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REVIEW ARTICLE

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Artificial intelligence in psoriasis: Where we are and where we are going

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Abstract

Artificial intelligence (AI) is a field of computer science that involves the development of programs designed to replicate human cognitive processes and the analysis of complex data. In dermatology, which is predominantly a visual-based diagnostic field, AI has become increasingly important in improving professional processes, particularly in the diagnosis of psoriasis. In this review, we summarized current AI applications in psoriasis: (i) diagnosis, including identification, classification, lesion segmentation, lesion severity and area scoring; (ii) treatment, including prediction treatment efficiency and prediction candidate drugs; (iii) management, including e-health and preventive medicine. Key challenges and future aspects of AI in psoriasis were also discussed, in hope of providing potential directions for future studies.

KEYWORDS
artificial intelligence, deep learning, dermatology, machine learning, psoriasis

1 | INTRODUCTION

Artificial intelligence (AI) has emerged as a promising technology in the field of medicine, including dermatology.[1,2] AI is designed to replicate human cognitive functions and, despite being in its nascent stage, is expected to revolutionize the practice of dermatology.[1] Dermatology, with its large patient base, is well-suited for big data analysis by AI, which can aid in diagnosis, treatment decision-making and management. The unique quality of dermatological images is that they can be captured by clinicians, patients and caregivers at home and provide valuable insight into disease progression in a timely manner. Consequently, dermatology has made significant strides in AI research, particularly in the automatic segmentation and diagnosis of lesions.[3–10]

Psoriasis is a chronic autoimmune skin disease that affects millions of people worldwide. The clinical manifestations of psoriasis

Abbreviations: AI, artificial intelligence; ANNs, artificial neural networks; BSA, body surface area; CNNs, convolutional neural networks; CV, computer vision; DL, deep learning; GLM, generalized linear model; HLA, human leukocyte antigen; ML, machine learning; NLP, natural language processing; PASI, psoriasis area and severity index; PCA, principal component analysis; PsA, psoriatic arthritis; SVM, support vector machine.

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are diverse, including erythematous scaly patches, papules, and plaques that are often pruritic and sometimes painful. The pathogenesis of psoriasis is multifactorial, with the involvement of genetic susceptibility, environmental factors, autoantigens and the immune system.[11,12] Due to its complex pathogenesis and varied clinical features, the development of accurate diagnosis and effective treatments for psoriasis has been a significant challenge.[13] Given that the disease is primarily evaluated and managed via visual inspection and has a high prevalence, AI can play a crucial role in tasks such as those described above.[14,15]

This review aims to provide an overview of the advances in applying AI to improve healthcare in psoriasis and discuss the challenges and future prospects of AI in the management of the disease.

2 | BASIC CONCEPT OF AI

In essence, the goal of AI is to mimic the cognitive functions of human beings.[16,17] Depending on their abilities and tasks, AI can be divided into three basic types: machine learning (ML), natural language processing (NLP) and computer vision (CV).[18] ML refers to the process of learning and training a large amount of data, allowing computers to automatically extract patterns and features from the data and make judgements and predictions based on them.[19] NLP is a subfield of AI that uses computers to analyse and process human languages, enabling tasks such as speech recognition, speech synthesis, and automatic translation.[20] CV is a type of AI that enables computers to understand and process images and videos, achieving tasks such as image recognition, object detection and facial recognition.[21]

This article will focus on ML, as it is the most widely used modality in psoriasis. ML is a subset of AI that aims to achieve the goals of AI by studying algorithms and statistical models that enable computers to perform tasks. This results in the analysis of data, which the machine uses to automatically learn tasks.[22] There are many types of ML, as shown in Figure 1. Deep learning (DL) is a subset of ML that applies artificial neural networks (ANNs) to make predictions.[23] It consists of multiple layers of 'neurons' with adjustable weights (mathematical functions). These ANNs work similarly to biological neurons, passing input data between interconnected nodes for executing intricate tasks. Thus, it has the ability to process what it has learned by itself.[24] Moreover, ML relies on various algorithms to solve data problems, such as reinforcement learning, k-means and others.[25] There is no single one-size-fits-all type of algorithm that is best to solve a problem perfectly. The particular algorithm employed depends on factors such as how many variables are involved, the type of model best suited to the problem and so on.

3 | AI APPLICATION IN PSORIASIS: WHERE WE ARE NOW

In recent years, AI has emerged as a valuable tool in the field of psoriasis research. AI has been applied to various aspects of psoriasis,

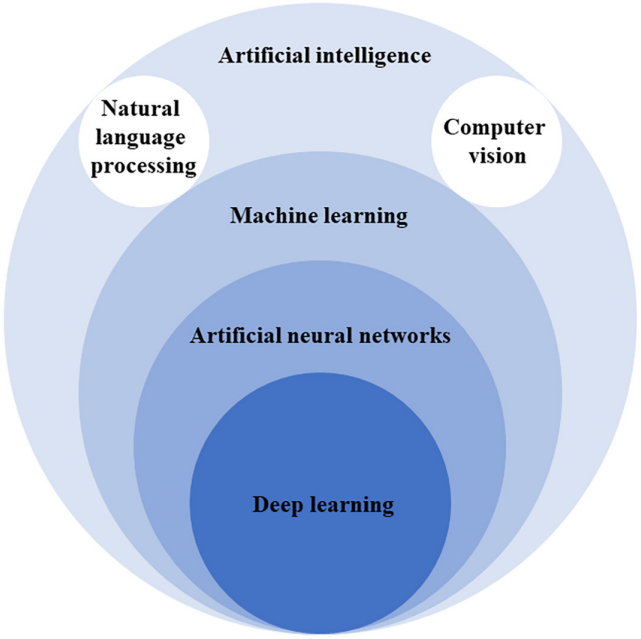

FIGURE 1 Venn diagram of artificial intelligence key terms.

including disease diagnosis, treatment decision-making and management (Table 1). These applications have the potential to revolutionize the way in which psoriasis is managed.[14,15]

