscopic images train the Residual DCNN model for feature extraction. The trained Residual DCNN model predicts one of the two classes: melanoma and nevus. The performance of this technique is assessed using precision, accuracy, recall, specificity, and F1-score parameters.

T. AUTOMATED ANALYSIS AND DIAGNOSIS OF SKIN MELANOMA USING CNN

The working flow of this method is described in Fig. 26. As shown in the figure, there are mainly two stages: (1) Cropping the affected region and (2) classification of the cropped image. Input to this method is the dermoscopic image. During stage (1), the bounding box is created around the affected region in the dermoscopic image using Mask R_CNN. Based on the bounding box, the region of interest is cropped. Subsequently, in stage (2), the cropped images are classified using the ResNet-152 model to predict one of the two classes: melanoma and benign. Accuracy, balanced accuracy, sensitivity, and specificity are used to gauge this method's effectiveness.

U. DIAGNOSIS AND SEGMENTATION OF BURN AREA USING RESNET-50

A computerized approach for precise segmentation and detection of burn regions is proposed in [93]. The method's workflow is illustrated in Fig. 27. To enhance the dataset,

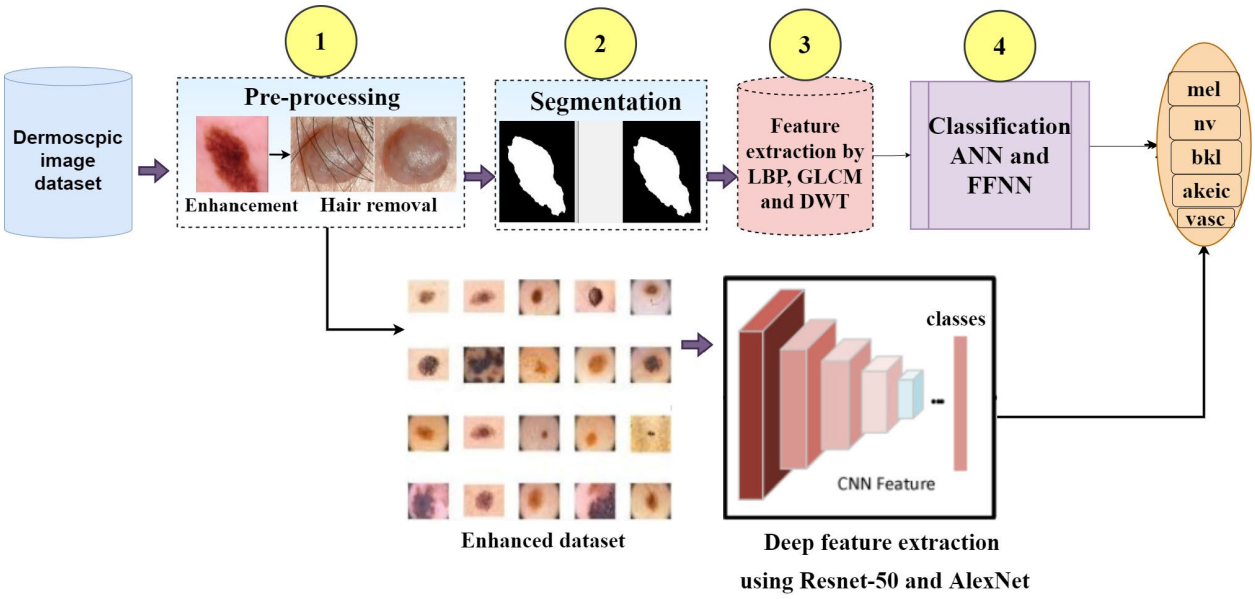

FIGURE 23. The working flow of detecting skin conditions using machine learning and deep learning.

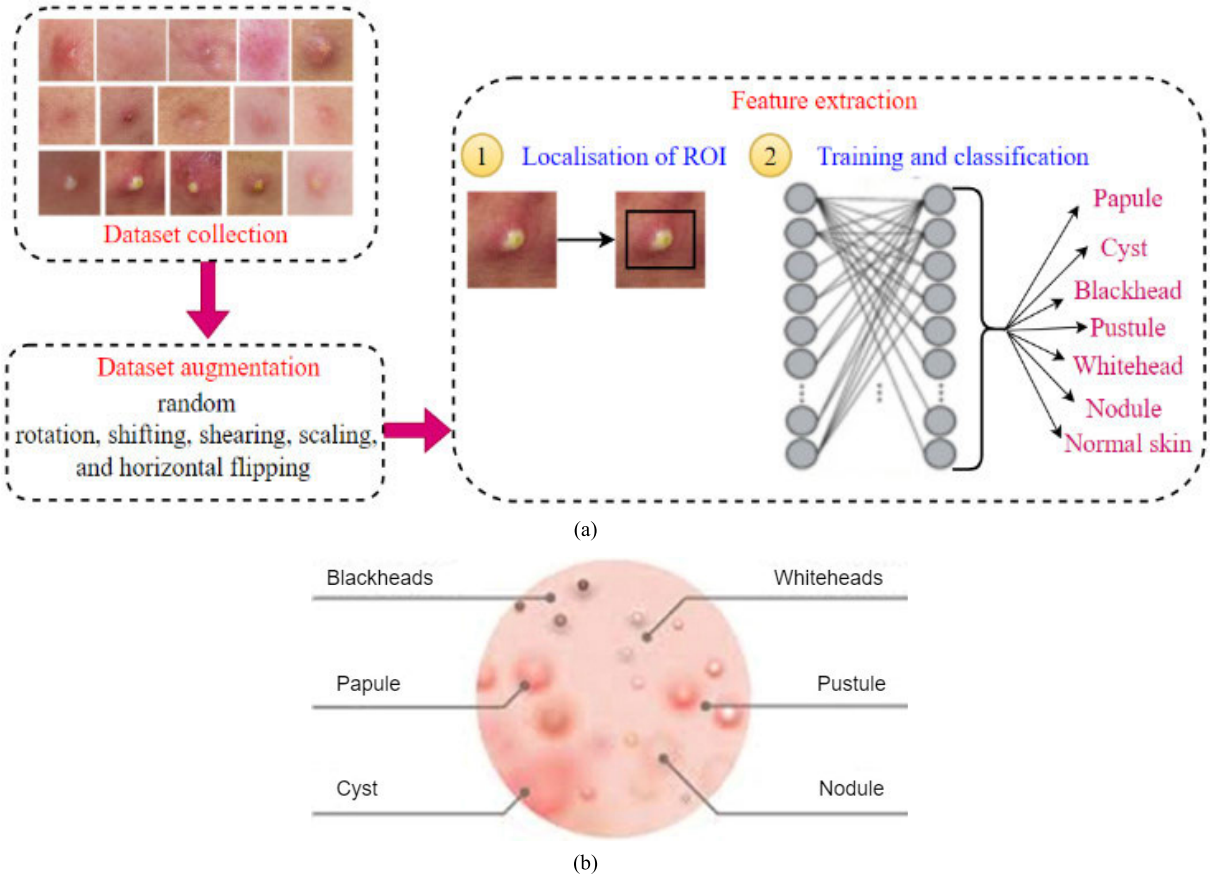

FIGURE 24. (A): Steps for detection of acne vulgaris using deep learning. (B): Different categories of acne vulgaris [85].

various data augmentation techniques such as flipping, bilateral filtering, Gaussian blur, and sharpening are employed, generating 1000 images from an initial set of 356 images. Following augmentation, the segmentation process is performed using a specialized HRNet V2 (High-Resolution Network) with C1, effectively capturing semantic feature maps from

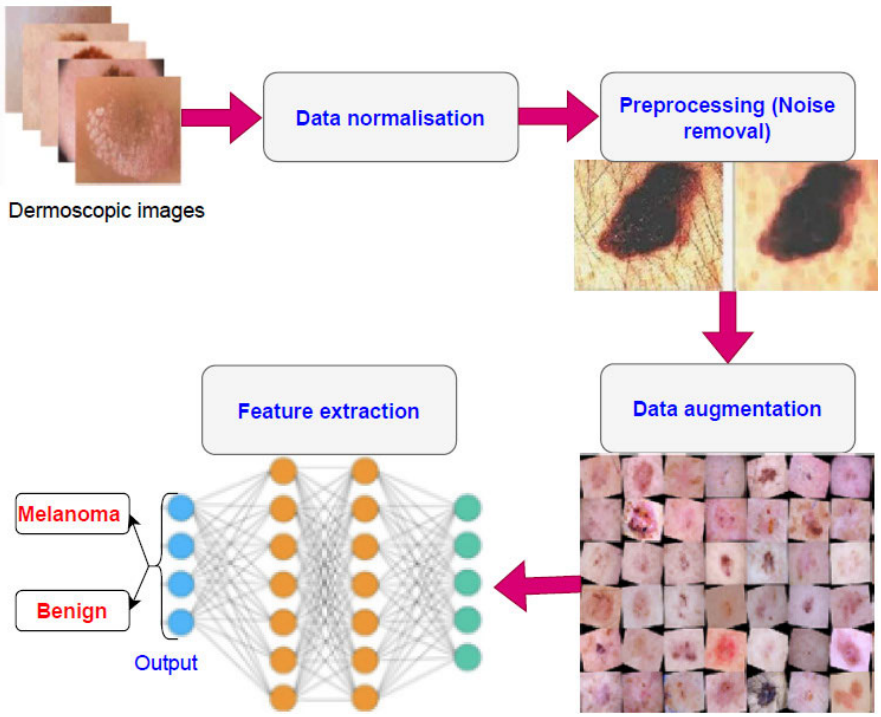

FIGURE 25. Functioning of melanoma classification from dermoscopic image.