3.1 | Diagnosis

3.1.1 | Identification

In recent years, significant strides have been made in the application of AI algorithms to detect skin lesions and identify and classify psoriasis. These algorithms have demonstrated performances similar to or exceeding that of dermatologists. Shrivastava et al. conducted a series of studies to identify psoriatic lesions, in which they employed ML techniques with principal component analysis (PCA) for skin-dominant feature selection, including higher order spectra, texture and colour. These features were then fed to support vector machine (SVM) classifiers, which were used to classify 540 skin images as healthy or diseased, with a classification accuracy of 100%.[26–28] A number of other research groups have also investigated how psoriasis can be detected from images that represent a variety of common skin diseases, including those that are often mistaken for psoriasis. For instance, images of five common skin diseases (acne, atopic dermatitis, impetigo, psoriasis and rosacea) were differentiated with a DL-based approach, in which augmentation could be used to increase the model's accuracy significantly.[29] Hsiao et al. developed a single shot multibox detector based on CNNs to detect psoriasis, atopic dermatitis and mycosis fungoides from skin images. The detector achieved the same level of recognition as traditional inspection methods.[30] Moreover, a ML technique was developed to ensemble five different data mining methods to identify six

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TABLE 1 Studies reviewed on AI applications to psoriasis.

Application category	Study	Objective and results	Methods	Data set
1. Diagnosis				
Identification	Shrivastava et al. (2015)	Developed a computer-aided diagnostic (CAD) system to classify skin images from psoriasis patients as healthy versus diseased using grayscale, colour, redness, and chaoticness features, with a classification accuracy of more than 99%	PCA, SVM	540 skin images (270 healthy and 270 diseased) from 30 psoriasis patients of Indian ethnic origin, captured by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Shrivastava et al. (2016)	Developed a dermatology decision support system to classify skin images from psoriasis patients as healthy versus diseased using higher order spectra, texture and colour features, with a classification accuracy of 99.39%	PCA, SVM	540 skin images (270 healthy and 270 diseased) from 30 psoriasis patients of Indian ethnic origin, captured by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Shrivastava et al. (2016)	Assessed the reliability of a method developed in a previous study to classify skin images from psoriasis patients as healthy versus diseased, with a mean reliability index of 100% for 11 higher order spectra features	PCA, SVM	540 skin images (270 healthy and 270 diseased) from 30 psoriasis patients of Indian ethnic origin, captured by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Aggarwal (2019)	Demonstrated that data augmentation can improve machine learning image recognition of 5 dermatological diseases: acne, atopic dermatitis, impetigo, psoriasis, and rosacea. Each of the 5 diseases had an increase in AUC after data augmentation, with an average increase in AUC of 0.132 and SD of 0.033. The AUC with data augmentation was 0.87 for psoriasis	DCNNs with data augmentation	332, 92, 138, 280, and 96 skin images for acne, atopic dermatitis, impetigo, psoriasis, and rosacea, respectively, from open-source dermatological images captured through DermNet, Dermatology Atlas, Hellenic Dermatological Atlas, and Google Images
	Verma et al. (2019)	Developed an ensemble data mining and machine learning method to classify 6 skin diseases: psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra. The multi model ensemble method got an accuracy of 98.64%	CART, SVM, DT, RF, GBDT	366 images of 35 patients from UC Irvine machine learning repository
	Kim et al. (2019)	Developed smartphone-based multispectral imaging and analysis to discriminate seborrheic dermatitis and psoriasis, with a higher sensitivity and specificity (Logi: 65%, 89%; SVM: 75%, 70%; MLP: 75%, 70%) than conventional methods (ED: 70%, 70%; SAM: 70%, 70%)	SVM, Logi, MLP	Clinical images from 60 patients (20 patients with seborrheic dermatitis, 20 patients with psoriasis, 20 patients without these disease) from Seoul National University Hospital
	Zhao et al. (2020)	Developed a set of DL models using CNNs to classify skin images of 9 common skin disorders (lichen planus, lupus erythematosus, basal cell carcinoma, squamous cell carcinoma, eczema, pemphigus, psoriasis, and seborrheic keratosis) as psoriasis vs. non-psoriasis. The two-stage CNN classifier showed superior performance (missed diagnosis rate:0.03, misdiagnosis rate:0.04) than 25 Chinese dermatologists (missed diagnosis rate:0.19, misdiagnosis rate:0.10) in diagnosis of psoriasis on 100 clinical images	CNN	8021 skin images of 9 common disorders including 900 psoriasis images, captured by dermatologists at Xiangya Hospital

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Wu et al. (2020)	Developed an artificial intelligence dermatology diagnosis assistant (AIDDA) to classify skin images of 3 different dermatologist-labelled diagnosis classification (Psoriasis, eczema and atopic dermatitis). AIDDA acquired an accuracy of 89.46% for psoriasis, an accuracy of 92.57% for eczema and atopic dermatitis.	CNN	4770 clinical skin images of 3 inflammatory skin disease and healthy skin, from Xiangya Hospital
	Huang et al. (2021)	Established a network called Xy-SkinNet to identify common skin disease (psoriasis, basal cell carcinoma, seborrheic keratosis, pemphigus, eczema, and lupus erythematosus). Xy-SkinNet achieved a higher accuracy of 84.77% than the average accuracy of dermatologists (78.15%)	CNN	150000 clinical images of 571 different skin diseases in the Chinese population from Xiangya Hospital (the largest and most diverse dermatological data)
	Zhu et al. (2021)	Constructed a novel framework based on DL trained to classify 14 categories (lichen planus, rosacea, viral warts, acne vulgaris, keloid and hypertrophic scar, eczema and dermatitis, dermatofibroma, seborrheic dermatitis, seborrheic keratosis, melanocytic nevus, hemangioma, psoriasis, port wine stain, and basal cell carcinoma), with the overall accuracy of 0.948	CNN	13 603 clinical images from 2538 patients of 14 different skin disease, from Peking Union Medical College Hospital
	Hsiao et al. (2021)	Developed a single shot multibox detector (SSD) model to detect mycosis fungoides, psoriasis and atopic dermatitis, with the overall accuracy of 93%	CNNs	948 skin images as training images and 292 test images of mycosis fungoides, psoriasis, atopic dermatitis and normal skin, from Chung Shan Medical University Hospital
	Yu et al. (2022)	Developed a new diagnostic method for discriminating scalp psoriasis and seborrheic dermatitis based on a DL model. The model exhibited good sensitivity, specificity and AUC (96.1, 88.2 and 0.922%), and resulted in significant improvements in diagnostic performance for one dermatology graduate student and two general practitioners (AUC values increased from 0.600, 0.537, and 0.575 to 0.849, 0.778 and 0.788)	CNNs	1624 dermoscopic images (obtained from 735 patients) of psoriasis and seborrheic dermatitis, from Affiliated Hospital of Inner Mongolia Medical University
	Wang et al. (2022)	Developed a CAD system to analyse the characteristics of skin lesions in children with psoriasis, with high sensitivity and specificity	2-3-dimensional hybrid CNNs	Three-dimensional skin CT from15 children with psoriasis and 15 children with other skin diseases, from Cangzhou Medical College
Classification	Aijaz et al. (2022)	Developed a DL-based application to classify different types of psoriasis, with the accuracy of 84.2%	CNN	172 images of normal skin from the Nanyang Technological University data and 301 images of psoriasis from the Dermnet dataset
Lesion segmentation	Taur et al. (2003)	Developed an automatic method for psoriasis image segmentation	Neuro-fuzzy classifier	N/A
	Taur et al. (2006)	Developed a MSSC for the segmentation of psoriasis images	MSSC	N/A
	Abbadi et al. (2010)	Developed a skin disease diagnosis system to recognize psoriasis lesion and healthy skin	Feed-forward neural networks	24 skin images from 12 psoriasis samples and 12 other different skin disease samples, derived from the library of skin texture of different human races
	Juang et al. (2011)	Developed a psoriasis image segmentation procedure to improve the accuracy	K-means clustering, morphological segmentation algorithm	N/A