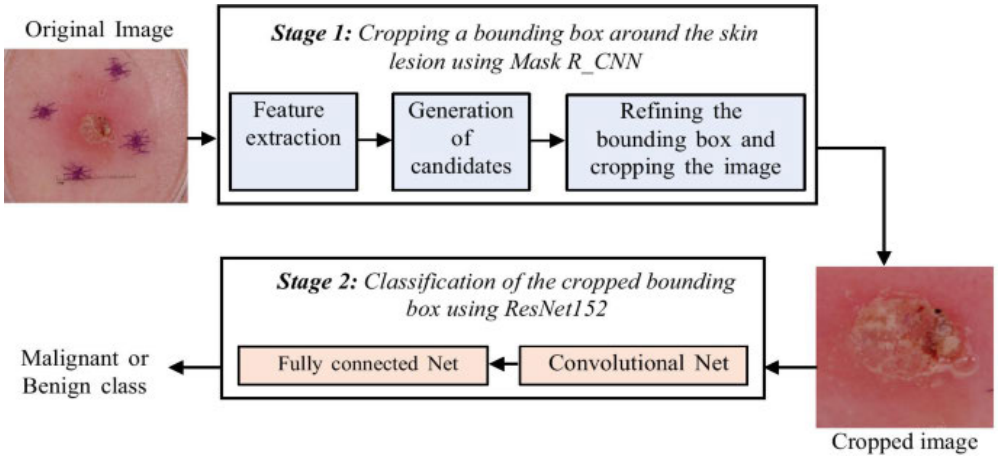

FIGURE 26. Workflow of automated analysis of skin melanoma using CNN [92].

high-resolution images. This network architecture aids in achieving accurate and reliable segmentation results. Subsequently, the segmented images are utilized for training the ResNet-50 model, enabling the prediction of burn regions and distinguishing them from non-burn regions. The method's performance is evaluated using essential metrics such as pixel accuracy, intersection over union, and dice coefficient, which assess the accuracy and quality of the segmentation output.

V. SKIN RASH DETECTION USING DCNN

An automated method to detect skin rash using ResNet-34, ResNet-50, and InceptionV3 has been proposed in [93]. The main steps of this technique are shown in Fig. 28. The dermoscopic image is resized at a size of 224 × 224 using the image resizing method. After resizing, the resized image is augmented using the horizontal flipping and rotation technique. Next, the augmented images train the CNN models to detect one of the two classes: skin rash and normal skin. The authors observed that among the CNN models (ResNet-34, ResNet-50, and InceptionV3), ResNet50 showed better classification accuracy with less computation time. The performance of this technique is evaluated using accuracy, sensitivity, and specificity.

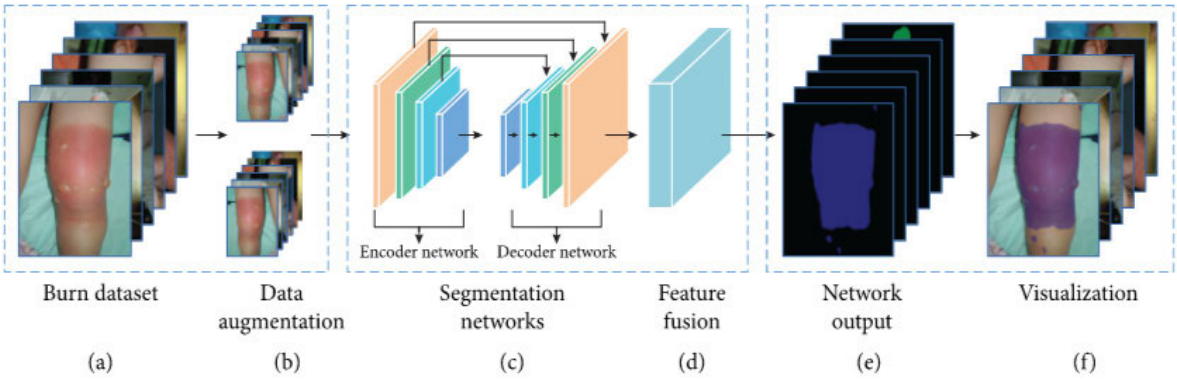

FIGURE 27. Procedure of deep learning-based framework for detection of burn region [93].

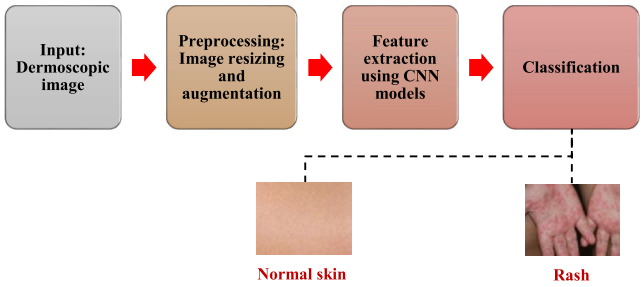

FIGURE 28. Steps to detect skin rash using CNN models.

V. ANALYSIS AND DISCUSSION

From the exhaustive study of deep learning-based methods, we have presented a thorough evaluation of deep learning-based dermatological condition detection methods in Tables 4, 5, and 6. Table 4 represents general information on these methods. Table 5 gives the summarization of dataset details used in these methods. Table 6 represents the summarization of publicly available datasets for dermoscopic images. Table 7 indicates the technical evaluation of these methods using identified parameters.

Table 4 represents the general information considering the parameters such as published year, objectives, dermatological conditions detected, and scope of improvement. The published year represents the article published by a journal/conference in a specific year. Objectives refer to the technique's main goal. Dermatological conditions represent various dermatological conditions identified by the method. The scope of improvement indicates the open research issues in these methods.

Table 5 illustrates the details of the dataset used by the deep learning-based dermatological condition detection methods. The dataset name specifies the name of the dataset and whether the dataset is publicly available or self-generated (collected from private hospitals). Additionally, Table 6 gives us a detailed description of the publicly available dataset for dermoscopic images. A dataset source represents a source of medical data where it is available. The number of images in the dataset specifies the number of dermoscopic images available. Image resolution describes the resolution in the form of pixels.

Table 7 represents the parametric evaluation of the deep learning-based dermatological condition detection methods considering the parameters such as pre-processing task, baseline DNN, loss function used, activation function, learning rate, and evaluation parameters. The preprocessing task specifies the processing of the raw data in the dataset. The loss function measures how far an estimated value is from its actual value. The activation function defines how a node in a network layer changes the input's weighted sum into an output. The learning rate is a hyperparameter that controls how much the model varies when the weights are adjusted in response to the projected error. Evaluation parameters describe the parameters used to evaluate the model. However, less work has been done to detect dermatological conditions such as rash, burn, swelling, shingles, sunburn, dark circles, blackheads, whiteheads, hives, lupus, mole, and redness from the dermoscopic image. The methods mentioned above have provided various benefits to the healthcare industry through potential applications.

However, the healthcare industry still faces significant technical and non-technical challenges in developing AI-powered applications. The above methods can be extended for the following major objectives.

- To diagnose a broad class of various skin diseases.
- To identify the severity level of skin diseases.
- To increase the classification accuracy using different color normalization and enhancement methods for low-resolution, blurry, and noisy dermoscopic images.
- To enhance the classification accuracy using supplementary metadata of the patient and related skin conditions.

To improve dermatological condition detection from images having variation in camera angles, configuration, skin textures, illumination, pen annotations, and ruler marks.

VI. CHALLENGES AND FUTURE DIRECTIONS

Recent advancements in deep learning have paved the way for several studies focusing on applying deep learning models

TABLE 4. General details of deep learning-based dermatological condition detection methods.