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Bogo et al. (2012)	Developed a novel approach to the segmentation of psoriasis lesions in "full body" digital photographs potentially involving dozens or even hundreds of separate lesions	PCA	20 digital photographs from 20 psoriasis vulgaris patients
	Ma et al. (2013)	Developed an interactive psoriasis lesion segmentation algorithm	GMM	282 psoriasis images of various kinds of psoriasis lesion from PUMC Hospital collect psoriasis database
	Lu et al. (2013)	Developed an automated method for segmentation of scaling in 2-D psoriasis digital images to evaluate disease severity	MRF, SCM	103 psoriasis skin images from University of Melbourne and St. Vincent's Hospital Melbourne Department of Dermatology
	George et al. (2017)	Developed an automated psoriasis lesion segmentation of 2-deimensinal psoriasis lesion images, with a pixel accuracy of 86.99%	Multiscale superpixel clustering, k-means clustering	676 psoriasis skin images from 44 psoriasis patients at the Royal Melbourne Hospital, Australia
	Shrivastava et al. (2017)	Developed an automated approach for segmentation of psoriasis lesions in skin images for accurate risk assessment using a Bayesian model, with a classification accuracy of 99.84%	SVM, DT, NN	670 cropped images from 110 psoriasis patient images captured by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Pal et al. (2018)	Developed an automated approach for accurate segmentation of psoriasis skin biopsy image into dermis, epidermis and non-tissue regions, with the fully CNN method achieving an accuracy of 88%	DCNNs	90 psoriasis skin biopsy images from West Bengal, India
	Dash et al. (2020)	Developed an automated psoriasis lesion segmentation method based on a modified U-Net architecture (PsLSNet), achieving an accuracy of 94.8% with 89.6% sensitivity and 97.6%, specificity	DCNNs with a PsLSNet	5241 skin images of psoriasis lesions from 1026 psoriasis patients at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
Lesion severity and area scoring	Savolainen et al. (1997)	Developed a colour segmentation method to assess involved surface area in psoriasis patients and compared performance to human eye assessments	CIA	26 psoriasis patients with chronic plaque psoriasis at Department of Dermatology and Venereology, Oulu University Hospital, Finland
	Savolainen et al. (1998)	Compared surface area estimates by human eye versus computer image analysis using colour segmentation. The human eye estimates were higher than computer estimates, tending to overestimate in cases where the PASI was under 15	CIA	15 psoriasis patients at Department of Dermatology and Venereology, Oulu University Hospital, Finland
	Gomez et al. (2007)	Compared available change detection techniques in the visualization and quantification of bi-temporal psoriasis images	PCA, MAD transform, simple image subtraction, post-classification comparison	6 temporal series of psoriasis images from Gentofte Hospital, Denmark
	Fadzi et al. (2013)	Developed an assessment method that incorporates 3D surface roughness with standard clustering techniques to objectively determine the scaliness score of PASI for psoriasis lesions, with an accuracy of 94.12%	3D surface roughness measurement, k-means clustering, fuzzy c-means clustering	1999 psoriasis lesion images from 204 Malaysian psoriasis patients at Hospital Kuala Lumpar, Malaysia
	Shrivastava et al. (2015)	Reviewed technology for psoriasis risk stratification in current and existing literature	CAD	N/A
	Raina et al. (2015)	Developed a method for the objective measurement of the psoriasis severity, with a good agreement with subjective assessment of erythema severity (kappa =0.4203)	Linear discriminant analysis classifier	80 psoriasis skin images from 20 psoriasis patients at Seton clinics including the University Medical Centre Brackenridge Dermatology Clinic, Seton Family of Doctors at Hays, and Trinity Clinic