Technique	Scope of improvement
Skin disease diagnosis using pre-trained CNN [73] [2017]	• Sensitivity and specificity can be enhanced, thereby improving accuracy. • Patient's medical information and clinical images can be utilized to detect skin diseases accurately. • Accuracy can be further improved by considering images of varying sizes.
Classification of skin disease using MobileNet V2 and LSTM [74] [2021]	• The scope can be expanded by incorporating various imaging modalities, such as MRI, histopathology, and CT-scan images. • Accuracy can be improved by incorporating supplementary data, such as genomic data, protein sequences, and pathological data. • Additionally, accuracy can be enhanced by considering images with varying illumination levels and blurriness.
Skin cancer diagnosis using ANN, CNN, KNN, and GAN [75] [2023]	• Detection accuracy can be enhanced by utilizing a large dataset. • Furthermore, accuracy can be further improved by considering images of varying resolutions. • Enhanced accuracy can be achieved by training the model using dermoscopic images exhibiting skin colour variations. A limited number of attributes can be considered to reduce the complexity of the algorithm,
Skin disease recognition using deep neural networks [76] [2021]	• Including additional medical information and a patient's history can improve the accuracy of disease classification. • It can be expanded to detect multiple skin diseases that vary in skin color. • It can identify the severity level of skin conditions. • It can be expanded to incorporate various imaging modalities, such as histopathological, MRI, and CT-scan images.
Detection of skin disease using a hybrid combination of LBP, GLCM, and ANN [77] [2022]	• The classification accuracy can be enhanced by incorporating dermoscopic images with varying illumination, lighting, and blurry conditions. • Utilizing supplementary patient data can contribute to improving classification accuracy. • It can be expanded to identify various dermatological conditions. • Training the model with dermoscopic images exhibiting skin color variations can improve classification accuracy. • Considering fewer features can help reduce complexity and prediction time.
Skin disease detection using DenseNet121, InceptionResNetv2 and ResNet152V2 [78] [2022]	• This technique can be expanded to diagnose a wide range of dermatological conditions. • Diagnosis accuracy can be enhanced by employing various color normalization and enhancement techniques specifically designed for low-resolution, blurry, and noisy images. • Incorporating additional medical data of the patient and considering the history of the skin condition can be utilized to enhance the classification accuracy
Skin disease classification using AlexNet and VGG-16 [79] [2022]	• It can be extended to detect the severity level of dermatological conditions. • The classification accuracy can be improved by incorporating additional patient medical data and considering the history of the skin condition. • It can also be expanded to detect various skin diseases, including rare skin cancers and tumors. • Training the model with a large annotated dataset can be beneficial in achieving better classification accuracy.
Acral melanoma detection using the VGG-16 model [80] [2021]	• The classification accuracy can be enhanced by integrating the information from both dermoscopic and clinical images. • It can be extended to diagnose various types of skin conditions in different patients, leading to improved diagnostic capabilities. • The method can be modified to effectively handle images with variations in camera angles, configuration, skin textures, illumination, pen annotations, and ruler marks.
Automatic melanoma diagnosis from dermoscopic images using handcrafted features with CNN [81] [2021]	• Including various types of skin diseases can broaden the scope of the analysis. • The classification accuracy can be improved by incorporating supplementary data such as genomic data, protein sequences, pathological data, and additional imaging test images. • The severity level of the disease can be incorporated into the analysis for a more comprehensive diagnosis. • The method can be extended to handle low-resolution images and challenging illumination conditions effectively.
Computerized analysis for different types of psoriasis using VGG-19 [82] [2020]	• Various types of skin diseases can be identified. • The classification accuracy can be enhanced by incorporating supplementary patient information. • The severity level of the disease can be included in the analysis. • Using fewer features can help mitigate computational complexity and reduce processing time.
Automated grading of acne vulgaris using DenseNet15, Inception V4 and ResNet-18 [83] [2022]	• The technique can be extended to detect various dermatological conditions. • Diagnosis accuracy can be improved using color normalization and enhancement techniques for low-resolution, blurry, and noisy images. • The model can be trained with a larger dataset to increase the classification accuracy further.
Skin conditions identification using DenseNet15, InceptionV4, and ResNet18 [84] [2023]	• Detection accuracy can be improved using a larger dataset. • The method can be extended to diagnose skin disease from different skin textures. • A more significant number of patient cases should be evaluated for better outcomes.
An ensemble lightweight combination of MobileNetV1 and DenseNet-121	• The model can be extended to detect severity levels of skin cancer.

TABLE 4. *(Continued.)* **General details of deep learning-based dermatological condition detection methods.**

network for skin cancer detection [85] [2022]	• It can be modified for the vast intraclass variation of melanomas with variations in skin types. • Various dermatologists' views can be included to increase classification accuracy.
Automated detection of melanoma using a fully convolutional residual network (FCRN) [86] [2019]	• Classification accuracy can be improved using different medical histories of patients. • Accuracy can be improved by training the model with a dataset of various skin colors and ethnicities. • It can be extended to detect more dermatological conditions and skin diseases. • It can be extended for different image modalities such as MRI, CT scan, and histopathological images.
Automated detection of melanoma using ResNet-152 and Inception ResNetV2 [87] [2021]	• Accuracy can be further improved to detect dermatological conditions from low-resolution images containing hair and bubble artifacts. • It can also be extended to detect different types of skin diseases. • A sufficient number of labeled datasets can be used for better classification accuracy. • Less number of attributes can be used to reduce the computational complexity.
Detection of skin conditions using machine learning and deep learning techniques [88] [2022]	• The method can be further extended to work with a dataset that involves various other skin diseases and has the standardized configuration of the camera device. • Additional information, such as the medical history of the patients, risk assessment of diseases, and clinical images, can be included to increase the classification accuracy. • It can be extended to diagnose various uncommon dermatological conditions.
Detection of different types of acne vulgaris using a deep Convolutional Neural Network [89] [2023]	• Larger datasets can be used to improve accuracy. • Various medical information about the patients can be included for better classification accuracy. • It can be extended to detect different types of dermatological conditions. • A sufficient number of labeled datasets can be used for precise diagnosis.
Classification of melanoma using DCNN [90] [2023]	• Noise removal techniques can be used for images having blurry and illumination conditions. • The medical history of the patient can be used for better classification accuracy. • The model can be trained with various types of skin color for detecting various skin diseases.
Skin cancer detection using CNN with transfer learning models [91] [2023]	• The model can be extended to detect different types of skin cancer and its severity level. • Color illumination conditions of the images can be rectified using color normalization techniques to increase classification accuracy. • Supplementary skin disease data can be used to improve classification accuracy. • The model can be trained with various types of skin colors, textures, and ethnicities for [illegible]

TABLE 4. *(Continued.)* **General details of deep learning-based dermatological condition detection methods.**

Automated analysis and diagnosis of skin melanoma using CNN [92] [2023]	• Selective feature extraction methods can extract additional features that contribute to accurately detecting melanoma. • Including various medical information about the patients can enhance classification accuracy. • The proposed method can be extended to diagnose various skin diseases, including rare skin cancers and common dermatological conditions.
Diagnosis and segmentation of burn area using ResNet-50 [93] [2023]	• The method can be further extended to diagnose the severity level of the burn. • Classification accuracy can be improved using different color enhancement and noise removal techniques for low-resolution, blurry, and noisy images. • The model can be trained with many images using data augmentation techniques to increase classification accuracy. • Supplementary data on the patient and the skin condition can be used for better classification accuracy.
Skin rash detection using DCNN [94] [2023]	• Training the model with large datasets that contain labeled information can significantly enhance classification accuracy. • The model can be further refined and adapted to diagnose a wide range of skin diseases and skin cancers. • The accuracy can be further improved by employing various enhancement techniques designed specifically for challenging conditions, such as low-resolution images, blurry images, images with varying lighting, images with hair or bubbles, and noisy images.

to diagnose dermatological conditions, yielding promising outcomes. However, developing a computer-aided system for real-life clinical diagnosis of dermatological conditions still faces certain challenges that must be addressed. These challenges, which encompass various aspects, are visually represented in Fig. 29, offering a comprehensive overview of the areas that require further attention and improvement.

A. LIMITED LABELLED DAT

Previous deep learning-based methods to detect dermatological conditions detection used datasets with limite labeled images to train and evaluate the model. The largest publicly accessible skin disease collection in literature is the ISIC dataset [71], which includes roughly 20000 dermoscopi images. It is possible to obtain a sizable amount of information about dermatological conditions from many websites or medical institutions without any diagnosis information. However, labeling this data requires specialist knowledge and can be expensive in terms of both time and money. Deep neural networks usually use a lot of data to train to perform exceptionally well when categorizing skin disorders. When

TABLE 5. Datasets used by deep learning-based dermatological condition detection methods.

Technique	Dataset name	Dataset source	Number of images in the dataset	Image resolution
[73-75][77]	Generated by the authors	https://www.natureindex.com/institution-outputs/china/institute-of-dermatology-hospital-for-skin-disease-cams-pumc	7192	1024x1024
[76-80]	HAM10000	https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000	3000	224x224
[81-83][85][87]	ISIC dataset, HAM10000, DermQuest, DermIS	https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000	1200	800x600
[84][86][88-90]	DermNet and ISIC Archive	https://dermnetnz.org/, and https://www.isic-archive.com	23000	331x331
[91-92]	PH2 Dataset, ISIC 2018 Dataset	https://www.fc.up.pt/addi/ph2%20database.html, and https://www.isic-archive.com	120, 10000	766x560
[76-80][88-89][92-94]	HAM10000	https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000	10015	400x400

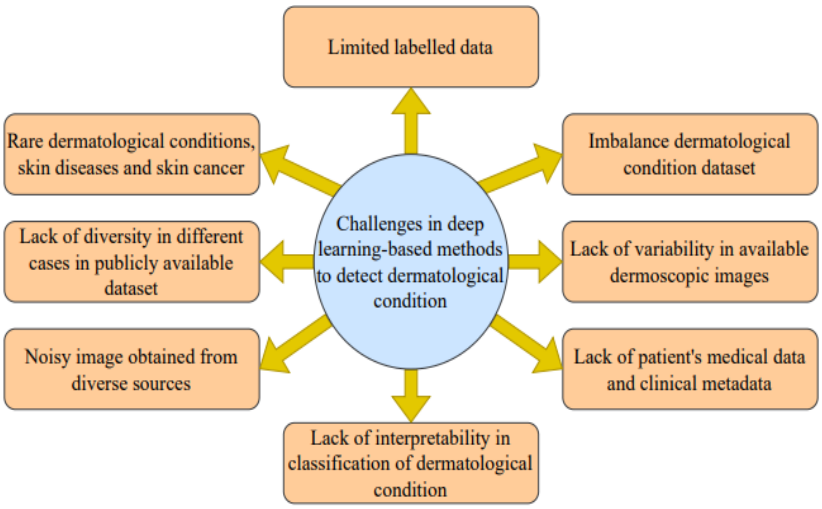

FIGURE 29. Challenges in deep learning-based dermatological condition detection methods.

only a small dataset is available, overfitting is more likely to happen. As a result, to train an efficient deep neural network for dermatological condition identification, huge datasets with tagged data are needed.