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Shrivastava et al. (2016)	Developed an automated psoriasis CAD system for psoriasis risk stratification from classification of psoriasis lesion and healthy skin using colour feature patterns, with an accuracy of more than 99%	SVM, PCA	540 skin images from 30 Indian psoriasis patients capture by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Shrivastava et al. (2016)	Developed a novel approach to multiclass psoriasis disease risk stratification	SVM, DT	848 skin images from Indian psoriasis patients captured by a dermatologist at the Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India
	Frink et al. (2018)	Designed a total body imaging software that can also automate PASI measurements	Total body imaging system designed by authors	10 psoriasis patients with 16 single body images per patients at University of Heidelberg Department of Dermatology, Germany
	George et al. (2018)	Developed a semi-supervised computer-aided system for automatic erythema severity scoring in psoriasis skin images	Random forest, SVM, ensemble learning, patch-based dictionary learning	676 psoriasis skin images from 44 psoriasis patients at the Royal Melbourne Hospital, Australia
	George et al. (2020)	Developed an automatic scale severity assessment method in psoriasis skin images using local descriptors, yielding a scale severity scoring accuracy of 80.81%	BoVWs, SVM, RF	96 psoriasis skin images at the Royal Melbourne Hospital (RMH), Australia
	Meienberger et al. (2020)	Developed an automated method to score psoriasis affected area, achieving an accuracy of more than 90% in 77% of the images and differing on average 5.9% from manually marked areas. The difference between algorithm-predicted and photograph-based estimated areas by physicians was 8.1% on average	DCNNs	259 plaque psoriasis skin images from Caucasian patients at University Hospital of Zurich Department of Dermatology in Switzerland
	Schaap et al. (2021)	Developed an image-based automated PASI scoring model by CNNs, performing similar to physicians for erythema, desquamation and induration scoring, while outperforming physicians for area scoring	CNNs	5844 skin images from psoriasis patients included in the Child-CAPTURE registry (Continuous Assessment of Psoriasis Treatment Use Registry)
	Okamoto et al. (2022)	Developed a simplified PASI system and associated AI models to assess psoriasis severity, which helped the medical student's scores get close to the teacher's close	CNNs, data augmentation	705 psoriasis images from Department of Dermatology, University of Yamanashi, Yamanashi, Japan
	Lin et al. (2022)	Developed an artificial neural network prediction model for BSA measurement, achieving dermatologist-level performance in estimating the involved BSA for psoriasis	U-net model	255 psoriasis images representing large anatomical sites captured by a dermatologist from department of dermatology, E-Da Cancer Hospital, Kaohsiung City, Taiwan
2. Treatment				
Prediction treatment efficiency	Liu et al. (2019)	Constructed the gene co-expression modules by weighted correlation network analysis (WGCNA), and found 22 co-expression modules were significantly correlated with treatment response of etanercept	WGCNA	176 DEGs from the blood of 6 psoriasis patients treated with etanercept 50 mg subcutaneously twice weekly for 12 weeks from a clinical trial

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Tomalin et al. (2020)	Developed a predictive model to predict the 12-week clinical endpoint for psoriasis following tofacitinib or etanercept though quantification of 157 inflammatory and cardiovascular proteins in the blood of psoriasis patients, which got the autoROC of 78% and 71% in tofacitinib and etanercept, respectively	Prediction of Microarrays (PAM), Threshold Gradient Descent Regularization (TGDR), Generalized Linear Models (GLMnet), Partial Least Squares (PLS), NN, SVMs, RF	157 disease proteins measured from the blood of 266 patients with moderate-to-severe psoriasis from ClinicalTrials.gov: NCT01241591
	Damiani et al. (2020)	Built a predictive model to predicte secukinumab fast-responder profile in psoriatic patients, displaying an overall accuracy of 91.88%	ANNs, Auto Contractive Map (Auto-CM), Training with Input Selection and Testing (TWIST)	23 patients with moderate-to-severe plaque psoriasis: including 19 responders and 4 non-responders, treated with secukinumab 300 mg and enrolled in a multicentre prospective open label pilot study
	Emam et al. (2020)	Developed a model with the best performance to predict long-term responses to biologics in terms of accuracy and runtime in a multinomial classification problem in six different modelling techniques	GLM, SVM, DT, RF, GBDT, DL	681 psoriasis patients from the Danish registry cohort, DERMBIO
	Gottlieb et al. (2020)	Identified predictors for additional benefit of secukinumab at a dosage of 300 mg in comparison to 150 mg.	Bayesian elastic net algorithm, individual patient efficacy meta-analysis (IPEM)	2049 psoriasis patients receiving secukinumab with the dose of 300 mg or 150 mg
	Pournara et al (2021)	Identified clinically relevant patient clusters by machine learning from the clinical development programme of secukinumab in psoriatic arthritis	Finite mixture models, ML	Over 2750 PsA patients treated with secukinumab across four phase 3 studies from ClinicalTrials.gov: NCT01241591, NCT01989468, NCT02294227, NCT02404350
Prediction candidate drugs	Patrick et al. (2019)	Developed a system to identify drugs that can be repurposed in the treatment of psoriasis, successfully predicting the potential use of budesonide and hydroxychloroquine for treating psoriasis.	MLR, word embedding	More than 20 million articles about drug information
	Sakaue et al.	Illustrated the correlation between a broad spectrum of genomic knowledge on psoriasis and clinical indication categories of currently used medications, identifying new potential therapeutic candidates.	GREP	Target chemical information on medications of current use or developed in the past, from two major drug data bases, Drug Bank and Therapeutic Target Database
3. Management				
E-Health	Singh et al. (2011)	Investigated the feasibility of the remote determination of PASI scores by comparing the results of face-to-face with digital image assessment, showing that PASI scores can be determined with moderate to good accuracy by dermatologists using standardized digital images	N/A	12 patients aged between 22 and 63 years with psoriasis were recruited consecutively from the Queensland Institute of Dermatology and Dermatology Outpatients at the Princess Alexandra Hospital, both in Brisbane, Australia
	Banu and Toacşe (2013)	Developed a mobile/desktop application that can accurately differentiate erythemato-squamous diseases into two groups: psoriasis or non-psoriasis, based solely on clinical features, with an accuracy of over 93%	SVM, DT	the erythemato-squamous diseases dataset taken from UCI (University of California, Irvine) machine repository

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Moreno-Ramírez et al. (2017)	Developed a mobile telephone application (MDi-Psoriasis) to make decisions on how to treat patients with moderate to severe psoriasis, comparable to those of experts.	N/A	10 cases and 10 patients from general hospitals in a Spanish autonomous community
	Armstrong et al. (2018)	Demonstrated equivalent clinical gains between online, collaborative connected-health model and in-person care	N/A	300 psoriasis patients from outpatient clinics and the general adult populations in Northern California, Southern California, and Colorado
	Zhu et al. (2019)	Created the cloud-based platform to improve patient management by improving communication with patients and their dermatologists	N/A	79 psoriasis patients from Institute of Dermatology, Chinese Academy of Medical Sciences and Peking Union Medical College, Nanjing, China
	Pangti et al. (2020)	Developed a novel mobile health application (mHealth app) to diagnose 40 common skin diseases, tested it in clinical settings and a large-scale feasibility study	CNNs	17 408 images from public databases (http://www.hellenicderma tlas.com/en and http://www.danderm.dk/atlas) trained for the app, and 5014 patients validated in urban, rural primary care and tertiary care settings
	Jethwa et al. (2021)	Developed an electronic survey with 18 questions covering demographics, treatment details, as well as types and effectiveness of telemedicine appointments	N/A	109 PsA patients
	Trettin et al. (2021)	Developed an mHealth app to support the self-management of psoriasis patients	N/A	N/A
	Garzorz-Stark et al. (2021)	Developed a new smartphone app (IMPROVE 1.0) for individual monitoring of disease activity and disease influencing factors	N/A	12 psoriasis patients from Department of Dermatology and Allergy, Technical University of Munich, Munich, Germany
	Young et al. (2023)	Demonstrated equivalent gains of functional impairment and depressive symptoms between online health model and in-person care	linear mixed-effects modelling	300 plaque psoriasis patients recruited from clinical sites in southern California, northern California, and Colorado
Preventive medicine	Love et al. (2011)	Developed a PsA prediction algorithm, achieving a positive predictive value of 93%	NLP, RF	1 365 000 patients at the Brigham and Women's hospital, Harvard Medical School Boston, USA
	Guo et al. (2014)	Developed a psoriasis prediction based on the microarray, achieving an average accuracy of 99.81%	SVM-RFE	Two microarray data sets with accession numbers GSE14905 and GSE13355 were retrieved from the Gene Expression Omnibus (GEO) Database
	Patrick et al. (2018)	Provided robust risk assessment of PsA development in psoriasis patients	ML	2703 PsA and 2681 PsC samples from five GWAS datasets (CASP, Exomechip with GWAS content, Genizon, Kiel, and PsA GWAS)
	Conic et al. (2020)	Indicated red cell distribution width (RDW) and mean platelet volume (MPV) may be a cost-effective manner to identify PsO and PsA patients at increasing risk of major adverse cardiac events	N/A	Over 50 million patient records compiled from 26 different healthcare systems
	Munger et al. (2020)	Determined top predictors of non-calcified coronary burden by coronary computed tomography angiography in psoriasis by machine learning algorithms	RF	263 consecutive patient records with 92 phenotypic variables measured at baseline from the Psoriasis Atherosclerosis Cardiometabolic Initiative
	Zhou et al. (2021)	Developed a powerful predictive model for psoriasis disease based only on routine hospital tests, achieving an average accuracy of 86.9%	Boruta, RF	Routine hospital tests of 466 psoriasis patients and 520 healthy controls from the Department of Dermatology, the Second Affiliated Hospital of Harbin Medical University, Harbin, China

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TABLE 1 (Continued)

Application category	Study	Objective and results	Methods	Data set
	Jalali-najafabadi et al. (2021)	Developed the feature selection and PsA risk prediction models based on a cross-sectional genetic dataset	ML	1462 PsA patients recruited from rheumatology center, UK
	Mulder et al. (2021)	Developed disease-special immune profiles to discriminate Pso and PsA patients (mean AUC = 0.95)	RF	41 PsA and 45 Pso patients
	Ardle et al. (2021)	Developed a serum protein biomarker panel separating patients with early-onset IA with PsA from those with RA	N/A	64 patients from American College of Rheumatology and European Alliance of Associations for Rheumatology
	Queiro et al. (2022)	Developed a minimal disease activity predictive model in patients with recent-onset PsA, achieving the percent-age of 85.94%	RF	158 PsA patients from 25 centres from 11 of the 17 Spanish autonomous communities

Abbreviations: AutoROC, area under the receiver operating characteristic curve; AUC, area under the curve; BoVWs, bag-of-visual-words; CART, classification and regression trees; DEGs, differentially expressed genes; DT, decision tree; DCCNs, deep convolutional neural works; GBDT, gradient boosted decision trees; GMM, gaussian mixture model; GLM, general linear model; IA, inflammatory arthritis; MRF, Markov random field; MSSC, multiresolution-based signature subspace classifier; MLR, multiple linear regression; NN, neural network; PsC, cutaneous-only psoriasis; RA, rheumatoid arthritis; RF, random forest; SD, standard deviation; SVM-RFE, support vector machine recursive feature elimination.

erythematous squamous diseases (psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, pityriasis rubra), which performed better than different classifier algorithms.[31] In addition, using a smartphone-based multispectral imaging system, seborrheic dermatitis and psoriasis on the scalp of patients could be discriminated with a sensitivity of 65%–75% and specificity of 70%–80%, enabling patients to self-monitor and self-diagnose the diseased regions via the smartphones.[32] In China, convolutional neural networks (CNNs) were applied to classify images of psoriasis and other inflammatory skin diseases that could be easily misdiagnosed. The CNNs achieved an expert-level diagnosis of inflammatory skin diseases and outperformed dermatologists across nine common disorders.[33,34] Furthermore, it is encouraging that Xiangya-Derm, the largest database for the Chinese population, has been created. Professionals at this institution are working on developing AI diagnostic instruments based on skin images, which is foreseen to change healthcare in a fundamental way.[35]

In addition to skin images, Chinese researchers and clinicians have attempted to utilize dermatoscopic images for AI diagnosis. For instance, based on a DL model, a new diagnostic method was developed for distinguishing scalp psoriasis and seborrheic dermatitis, which demonstrated superior accuracy to dermatologists trained with dermoscopy.[14,15] Similarly, Zhu et al. constructed a novel framework based on a dataset representing the actual clinical environment in a Chinese tertiary class hospital. This framework classified 14 categories of diseases, including psoriasis, with a comparable performance level to that of dermatologic physicians.[36] Furthermore, there are teams that have combined skin computed tomography and confocal laser scanning microscopy with AI algorithms as an emerging examination of psoriasis. The results have shown that psoriasis-like hyperplasia and Munro microabscess have high specificity and sensitivity, which could provide important clues to the diagnosis of psoriasis in children, worthy of clinical promotion.[37]

3.1.2 | Classification

After identifying an image containing psoriasis, it is necessary to classify the different types of psoriasis present, including pustular, guttate, inverse, plaque and erythrodermic.[38] It is only after this classification that treatment for psoriasis can be initiated.[39] To achieve accurate classification, Aijaz et al. employed two DL algorithms, namely CNNs and long short-term memory, to develop classification models and achieved accuracies of 84.2% and 72.3%, respectively.[40] These results demonstrate the future potential of DL applications in dermatological diagnosis, paving the way for more accurate and reliable diagnosis of psoriasis.