B. IMBALANCE DERMATOLOGICAL CONDITION DATASE

One of the prevalent concerns for dermatological condition diagnosis is the imbalance of the samples in the dataset. The dataset may include large disparities between various dermatological condition classes, i.e., the dataset may have many negative samples but a limited number of positive samples. Training deep learning models with imbalanced datasets may hinder classification accuracy.

C. LACK OF VARIABILITY IN AVAILABLE DERMOSCOPIC IMAGE

As observed from the preceding section, most deep learning-based methods diagnose a few dermatological conditions [73], [74], [75]. The procedure to determine whether a skin sample is a predefined category of dermatological condition or its subtype is an important task and can be done by an experienced pathologist. Therefore, there is a tremendous demand for a more authoritative and consistent

TABLE 6. Additional publicly available datasets of dermoscopic images.

Dataset name	Dataset source	Number of images in the dataset	Image resolution
BCN20000	https://forum.isic-archive.com/t/dataset-description-bcn20000/1268	19424	800x600
Dermoscopy skin lesion multispectral database	https://lezoray.users.greyc.fr/researchDatabasesDermoscopy.php	15486	800x600
MSK (Memorial Sloan-Kettering Cancer Center)	https://paperswithcode.com/dataset/msk	3918	400x400
Asan and Hallym	https://figshare.com/articles/Asan_and_Hallym_Dataset_Thumbnails_/5406136	2456	331x331
Atlas Dermatologico	http://www.atlasdermatologico.com.br	12168	800x800
Dermatlas	http://www.dermatlas.net/	1000	400x400
SKINCON	https://skincon-dataset.github.io/index.html	3230	800x800
SD198	https://drive.google.com/file/d/1YgnKz3hnzD3umEYHAgd29n2AwedV1Jmg/view	1000	400x400
PAD-UFES-20	https://data.mendeley.com/datasets/zr7vgbcyr2/1	2298	800x800
Med- Node	https://www.cs.rug.nl/~imaging/databases/melanoma_naevi/	170	400x400
MedMNIST	https://medmnist.com/	10015	800x800
Derm7pt	https://derm.cs.sfu.ca/Welcome.html	2000	400x400
Dermofit	https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofit-image-library	1300	800x800

dermatological condition diagnosis system that can be modified to assess all dermatological conditions. As a result, existing dermoscopic image datasets must be expanded, comprising different dermatological conditions, various cutaneous skin diseases, rare skin cancers and their subtypes, and skin type variations of different ethnicity groups.

D. LACK OF PATIEN'S MEDICAL HISTORY AN CLINICAL META-DATA

The dermatologist additionally takes into account the patient's medical history, risk assessment, and clinical information before undertaking a visual inspection using a dermatoscopy to diagnose the suspected skin lesion. It is essential to be familiar with diagnostic metadata including skin cancer history, age, sex, ethnicity, general anatomic site, size, and structure of patients' skin lesions to correctly diagnose the dermatological condition the patient is suffering from (and occasionally associated information from their family). It has been demonstrated in the work [20], [47], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86] that more clinical information can enhance the performance of both novice and experienced dermatologists. However, most previous deep learning-based methods to detect dermatological conditions have focused on giving dermoscopic or histopathological images as input, ignoring the patient's medical history and clinical data. In clinical settings, proper diagnosis is based on the patient's history of skin lesions, overall skin assessment, and risk profile. As a result, dermatologists frequently use extra clinical information to detect the dermatological condition and its severity level.

E. LACK OF INTERPRETABILITY IN THE CLASSIFICATION OF DERMATOLOGICAL CONDITION

The concept of the ''black box'' in deep learning models has sparked much debate. That is, individuals may be unable to comprehend how deep neural networks choose output. Because of this opacity, demand for explainability has risen before a deep learning system may be used in

TABLE 7. Technical information on the deep learning-based dermatological condition detection methods.

Technique	Preprocessing task	Baseline DNN	Loss function used	Activation function	Learning rate	Evaluation Parameters
Skin disease diagnosis using pretrained CNN [73] [2017]	Morphological operations	GoogleNet Inception V3	Cross entropy mean	Gradient Descent Optimizer	0.01	Accuracy, sensitivity, and specificity
Classification of skin disease using MobileNet V2 and LSTM [74] [2021]	Morphological operations	MobileNet V2 and LSTM	Joint Discriminative	ReLu6	0.1	Accuracy, sensitivity, and specificity
Skin cancer diagnosis using ANN, CNN, KNN and GAN [75] [2023]	Morphological operations	VGG-16	Joint Discriminative	ReLu6	0.1	Accuracy, specificity, sensitivity, and AUC
Skin disease recognition using deep neural networks [76] [2021]	Mean normalization, standardization, and whitening	Inception V4	Weighted Loss	URL	0.01	Accuracy, Sensitivity, Specificity, AUC, MCA, and ROC
Detection of skin disease using hybrid combination of LBP, GLCM, and ANN [77] [2022]	Morphological pre-processing	CNN	Cross-Entropy mean	URL	0.001	Accuracy, Sensitivity, Specificity, AUC, and ROC
Skin disease detection using DenseNet121, InceptionResNetv2 and ResNet152V2 [78] [2022]	Mean normalization, standardization, and whitening	Inception V4	Weighted Loss	URL	0.01	Accuracy, sensitivity, specificity, AUC, MCA, ROC
Skin disease classification using AlexNet and VGG-16 [79] [2022]	Gaussian Filter Method	AlexNet and ResNet50	Cross-Entropy and Angular Softmax	ReLU	0.0001	Specificity, sensitivity, precision, recall, and F1 score
Acral melanoma detection using the VGG-16 model [80] [2021]	Morphological operations	LBP, GLCM, DWT, ResNet-50 and AlexNet	Joint Discriminative	ReLu6	0.1	Accuracy, specificity, sensitivity, and AUC
Automatic melanoma diagnosis from dermoscopic images using handcrafted features with CNN [81] [2021]	Resizing and cropping	CNN with Transfer Learning	Mean Squared Error and Mean Squared Logarithmic Error Loss	Linear Activation Function and Sigmoid/Logistic Activation Function.	0.01	Sensitivity, accuracy, and specificity
Computerized analysis for different types of psoriasis using VGG-19 [82] [2020]	Gaussian Filter Method	AlexNet and ResNet50	Cross-Entropy and Angular Softmax	ReLU	0.0001	Specificity, sensitivity, precision, recall, and F1 score
Automated grading of acne vulgaris using DenseNet15, Inception V4 and ResNet-18 [83] [2022]	Rotation, flipping, zooming, contrast/brightness adjustment	R_CNN	Weighted Loss	Softmax	0.001	Sensitivity, accuracy, and specificity
Skin conditions identification using DenseNet15, InceptionV4, and ResNet18 [84] [2023]	Cropping and resizing	FCN	Hybrid loss function (Cross-Entropy and focal loss)	ReLU and Softmax	0.0001	Accuracy, Sensitivity, Specificity, AUC, ROC
An ensemble lightweight combination of MobileNetV1 and DenseNet-121 network for skin cancer detection [85] [2022]	Morphological operations	GoogleNet Inception V3	Cross entropy mean	Gradient Descent Optimizer	0.01	Accuracy, specificity, and sensitivity
Automated detection of melanoma using fully convolutional residual network (FCRN) [86] [2019]	Gaussian Filter Method	AlexNet and ResNet50	Cross-Entropy mean	ReLU	0.0001	Specificity, sensitivity, precision, and recall
Automated detection of melanoma using ResNet-152 and Inception ResNetV2 [87] [2021]	Morphological operations	FCN	Hybrid loss function (Cross-Entropy and focal loss)	ReLU and Softmax	0.0001	Accuracy, Sensitivity, Specificity, AUC, ROC