3.1.3 | Lesion segmentation

Automating the identification and classification of psoriasis based on skin images is a critical step in the management of this condition.

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However, the need for automation of segmentation is also essential, as it allows for subsequent higher-level tasks, such as automated Body Surface Area (BSA), Psoriasis Area and Severity Index (PASI) and skin biopsy.[41–43] To this end, several studies have been conducted to develop automatic methods for psoriasis image segmentation.

Taur et al. proposed an automatic method for psoriasis image segmentation using neuro-fuzzy classifiers and orthogonal subspace classifiers in a therapy evaluation system.[44,45] Subsequently, a segmentation algorithm based on feed-forward skin features and ANNs was used to deal with images of psoriasis and other diseases, achieving promising results during the ANNs training and generalization phase.[46] Other groups applied visual depiction to accurate segmentation of plaques.[47,48] In 2013, a technique combining a Markov random field and a SVM was developed to segment scaling in 2-D digital images as an integral part of developing a reliable evaluation method for psoriasis.[49] Additionally, the accuracy of psoriasis image segmentation was successfully improved by the procedure based on k-means clustering with morphological processing techniques.[50] Building on these studies, the subsequent automatic lesion segmentation methods achieved markedly better performance by leveraging multiscale superpixels, k-means clustering,[41–43] and a combination of SVM and Fisher Discriminant Ratio.[51] Furthermore, psoriasis lesions are automatically segmented into RGB colour images using a CNN trained on 5241 skin images from 1026 psoriasis patients. This model overcame the limitations of previous research, such as high dependence on feature engineering and failure to consider challenging cases and achieved an accuracy of 94.8%, with 97.6% specificity and 89.6% sensitivity.[52]

In addition, automatic approaches for accurate segmentation of skin biopsy images have been developed to overcome the difficulties encountered by pathologists. Pal et al. used deep neural architectures to segment psoriasis skin biopsy images. In order to classify the super-pixels generated by Simple Linear Iterative Clustering, deep models were used and led to superior segmentation performance than traditional hand-crafted feature-based classification.[53]

3.1.4 | Lesion severity and area scoring

Dermatologists currently grade psoriasis severity based on the BSA and PASI.[54] However, relying on subjective evaluations of dermatologists may lead to deviations in disease diagnosis.[55] Therefore, there is a need for an automated system to evaluate psoriasis lesion severity and affected area in the diagnosis and treatment of psoriasis. This can be achieved through segmentation of psoriasis lesions in skin images from psoriasis patients, which enables the automation of lesion severity and affected area evaluation. Consequently, automatic scoring models have been developed after the establishment of automatic methods for psoriasis image segmentation.

PASI is a composite score based on the clinical assessment of BSA, erythema, induration and scaling of psoriasis on different areas of the body (head, trunk, upper limbs and lower limbs) by dermatologists.[56] Savolainen et al. discovered that the computer image analysis system offers a possibility to quantify the actual surface area in patients with psoriasis, which could be used for developing quality control when evaluating different treatment efficacies.[57,58] Additionally, psoriasis area assessment methods are being developed based on ML technology, achieving an accuracy of more than 90% in 77% of images with an 8.1% difference from physician's area.[59] Subsequently, progression was achieved by ML methods, particularly U-net models, to develop an ANNs prediction model for automated BSA measurement, achieving dermatologist-level performance.[41–43]

Furthermore, the computer-aided diagnosis systems were conducted to assess psoriasis images into five severity grades (healthy, mild, moderate, severe and very severe) based on lesion features and proposed a psoriasis risk assessment system accordingly.[26,60,61] Other research groups have also applied ML methods to further enhance automatic scoring of erythema and scaliness.[62] However, the three-dimensional nature of induration poses a greater challenge to automate scores from two-dimensional images. In this regard, Schaap et al. automated the PASI score of images using CNNs. For erythema, scaliness, and induration scoring, CNNs performed similarly to dermatologists, while for BSA scoring, CNNs outperformed dermatologists on image-based PASI scoring.[63] Building on this, a simplified PASI system (Single-Shot PASI) was developed, which can assess psoriasis severity simply by uploading a clinical image and can closely approximate dermatologist evaluation.[55] Recently, a portable device has been clinically employed for automated PASI measurements after total body imaging and digital image analysis. This device has shown high reproducibility and agreement with results obtained by PASI-trained dermatologists in pilot clinical validation.[64] Overall, AI-guided PASI measurements hold great promise for significantly reducing the workload of dermatologists while ensuring high levels of reproducibility and standardization.

3.2 | Treatment

3.2.1 | Prediction treatment efficiency

A personalized approach to treating psoriasis based on clinical phenotypes is a crucial unmet need that could significantly improve patients' quality of life and functional ability. Predicting the therapeutic effects of drugs can facilitate the formulation and implementation of personalized treatment plans.[65] Tomalin et al. employed statistical and machine-learning techniques to predict drug efficacy in psoriasis. They developed a classifier that predicts whether a given patient will be a PASI 75 responder after 12 weeks of tofacitinib or etanercept treatment using patient blood samples detecting 92 inflammation-associated proteins and 65 proteins associated with cardiovascular disease.[66] This is similar to another experiment, where they analysed the global gene expression profile of peripheral blood mononuclear cells at 6th and 12th week of etanercept treatment to identify potential biomarkers and understand the

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molecular mechanism of action.[67] Then Damiani et al. developed a predictive model employing ANNs to assess the 'fast responder' patient profile, which predicts whether psoriatic patients treated with secukinumab will achieve at least PASI 75 at the end of the induction phase using preliminary complete blood count and clinical examination data. After a training testing protocol, the model showed an overall accuracy of 91.88% (90% for responders and 93.75% for non-responders).[68] In addition to blood samples, other groups have also investigated hundreds of predictors (based on disease characteristics and interaction terms) to predict treatment efficiency. With ML techniques, they found that secukinumab 300 mg than 150 mg provides additional additional benefits for patients who are anti-tumour necrosis factor (TNF)-naïve, or have been treated with 1 prior anti-TNF agent, or are not receiving methotrexate, or have enthesitis at baseline, or have a shorter PsA disease duration and a higher PASI.[69,70] In addition, researchers examined whether ML could help predict long-term responses to biologics. They analysed generalized linear model (GLM), SVM, decision tree, random forest, gradient-boosted trees and DL and found that GLM outperformed other models in terms of accuracy and computational efficiency in predicting long-term responses to biologics in psoriasis.[2,71]