TABLE 7. *(Continued.)* **Technical information on the deep learning-based dermatological condition detection methods.**

deep learning techniques [88] [2022]	standardization, and whitening					AUC, MCA, and ROC
Detection of different types of acne vulgaris using a deep Convolutional Neural Network [89] [2023]	Morphological operations	VGG-16	Joint Discriminative	ReLu6	0.1	Accuracy, specificity, sensitivity, and AUC
Classification of melanoma using DCNN [90] [2023]	Mean normalization, standardization, and whitening	Inception V4	Weighted Loss	URL	0.01	Accuracy, Sensitivity, Specificity, AUC, MCA, and ROC
Skin cancer detection using CNN with transfer learning models [91] [2023]	Denoising	FCN	Hybrid loss function (Cross-Entropy and focal loss)	ReLU and Softmax	0.0001	Accuracy, Sensitivity, Specificity, AUC, ROC
Automated analysis and diagnosis of skin melanoma using CNN [92] [2023]	Resizing and cropping	CNN with Transfer Learning	Mean Squared Error and Mean Squared Logarithmic Error Loss	Linear Activation Function and Sigmoid/Logistic Activation Function.	0.01	Sensitivity, accuracy, and specificity
Diagnosis and segmentation of burn area using ResNet-50 [93] [2023]	Morphological operations	AlexNet	Joint Discriminative	ReLu6	0.1	Accuracy, specificity, sensitivity, and AUC
Skin rash detection using DCNN [94] [2023]	Mean normalization, standardization, and whitening	ResNet 50	Weighted Loss	URL	0.01	Accuracy, Sensitivity, Specificity, AUC, MCA, and ROC

clinical diagnosis. A clear description of how a neural network decides in a particular situation would be helpful to clinicians, scientists, patients, and regulators. For example, the dermatologist wants to know what hidden factors the network uses to forecast whether a patient has a dermatological condition. Most of the deep neural network is considered a black box with a multilayer nonlinear structure. It gives diagnosis results with no less convincing explanation and leads to a lack of trust in medical experts. Therefore, the interpretability of classifying skin disease should be known to ensure the patient's and system's reliability and safety.

F. NOISY IMAGES OBTAINED FROM DIVERSE SOURCE

Dermoscopic images in various publicly available datasets are captured using high-resolution cameras in different capturing and lighting environments [75], [76], [77], [78], [79], [80]. Deep learning models achieve excellent classification accuracy using high-resolution images. However, when tested with low-resolution images in different lighting variations, the same deep-learning models do not work well and achieve less accuracy [81], [82]. Also, it has been proven that deep learning is extremely sensitive to images recorded by various devices. Furthermore, self-captured images are frequently of poor quality and contain a lot of noise. As a result, noisy data from various sources complicates deep learning-based dermatological condition detection.

G. LACK OF DIVERSITY IN DIFFERENT CASES IN EXISTING PUBLICLY AVAILABLE SKIN DISEASE DATASET

Mostly in publicly available skin disease dataset, there are cases of individuals that includes only fair-skinned color instead of dark-skinned color cases [73]. Though the fair skin color population has a higher rate of suffering from dermatological conditions, dark skin color populations also suffer from the same conditions but are diagnosed at a later stage. Deep learning models can better accurately classify skin diseases from fair skin than dark skin [74], [75]. In a recent study, Han et al. [91] built a deep-learning algorithm using a training dataset of Asian skin lesions. On the Asian testing set (fair-skinned people), they reported an accuracy of 81 percent, but only 56 percent on the Dermofit dataset, which included European American skin lesions (dark-skinned people). As a result, the decline in accuracy suggests that deep learning models that acquire traits across datasets containing people of various races, ethnicities, or populations are not transferable.

H. RARE DERMATOLOGICAL CONDITIONS, SKIN DISEASES, AND SKIN CANCER

Acne, mole, rash, swelling, and redness are considered one of the common dermatological conditions. Also, basal cell carcinoma, squamous cell carcinoma, melanoma, and nevus are considered common skin cancers. However, there are various other dermatological conditions and skin cancers such as cutaneous dermatitis, dermatomyositis, lupus, scleroderma, vitiligo, DermatoFibroSarcoma Protuberans (DFSP), Kaposi's sarcoma, Microcystic Adnexal Carcinoma (MAC), Merkel Cell Carcinoma (MCC), sebaceous carcinoma, undifferentiated pleomorphic sarcoma, and Extra-Mammary Paget's Disease (EMPD) that are ignored by most deep learning-based methods. When deep learning models are trained on datasets with insufficient samples of these rare dermatological conditions and skin cancers, there is a high risk of misdiagnosis when these dermatological conditions and skin cancers are tested.

VII. FUTURE DIRECTIONS

Numerous papers in this area will probably be published shortly given the growing trend of applying deep learning-based algorithms to identify dermatological diseases. But as was already said, there are several obstacles to overcome. A few alternative strategies can be applied to deal with the difficulties. In the following, we provide possible guidelines and directions for future work based on findings from the literature in diagnosing dermatological conditions and other fields (such as computer vision and pattern recognition).

A. BUILDING A COMPREHENSIVE LABELLED DATASE

Deep neural networks often require a large amount of labeled data to achieve excellent performance in detecting dermatological conditions. However, obtaining a substantial labeled dataset for dermatological conditions can be challenging. This limitation can be addressed in different ways. Firstly, one option is to employ expert-certified dermatologists to annotate dermoscopic images representing different dermatological conditions manually. However, this approach is time-consuming and costly. Alternatively, automated or semi-automated data labeling methods such as LabelMe, Fiji [92], and Imagetagger can be leveraged to label large quantities of data efficiently. These methods offer potential solutions for streamlining the labeling process. Secondly, publicly available dermoscopic image datasets can be amalgamated to create a comprehensive and diverse dataset. This approach allows for compiling a larger-scale dataset by pooling together existing resources.

B. UTILIZE GANS TO GENERATE SYNTHETIC DAT FOR TRAINING DEEP NEURAL NETWORK

The capacity of GANs [93] to produce real synthetic images for diverse applications has piqued the interest of the computer vision field. These generated images as extra labeled data can be used to train deep learning models. As a result, the models frequently achieve greater performance with these data than those trained with limited data. This capability of GANs can be extremely useful for dermatological condition diagnosis where large labeled datasets are unavailable. However, extreme caution should be taken when using GANs in the medical domain. GANs strive to imitate realistic images rather than learning the original image distribution. As a result, GAN-generated images may differ significantly from the originals. Therefore, it is possible to start training a deep learning model with synthetic images generated by GAN and fine-tune the final model using only the real images for accurate classification.

C. INCLUDE ADDITIONAL CLINICAL INFORMATION TO AID IN DIAGNOSING DERMATOLOGICAL CONDITIONS

In most situations, deep learning-based methods for detecting dermatological conditions use dermoscopic images as input. In clinical settings, however, proper diagnosis is also based on the patient's history of skin lesions, risk profile, and comprehensive skin examination. As a result, dermatologists frequently use extra clinical information to detect dermatological conditions. The authors explored the effect of integrating more evidence and close-up photographs for dermatological condition detection [20], [46], [47], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], and they discovered a significant performance improvement. As a result, supplementary clinical data can be merged into the model training and testing processes. Further, prevailing medical record data, such as unorganized manuscripts, can be analyzed using procedures like NLP, article analysis, and data mining. A computer-aided diagnosis can be proposed to detect different dermatological conditions, precisely combining the dermoscopic images and relevant metadata of the patient's condition. Furthermore, incorporating human expertise into prevailing deep learning-based methods can help increase diagnostic accuracy.

D. INTERPRETABLE PREDICTIONS FROM DEEP LEARNING MODELS

The lack of explainability is a significant obstacle in deploying deep learning models for clinical diagnosis. Deep learning models must provide semantic explanations rather than just confidence scores when predicting dermatological conditions. The 7-point skin lesion malignancy checklist, which includes the pigment network, regression structures, pigmentation, vascular structures, streaks, dots and globules, and blue-whitish veil, is one method of providing a semantic explanation based on criteria like ABCDE or the 7-point skin lesion malignancy checklist.

E. HANDLING COLOUR AND ILLUMINATION VARIATIONS IN DERMOSCOPIC IMAGE DATASETS

Dermoscopic images captured in clinical and publicly available datasets often exhibit variations in lighting conditions and acquisition devices. These variations can impact the performance of AI systems. Several color normalization and illumination constancy techniques have been proposed in the literature to address this issue. These techniques aim to mitigate the impact of varying illumination and equalize the lighting effects on dermoscopic skin lesion images, improving the performance of AI algorithms for dermatological condition classification from multi-source images.

F. DIVERSITY IN DERMATOLOGICAL CONDITION DATASETS [93], [94]

Deep learning models are frequently criticized for their limited accuracy when predominantly applied to datasets consisting of fair-skinned individuals. Including diverse racial representation in skin lesion datasets is crucial to address potential social or ethnic biases in deep learning models. These datasets should encompass a balanced distribution of skin lesion instances from fair and dark-skinned individuals. Similarly, consideration should be given to age and ethnicity,

as factors such as skin ageing, different ethnic groups, and sun damage may impact the dataset and decision-making. Therefore, the development of accurate dermatological condition diagnosis systems necessitates the generation of diverse dermatological condition datasets.

VIII. CONCLUSION

Dermatological conditions are highly prevalent worldwide and necessitate prompt and accurate diagnosis for effective treatment and management. In this comprehensive survey, we provide an overview of dermatological conditions, common diseases associated with them, and clinical diagnostic tests. We then present a systematic analysis of existing deep learning-based methods for detecting dermatological conditions, examining their performance based on identified parameters. Our findings indicate that most of these methods exhibit efficient detection capabilities and achieve high classification accuracy. However, only a few methods address identifying severity levels in dermatological conditions from dermoscopic images. Furthermore, we discuss the significant challenges in this field and outline future research opportunities. Our survey offers researchers a comprehensive understanding of manual diagnostic tests and computerized methods for dermatological condition detection. Dermatologists can leverage this exhaustive survey to gain insights into computerized techniques and leverage technological advancements for automated diagnosis, ultimately improving patient care and outcomes.

DECLARATION

CONFLICT OF INTEREST

The authors declare that they do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

REFERENCES

[1] C.-Y. Zhu, Y.-K. Wang, H.-P. Chen, K.-L. Gao, C. Shu, J.-C. Wang, L.-F. Yan, Y.-G. Yang, F.-Y. Xie, and J. Liu, "A deep learning based framework for diagnosing multiple skin diseases in a clinical environment," *Frontiers Med.*, vol. 8, Apr. 2021, Art. no. 626369.

[2] G. Zhang, J. Yin, Z. Li, X. Su, G. Li, and H. Zhang, "Automated skin biopsy histopathological image annotation using multi-instance representation and learning," *BMC Med. Genomics*, vol. 6, no. 3, pp. 1–14, 2013.

[3] C. Yu, S. Yang, W. Kim, J. Jung, K.-Y. Chung, S. W. Lee, and B. Oh, "Acral melanoma detection using a convolutional neural network for dermoscopy images," *PLoS ONE*, vol. 13, no. 3, Mar. 2018, Art. no. e0193321.

[4] A. T. Young, M. Xiong, J. Pfau, M. J. Keiser, and M. L. Wei, "Artificial intelligence in dermatology: A primer," *J. Investigative Dermatol.*, vol. 140, no. 8, pp. 1504–1512, Aug. 2020.

[5] Y. Xue, J. Ye, Q. Zhou, L. R. Long, S. Antani, Z. Xue, C. Cornwell, R. Zaino, K. C. Cheng, and X. Huang, "Selective synthetic augmentation with HistoGAN for improved histopathology image classification," *Med. Image Anal.*, vol. 67, Jan. 2021, Art. no. 101816.

[6] H. Xu and M. Mandal, "Epidermis segmentation in skin histopathological images based on thickness measurement and k-means algorithm," *EURASIP J. Image Video Process.*, vol. 2015, no. 1, pp. 1–14, Dec. 2015.

[7] F. Xing, Y. Xie, H. Su, F. Liu, and L. Yang, "Deep learning in microscopy image analysis: A survey," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 10, pp. 4550–4568, Nov. 2017.

[8] Y. Xiao, E. Decencière, S. Velasco-Forero, H. Burdin, T. Bornschlögl, F. Bernerd, E. Warrick, and T. Baldeweck, "A new color augmentation method for deep learning segmentation of histological images," in *Proc. IEEE 16th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2019, pp. 886–890.

[9] Z. Wu, Y. Wang, H. Mi, H. Xu, W. Zhang, and L. Feng, "OADA: An online data augmentation method for raw histopathology images," in *Proc. Int. Conf. Neural Inf. Process.*, vol. 28. Sanur, Indonesia, Dec. 2021, pp. 249–256.

[10] H. Wu, "A deep learning, image based approach for automated diagnosis for inflammatory skin diseases," *Ann. Transl. Med.*, vol. 8, no. 9, p. 581, May 2020.

[11] F. Grignaffini, F. Barbuto, L. Piazzo, M. Troiano, P. Simeoni, F. Mangini, G. Pellacani, C. Cantisani, and F. Frezza, "Machine learning approaches for skin cancer classification from dermoscopic images: A systematic review," *Algorithms*, vol. 15, no. 11, p. 438, Nov. 2022.

[12] H. K. Jeong, C. Park, R. Henao, and M. Kheterpal, "Deep learning in dermatology: A systematic review of current approaches, outcomes, and limitations," *JID Innov.*, vol. 3, no. 1, Jan. 2023, Art. no. 100150.

[13] Y. Wang, Y. Wang, J. Cai, T. K. Lee, C. Miao, and Z. J. Wang, "SSD-KD: A self-supervised diverse knowledge distillation method for lightweight skin lesion classification using dermoscopic images," *Med. Image Anal.*, vol. 84, Feb. 2023, Art. no. 102693.

[14] S.-Q. Wang, X.-Y. Zhang, J. Liu, C. Tao, C.-Y. Zhu, C. Shu, T. Xu, and H.-Z. Jin, "Deep learning-based, computer-aided classifier developed with dermoscopic images shows comparable performance to 164 dermatologists in cutaneous disease diagnosis in the Chinese population," *Chin. Med. J.*, vol. 133, no. 17, pp. 2027–2036, Sep. 2020.

[15] Y. Vijaya and E. S. Reddy, "Automatic identification and classification of allergic skin disorders using DeepPattern recognition neural networks," *Int. J. Pure Appl. Math.*, vol. 118, no. 20, pp. 623–633, 2018. [Online]. Available: http://www.ijpam.eu

[16] B. Vedula, S. Raksha, K. S. Reddy, and S. R. Naidu, "Histopathological spectrum of dermatological lesions—A retrospective study," *J. Evidence Based Med. Healthcare*, vol. 7, no. 25, pp. 1198–1202, Jun. 2020, doi: 10.18410/jebmh/2020/256.

[17] P. Thapar, M. Rakhra, G. Cazzato, and M. S. Hossain, "A novel hybrid deep learning approach for skin lesion segmentation and classification," *J. Healthcare Eng.*, vol. 2022, pp. 1–21, Apr. 2022.

[18] M. Stritt, A. K. Stalder, and E. Vezzali, "Orbit image analysis: An open-source whole slide image analysis tool," *PLOS Comput. Biol.*, vol. 16, no. 2, Feb. 2020, Art. no. e1007313.

[19] A. A. Bataineh, "A comparative analysis of nonlinear machine learning algorithms for breast cancer detection," *Int. J. Mach. Learn. Comput.*, vol. 9, no. 3, pp. 248–254, Jun. 2019.

[20] P. N. Srinivasu, J. G. Sivasai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with MobileNet v2 and LSTM," *Sensors*, vol. 21, no. 8, p. 2852, Apr. 2021.

[21] G. Litjens, C. I. Sánchez, N. Timofeeva, M. Hermsen, I. Nagtegaal, I. Kovacs, C. Hulsbergen- van de Kaa, P. Bult, B. van Ginneken, and J. van der Laak, "Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis," *Sci. Rep.*, vol. 6, no. 1, pp. 1–11, May 2016.

[22] X. Shen, J. Zhang, C. Yan, and H. Zhou, "An automatic diagnosis method of facial acne vulgaris based on convolutional neural network," *Sci. Rep.*, vol. 8, no. 1, p. 5839, Apr. 2018.

[23] H. K. S. Juboori, "Detection of skin melanoma using deep learning approach," *Sci. Arch.*, vol. 2, no. 4, pp. 330–334, 2021.

[24] T. Rai Dastidar and R. Ethirajan, "Whole slide imaging system using deep learning-based automated focusing," *Biomed. Opt. Exp.*, vol. 11, no. 1, p. 480, Jan. 2020.

[25] P. Puri, N. Comfere, L. A. Drage, H. Shamim, S. A. Bezalel, M. R. Pittelkow, M. D. P. Davis, M. Wang, A. R. Mangold, M. M. Tollefson, J. S. Lehman, A. Meves, J. A. Yiannias, C. C. Otley, R. E. Carter, O. Sokumbi, M. R. Hall, A. G. Bridges, and D. H. Murphree, "Deep learning for dermatologists: Part II. Current applications," *J. Amer. Acad. Dermatol.*, vol. 87, no. 6, pp. 1352–1360, Dec. 2022.

[26] S. Öztürk and T. Çukur, "Deep clustering via center-oriented margin free-triplet loss for skin lesion detection in highly imbalanced datasets," *IEEE J. Biomed. Health Informat.*, vol. 26, no. 9, pp. 4679–4690, Sep. 2022.

[27] Y. Nie, J. Lundgren, M. O'Nils, C. Lundström, and T. O. Medier, "Automatic melanoma diagnosis in dermoscopic imaging base on deep learning system," *Mittuniversitetet Fakulteten Für Naturvetenskap*, vol. 13, no. 10, pp. 1–15, May 2022.

[28] L. Nanni, M. Paci, G. Maguolo, and S. Ghidoni, "Deep learning for actinic keratosis classification," *AIMS Electron. Electr. Eng.*, vol. 4, no. 1, pp. 47–56, 2020.