3.2.2 | Prediction candidate drugs

In the context of improving psoriasis treatment, the development of novel drugs is a critical aspect, albeit time-consuming and expensive. An alternative, cost-effective approach is drug repurposing, which involves finding drugs that could potentially be used to treat conditions beyond their primary indications.[72] In this regard, Patrick et al. developed a system to identify drugs that can be repurposed in the treatment of psoriasis. To achieve this, the authors employed word embedding to summarize information from over 20 million articles on drugs and applied ML to model drug-disease relationships. The approach successfully predicted the potential use of budesonide and hydroxychloroquine for treating psoriasis. Notably, the targets of drug candidates predicted by the approach were verified by a large-scale RNA sequencing cohort that they were significantly enriched among genes differentially expressed in psoriatic lesional skin. Overall, this approach offers an efficient way of identifying potential drug candidates for psoriasis treatment using a combination of NLP and ML techniques.[73]

Psoriasis is a multifactorial genetic disorder with approximately 70% of disease susceptibility attributable to genetic factors.[74] Therefore, comprehending the genetic basis of psoriasis is crucial for elucidating the disease's biology, pinpointing clinical biomarkers, identifying new drug targets and hastening the progression towards personalized medicine. Over the past decade, extensive genome-wide association studies (GWASs) on psoriasis have been conducted across diverse populations, significantly expanding the number of genetic loci linked to psoriasis susceptibility ($n > 80$).[75] On this basis, Sakaue et al. developed the Python-based software, Genome for REPositioning drugs (GREP), capable of quantifying the enrichment of a user-selected gene set in the targets of clinical categories, thereby identifying potential therapeutic agents. They successfully illustrated the correlations between a broad spectrum of genomic knowledge on psoriasis and clinical indication categories of currently used medications. The results encompass many drugs already employed in psoriasis treatment, in addition to identifying new potential therapeutic candidates. Further validation of these newly identified drugs could potentially enhance psoriasis treatment strategies.[76]

3.3 | Management

3.3.1 | E-Health

E-Health refers to the utilization of digital, mobile, and wireless technologies for accessing health-related information, resources and services.[77] This technology is increasingly being used by doctors and patients for managing psoriasis.[78] Psoriasis management through e-health is broadly divided into two categories: mobile phone applications and teledermatology.

In 2013, researchers developed a mobile/desktop application using six classification algorithms that can accurately differentiate erythemato-squamous diseases into two groups: psoriasis or non-psoriasis, based solely on clinical features, with an accuracy of over 93%.[79] Subsequently, Pangti et al. conducted the first large-scale feasibility study: a mobile health application was developed using a CNNs-based algorithm and was utilized to diagnose 40 dermatological conditions, including psoriasis. This application could assist patients in diagnosing common skin diseases at home.[80] Another smartphone application (MDi-Psoriasis) was developed with an algorithm incorporating 60 variables related to patient demographics, clinical characteristics and medication history for providing treatment recommendations to patients who have moderate to severe psoriasis. And the result revealed that the recommendations made by the application could be treated as a clinical decision aid since they were comparable to those of experts.[81] However, it does not consider personal preferences or medication experience from a doctor, which can affect treatment decisions. To solve this, a smartphone application was designed and facilitated long-term management of patients on biological therapy for psoriasis. This application could replace some of the follow-up visits and reduce commute time for patients while meeting their needs.[82] Recently, there is a new study to investigate the potential of a new smartphone application to monitor the progression of psoriasis. Patients entered life quality, stress questionnaires, self-PASI, and lifestyle factors over 12 months, and the data was compared with dermatologists' collected data. The application can detect lifestyle changes preceding a shift in PASI, potentially serving as an alert system by drawing patients' attention to increasing stress levels or weight gain and preventing a flare.[83] Moreover, patient-reported outcome measures (PROMs) have gained popularity in clinical practice. PROMs assess subjective aspects of patient conditions and aid in evaluating

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disease and treatment burden from patient viewpoints.[84] Electronic patient-reported outcome measures (ePROMs) replace paper-based alternatives with an electronic system, making it more convenient and popular to complete.[85] Furthermore, the COVID-19 pandemic has accelerated the acceptance of ePROMs by patients and doctors. ePROMs allow for the rapid collection and reporting of real-time patient symptoms and disease activity, enabling physicians to conduct remote patient assessments and treatment. However, the supporting software requires further development and refinement in the future.[86]

Teledermatology also shows positive promise. A study in 2021 demonstrates that PASI scores could be accurately determined using digital images.[87] Subsequently, randomized clinical trials were conducted to evaluate the effectiveness of teledermatology care versus in-person care for adults with psoriasis. The trials revealed that teledermatology was equally effective in managing psoriasis and psychological impact as in-person visits.[88,89] In another study, a multimedia application was used to investigate the feasibility and efficacy of a cloud-based interactive patient and physician management of psoriasis. The application included daily photographs of the skin, a visual analogue scale to assess the degree of itching or pain from lesions, an anxiety and depression scale to evaluate psychological questions, and psoriasis-related images, texts and videos and its management. The results indicated that the interactive patient-physician management using the application improved treatment outcomes for patients with psoriasis.[90] Recently, researchers evaluated telemedicine services provided to a cohort of PsA patients during the ongoing COVID-19 pandemic. Patients were willing to interact with their healthcare providers through telephone calls or live video calls, upload photographs and images, depict their manifestations online, and receive laboratory and/or instrumental exams and reports via emails. During these services, patients could receive additional, switched, or tapered medication.[91–93]

In summary, a series of studies suggest in comparison with clinic dermatology, both store-and-forward and live interactive teledermatology provide acceptable diagnostic and concordance results, and enable patients to receive timely and personalized care with high levels of satisfaction while reducing their travel and wait times.[78,94,95]

3.3.2 | Preventive medicine

Although AI has shown great potential in psoriasis treatment and management, it is not yet widely adopted in clinical practice. As algorithms continue to develop, AI may play a significant role in preventive medicine. Preventive medicine can be divided into primary, secondary, and tertiary prevention, with primary and secondary prevention having significant cost savings potential.[96] Therefore, AI-based primary and secondary prevention techniques are currently being studied in psoriasis.