[29] S. Nam, Y. Chong, C. K. Jung, T.-Y. Kwak, J. Y. Lee, J. Park, M. J. Rho, and H. Go, "Introduction to digital pathology and computer-aided pathology," *J. Pathol. Transl. Med.*, vol. 54, no. 2, pp. 125–134, Mar. 2020.

[30] K. Munir, H. Elahi, A. Ayub, F. Frezza, and A. Rizzi, "Cancer diagnosis using deep learning: A bibliographic review," *Cancers*, vol. 11, no. 9, p. 1235, Aug. 2019.

[31] H. Mahantappa, S. Mruthyunjayappa, M. Gopal, and S. Venugopal, "A study of spectrum of histopathological features in patients presenting with hyperpigmented skin lesions," *Arch. Med. Health Sci.*, vol. 4, no. 2, p. 189, 2016.

[32] S. T. M. Ataky, J. de Matos, A. d. S. Britto, L. E. S. Oliveira, and A. L. Koerich, "Data augmentation for histopathological images based on Gaussian–Laplacian pyramid blending," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2020, pp. 1–8.

[33] E. Mercan, S. Aksoy, L. G. Shapiro, D. L. Weaver, T. T. Brunyé, and J. G. Elmore, "Localization of diagnostically relevant regions of interest in whole slide images: A comparative study," *J. Digit. Imag.*, vol. 29, no. 4, pp. 496–506, Aug. 2016.

[34] N. Absar, B. Mamur, A. Mahmud, T. B. Emran, M. U. Khandaker, M. R. I. Faruque, H. Osman, A. Elzaki, and B. A. Elkhader, "Development of a computer-aided tool for detection of COVID-19 pneumonia from CXR images using machine learning algorithm," *J. Radiat. Res. Appl. Sci.*, vol. 15, no. 1, pp. 32–43, Mar. 2022.

[35] X. Lu and Y. A. F. A. Zadeh, "Deep learning-based classification for melanoma detection using XceptionNet," *J. Healthcare Eng.*, vol. 2022, pp. 1–10, Mar. 2022.

[36] C. Lu and M. Mandal, "Automated analysis and diagnosis of skin melanoma on whole slide histopathological images," *Pattern Recognit.*, vol. 48, no. 8, pp. 2738–2750, Aug. 2015.

[37] C.-M. Lo, Y.-H. Wu, Y.-C. Li, and C.-C. Lee, "Computer-aided Bacillus detection in whole-slide pathological images using a deep convolutional neural network," *Appl. Sci.*, vol. 10, no. 12, p. 4059, Jun. 2020.

[38] Z. V. Lim, F. Akram, C. P. Ngo, A. A. Winarto, W. Q. Lee, K. Liang, H. H. Oon, S. T. G. Thng, and H. K. Lee, "Automated grading of acne vulgaris by deep learning with convolutional neural networks," *Skin Res. Technol.*, vol. 26, no. 2, pp. 187–192, Mar. 2020.

[39] Y. Nie, P. Sommella, M. Carratù, M. Ferro, M. O'Nils, and J. Lundgren, "Recent advances in diagnosis of skin lesions using dermoscopic images based on deep learning," *IEEE Access*, vol. 10, pp. 95716–95747, 2022.

[40] G. Alwakid, W. Gouda, M. Humayun, and N. Z. Jhanjhi, "Diagnosing melanomas in dermoscopy images using deep learning," *Diagnostics*, vol. 13, no. 10, p. 1815, May 2023.

[41] H. Li, Y. Pan, J. Zhao, and L. Zhang, "Skin disease diagnosis with deep learning: A review," *Neurocomputing*, vol. 464, pp. 364–393, Nov. 2021.

[42] D. Komura and S. Ishikawa, "Machine learning methods for histopathological image analysis," *Comput. Structural Biotechnol. J.*, vol. 16, pp. 34–42, Jan. 2018.

[43] P. Khosravi, E. Kazemi, M. Imielinski, O. Elemento, and I. Hajirasouliha, "Deep convolutional neural networks enable discrimination of heterogeneous digital pathology images," *EBioMedicine*, vol. 27, pp. 317–328, Jan. 2018.

[44] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, no. 4, pp. 321–331, Jan. 1988.

[45] M. H.-M. Khan, N. G. Sahib-Kaudeer, M. Dayalen, F. Mahomedaly, G. R. Sinha, K. K. Nagwanshi, and A. Taylor, "Multi-class skin problem classification using deep generative adversarial network (DGAN)," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–13, Mar. 2022.

[46] O. Jimenez-del-Toro, S. Otálora, M. Andersson, K. Eurén, M. Hedlund, M. Rousson, H. Müller, and M. Atzori, "Analysis of histopathology images: From traditional machine learning to deep learning," in *Biomedical Texture Analysis*. New York, NY, USA: Academic, 2017, pp. 281–314.

[47] S. W. Jahn, M. Plass, and F. Moinfar, "Digital pathology: Advantages, limitations and emerging perspectives," *J. Clin. Med.*, vol. 9, no. 11, p. 3697, Nov. 2020.

[48] S. Manzoor, H. Qayyum, A. Ullah F. Hassan, A. Nawaz, and A. Ur, "Melanoma detection using a deep learning approach," *Int. J. Innov. Sci. Technol.*, vol. 4, no. 1, pp. 222–232, 2022.

[49] J. D. Ianni, R. E. Soans, S. Sankarapandian, R. V. Chamarthi, D. Ayyagari, T. G. Olsen, M. J. Bonham, C. C. Stavish, K. Motaparthi, C. J. Cockerell, T. A. Feeser, and J. B. Lee, "Tailored for real-world: A whole slide image classification system validated on uncurated multi-site data emulating the prospective pathology workload," *Sci. Rep.*, vol. 10, no. 1, p. 3217, Feb. 2020.

[50] S. H. Kassani and P. H. Kassani, "A comparative study of deep learning architectures on melanoma detection," *Tissue Cell*, vol. 58, pp. 76–83, Jun. 2019.

[51] A. Hekler, J. S. Utikal, A. H. Enk, W. Solass, M. Schmitt, J. Klode, D. Schadendorf, W. Sondermann, C. Franklin, F. Bestvater, M. J. Flaig, D. Krahl, C. von Kalle, S. Fröhling, and T. J. Brinker, "Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images," *Eur. J. Cancer*, vol. 118, pp. 91–96, Sep. 2019.

[52] S. Chattopadhyay, A. Dey, P. K. Singh, and R. Sarkar, "DRDA-Net: Dense residual dual-shuffle attention network for breast cancer classification using histopathological images," *Comput. Biol. Med.*, vol. 145, Jun. 2022, Art. no. 105437.

[53] S. Jahanbani, P. S. Hansen, L. K. Blum, E. E. Bastounis, N. S. Ramadoss, M. Pandrala, J. M. Kirschmann, G. S. Blacker, Z. Z. Love, I. L. Weissman, F. Nemati, M. C. Tal, and W. H. Robinson, "Increased macrophage phagocytic activity with TLR9 agonist conjugation of an anti-borrelia burgdorferi monoclonal antibody," *Clin. Immunol.*, vol. 246, Jan. 2023, Art. no. 109180.

[54] Y. Fujisawa, S. Inoue, and Y. Nakamura, "The possibility of deep learning-based, computer-aided skin tumor classifiers," *Frontiers Med.*, vol. 6, p. 91, Aug. 2019.

[55] K. Faryna, J. van der Laak, and G. Litjens, "Tailoring automated data augmentation to H&E-stained histopathology," in *Medical Imaging With Deep Learning*. Lübeck, Germany, 2021.

[56] A. M. Chekroud, R. J. Zotti, Z. Shehzad, R. Gueorguieva, M. K. Johnson, M. H. Trivedi, T. D. Cannon, J. H. Krystal, and P. R. Corlett, "Cross-trial prediction of treatment outcome in depression: A machine learning approach," *Lancet Psychiatry*, vol. 3, no. 3, pp. 243–250, Mar. 2016.

[57] A. Esteva, K. Chou, S. Yeung, N. Naik, A. Madani, A. Mottaghi, Y. Liu, E. Topol, J. Dean, and R. Socher, "Deep learning-enabled medical computer vision," *NPJ Digit. Med.*, vol. 4, no. 1, p. 5, Jan. 2021.

[58] N. Dimitriou, O. Arandjelović, and P. D. Caie, "Deep learning for whole slide image analysis: An overview," *Frontiers Med.*, vol. 6, p. 264, Nov. 2019.

[59] M. Dildar, S. Akram, M. Irfan, H. U. Khan, M. Ramzan, A. R. Mahmood, S. A. Alsaiari, A. H. M. Saeed, M. O. Alraddadi, and M. H. Mahnashi, "Skin cancer detection: A review using deep learning techniques," *Int. J. Environ. Res. Public Health*, vol. 18, no. 10, p. 5479, 2021.

[60] W.-Y. Chang, A. Huang, C.-Y. Yang, C.-H. Lee, Y.-C. Chen, T.-Y. Wu, and G.-S. Chen, "Computer-aided diagnosis of skin lesions using conventional digital photography: A reliability and feasibility study," *PLoS ONE*, vol. 8, no. 11, Nov. 2013, Art. no. e76212.

[61] S. Bekmirzaev, S. Oh, and S. Yo, "RethNet: Object-by-object learning for detecting facial skin problems," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. Workshop (ICCVW)*, Oct. 2019, pp. 425–433.

[62] M. N. Bajwa, K. Muta, M. I. Malik, S. A. Siddiqui, S. A. Braun, B. Homey, A. Dengel, and S. Ahmed, "Computer-aided diagnosis of skin diseases using deep neural networks," *Appl. Sci.*, vol. 10, no. 7, p. 2488, Apr. 2020.

[63] G. Reshma, C. Al-Atroshi, V. K. Nassa, B. T. Geetha, G. Sunitha, M. G. Galety, and S. Neelakandan, "Deep learning-based skin lesion diagnosis model using dermoscopic images," *Intell. Autom. Soft Comput.*, vol. 31, no. 1, pp. 621–634, 2022.

[64] H. Ashraf, A. Waris, M. F. Ghafoor, S. O. Gilani, and I. K. Niazi, "Melanoma segmentation using deep learning with test-time augmentations and conditional random fields," *Sci. Rep.*, vol. 12, no. 1, p. 3948, Mar. 2022.

[65] D. Arora, F. Ahmad, A. Mittal, A. Kumar, S. Awasthi, and S. Dutta, "A comparative study of histopathological findings in psoriatic lesions with and without treatment," *Acta Medica Int.*, vol. 6, no. 1, p. 2, 2019.

[66] F. W. Alsaade, T. H. H. Aldhyani, and M. H. Al-Adhaileh, "Developing a recognition system for diagnosing melanoma skin lesions using artificial intelligence algorithms," *Comput. Math. Methods Med.*, vol. 2021, pp. 1–20, May 2021.

[67] M. Z. Alom, T. Aspiras, T. M. Taha, V. K. Asari, T. Bowen, D. Billiter, and S. Arkell, "Advanced deep convolutional neural network approaches for digital pathology image analysis: A comprehensive evaluation with different use cases," 2019, *arXiv:1904.09075*.

[68] S. Alheejawi, M. Mandal, H. Xu, C. Lu, R. Berendt, and N. Jha, "Deep learning-based histopathological image analysis for automated detection and staging of melanoma," in *Deep Learning Techniques for Biomedical and Health Informatics*. New York, NY, USA: Academic, 2020, pp. 237–265.

[69] F. Ahmad, A. Mittal, K. Bharadwaj, S. Awasthi, and S. Dutta, "Histopathological study of non-neoplastic skin lesions—A retrospective approach," *Indian J. Pathol. Oncol.*, vol. 6, no. 4, pp. 552–555, Nov. 2019.

[70] N. Abas, S. Dilshad, A. Khalid, M. S. Saleem, and N. Khan, "Power quality improvement using dynamic voltage restorer," *IEEE Access*, vol. 8, pp. 164325–164339, 2020.

[71] S. Gupta, A. Panwar, and K. Mishra, "Skin disease classification using dermoscopy images through deep feature learning models and machine learning classifiers," in *Proc. IEEE EUROCON 19th Int. Conf. Smart Technol.*, Jul. 2021, pp. 170–174.

[72] M. F. J. Acosta, L. Y. C. Tovar, M. B. Garcia-Zapirain, and W. S. Percybrooks, "Melanoma diagnosis using deep learning techniques on dermatoscopic images," *BMC Med. Imag.*, vol. 21, no. 1, pp. 1–11, Dec. 2021.

[73] S. K. Bandyopadhyay, P. Bose, A. Bhaumik, and S. Poddar, "Machine learning and deep learning integration for skin diseases prediction," *Int. J. Eng. Trends Technol.*, vol. 70, no. 2, pp. 11–18, Feb. 2022.

[74] S. Jha and A. K. Mehta, "An evolutionary algorithm based feature selection and fuzzy rule reduction technique for the prediction of skin cancer," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 5, Feb. 2022, Art. no. e6694.

[75] S. Jha and A. K. Mehta, "A hybrid approach using the fuzzy logic system and the modified genetic algorithm for prediction of skin cancer," *Neural Process. Lett.*, vol. 54, no. 2, pp. 751–784, Apr. 2022.

[76] A. H. Haenssle, C. Fink, R. Schneiderbauer, F. Toberer, T. Buhl, A. Blum, and A. Kalloo, "Man against machine: Diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists," *Ann. Oncol.*, vol. 29, no. 8, pp. 1836–1842, 2018.

[77] U.-O. Dorj, K.-K. Lee, J.-Y. Choi, and M. Lee, "The skin cancer classification using deep convolutional neural network," *Multimedia Tools Appl.*, vol. 77, no. 8, pp. 9909–9924, Apr. 2018.

[78] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang, "Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm," *J. Investigative Dermatol.*, vol. 138, no. 7, pp. 1529–1538, Jul. 2018.

[79] B. Erkol, R. H. Moss, R. Joe Stanley, W. V. Stoecker, and E. Hvatum, "Automatic lesion boundary detection in dermoscopy images using gradient vector flow snakes," *Skin Res. Technol.*, vol. 11, no. 1, pp. 17–26, Feb. 2005.

[80] S. Gilmore, R. Hofmann-Wellenhof, and H. P. Soyer, "A support vector machine for decision support in melanoma recognition," *Experim. Dermatol.*, vol. 19, no. 9, pp. 830–835, Sep. 2010.

[81] R. Marks, "Epidemiology of melanoma," *Clin. Experim. Dermatol.*, vol. 25, no. 6, pp. 459–463, 2000.

[82] M. A. Kadampur and S. Al Riyaee, "Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images," *Informat. Med. Unlocked*, vol. 18, Jan. 2020, Art. no. 100282.

[83] M. Tahir, A. Naeem, H. Malik, J. Tanveer, R. A. Naqvi, and S.-W. Lee, "DSCC_Net: Multi-classification deep learning models for diagnosing of skin cancer using dermoscopic images," *Cancers*, vol. 15, no. 7, p. 2179, Apr. 2023, doi: 10.3390/cancers15072179.

[84] T. Mazhar, I. Haq, A. Ditta, S. A. H. Mohsan, F. Rehman, I. Zafar, J. A. Gansau, and L. P. W. Goh, "The role of machine learning and deep learning approaches for the detection of skin cancer," *Healthcare*, vol. 11, no. 3, p. 415, Feb. 2023.

[85] S. M. Jaisakthi, P. Mirunalini, C. Aravindan, and R. Appavu, "Classification of skin cancer from dermoscopic images using deep neural network architectures," *Multimedia Tools Appl.*, vol. 82, no. 10, pp. 15763–15778, Apr. 2023.

[86] N. Melarkode, K. Srinivasan, S. M. Qaisar, and P. Plawiak, "AI-powered diagnosis of skin cancer: A contemporary review, open challenges and future research directions," *Cancers*, vol. 15, no. 4, p. 1183, Feb. 2023.

[87] S. Q. Gilani, T. Syed, M. Umair, and O. Marques, "Skin cancer classification using deep spiking neural network," *J. Digit. Imag.*, vol. 36, no. 3, pp. 1137–1147, Jan. 2023.

[88] A. Lembhe, P. Motarwar, R. Patil, and S. Elias, "Enhancement in skin cancer detection using image super resolution and Convolutional Neural Network," *Proc. Comput. Sci.*, vol. 218, pp. 164–173, Jan. 2023.

[89] V. Venugopal, N. I. Raj, M. K. Nath, and N. Stephen, "A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images," *Decis. Anal. J.*, vol. 8, Sep. 2023, Art. no. 100278.

[90] N. Priyadharshini, S. N., B. Hemalatha, and C. Sureshkumar, "A novel hybrid extreme learning machine and teaching–learning-based-optimization algorithm for skin cancer detection," *Healthcare Anal.*, vol. 3, Nov. 2023, Art. no. 100161.

[91] M. Zafar, M. I. Sharif, M. I. Sharif, S. Kadry, S. A. C. Bukhari, and H. T. Rauf, "Skin lesion analysis and cancer detection based on machine/deep learning techniques: A comprehensive survey," *Life*, vol. 13, no. 1, p. 146, Jan. 2023.

[92] D. Keerthana, V. Venugopal, M. K. Nath, and M. Mishra, "Hybrid convolutional neural networks with SVM classifier for classification of skin cancer," *Biomed. Eng. Adv.*, vol. 5, Jun. 2023, Art. no. 100069.

[93] H. K. Gajera, D. R. Nayak, and M. A. Zaveri, "A comprehensive analysis of dermoscopy images for melanoma detection via deep CNN features," *Biomed. Signal Process. Control*, vol. 79, Jan. 2023, Art. no. 104186.

[94] Y. Zhou, C. Koyuncu, C. Lu, R. Grobholz, I. Katz, A. Madabhushi, and A. Janowczyk, "Multi-site cross-organ calibrated deep learning (MuSClD): Automated diagnosis of non-melanoma skin cancer," *Med. Image Anal.*, vol. 84, Feb. 2023, Art. no. 102702.

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