Guo et al. were the first to design an AI program for predicting psoriasis. Their system applied three feature selection algorithms to microarray-based gene expression profiles to identify 21 psoriasis-associated features. These features were then used to create a classifier with an average overall accuracy of 99.81% over three independent validation strategies, providing a psoriasis prediction model.[97,98] Moreover, a powerful predictive model for psoriasis disease was carried out based only on routine hospital tests. Researches applied the Boruta feature selection method to select the most relevant features, with which they constructed a Random Forest model. The resulting classification model yielded an average accuracy of 86.9% based on the 26 notable features selected.[99] Furthermore, a psoriasis risk prediction model was build based on genetic/genomics data from 1462 PsA and 1132 psoriatic patients. The study applied seven supervised AI-based algorithms and showed two human leukocyte antigen (HLA) genes (HLA_C_06 and HLA_B_27) might be the most important genetic features.[100]

AI programs have also been used in early detection studies of comorbidities in psoriasis, such as PsA,[101] cardiovascular disease,[102] and diabetes.[103] Characteristics that correlate with psoriasis patients' risk of complications can be identified with ML. The NLP and genetic data were adopted in electronic medical records to identify 31 PsA-related predictors and assess the risk of PsA.[104,105] Besides, other studies built ML models based on blood immune profiling and serum proteomics to discriminate between PsA and psoriatic patients.[106,107] Based on these models, a minimal disease activity (a clinical state characterized by low levels of disease activity) predictive model was developed, with the variables of global pain, impact of the disease (PsAID), patient global assessment of disease, and physical function (HAQ-Disability Index) having the greatest predictive ability.[108] Besides PsA, patient records were detected to identify the top predictors of noncalcified coronary plaque burden in psoriasis, which included obesity, dyslipidemia, and inflammation factors.[109] Moreover, in a study conducted by Conic et al., the distribution width of red blood cells and mean platelet volume were examined as predictors of major cardiovascular events in persons with PsA, and the result indicated that parameter values above a certain threshold were associated with an increased cardiovascular risk and a poor therapeutic response.[110]

Overall, AI-based methods are proving to be promising tools for predicting psoriasis and its comorbidities, and for developing personalized treatment plans. However, further studies are needed to validate these models and to translate them into clinical practice.

4 | CHALLENGES AND FUTURE ASPECT OF AI IN PSORIASIS

Bringing AI into the dermatologist's office presents challenges in the treatment of psoriasis. These challenges primarily revolve around the quality and quantity of data. Data quality determines the accuracy of AI medicine, so clinical researchers must emphasize this limitation when collecting data for ML researchers to use. One major challenge is the data standardizing, particularly for skin images that

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are often captured without a standardized protocols. This leads to variations in parameters that make it difficult for ML algorithms to differentiate whether the differences between captured lesions are real or artificial. In order to resolve this issue, the skin lesion imaging techniques should be standardized. Furthermore, some algorithms require a large dataset to produce generalizable output, particularly for computationally expensive systems like DNNs. An unrepresentative and small dataset of diverse skin types used to generate ML models can be erroneous for underrepresented groups. Additionally, many algorithms developed for psoriasis have not yet been tested in a clinical setting or evaluated for important clinical metrics, and their clinical utility remains to be determined. For example, there are some differences in the onset site and skin lesion characteristics between paediatric and adult psoriasis. Children tend to have more involvement of the face and anogenital regions compared to adults. The lesions of plaque psoriasis in a subset of children may be smaller, thinner and less scaly than those seen in adults.[111] However, most of relative researches using skin and dermatopic images for AI diagnosis of psoriasis did not show detailed information on patients' age. Therefore, further validation is necessary to determine whether these models can be effectively used for the diagnosis of paediatric psoriasis.

Currently, there is a lack of a comprehensive psoriasis algorithm. To make an holistic diagnosis and treatment recommendation for psoriasis, an effective algorithm should be trained to integrate clinical signs from a single patient. For example, the algorithm could determine that spot-treated with topicals are best used for treating single small lesions, whereas phototherapy is better suited to treating many small lesions all over the body. However, automating the evaluation of clinical signs presents a significant challenge, especially when it comes to accurately scoring two-dimensional images due to the three-dimensional nature of induration. In addition, it is also possible to have post-inflammatory hyperpigmentation or hypopigmentation in skin of colour after psoriasis plaques has been cleared up.[112,113] And this could lead to confusion for calculating erythema with ML model if it has not been trained to distinguish between active lesions and post-treatment pigmentation abnormalities. Therefore, developing a suitable algorithm to distinguish between erythema and pigment abnormalities is an attractive direction to pursue.

Finally, AI has the potential to revolutionize the field of psoriasis healthcare by improving diagnostic accuracy, predicting disease progression and identifying novel treatment targets. ML algorithms can scrutinize vast amounts of data, such as patient medical records, genetic profiles, and imaging data, to identify patterns and correlations that may be overlooked by human experts. This can lead to earlier and more precise diagnosis, personalized treatment plans and improved outcomes for patients. Additionally, AI may facilitate the development of new psoriasis treatments by identifying new drug targets and predicting the efficacy of existing and experimental drugs. By simulating the effects of drugs on psoriasis in silico, AI can help to reduce the time and cost of drug development and improve the success rate of clinical trials.

5 | CONCLUSIONS

AI is developing at lightning speed in dermatology. We can expect the use of AI in dermatology clinics in coming years. At the same time, AI has the incredible potential to revolutionize the diagnosis, treatment and management in psoriasis. Despite being in its nascent stage and facing many challenges, with the continued development of AI technology, its implementation may enhance the efficiency of dermatologists, widen access to dermatologic care and ultimately lead to improved patient outcomes.

AUTHOR CONTRIBUTIONS

Zhenhua Liu: Writing—Original draft preparation; Xinyu Wang: Conceptualization; Yao Ma: Visualization; Yiting Lin: Writing- Reviewing and Editing, Funding Acquisition; Gang Wang: Writing- Reviewing and Editing, Funding Acquisition.

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CONFLICT OF INTEREST STATEMENT

Authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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