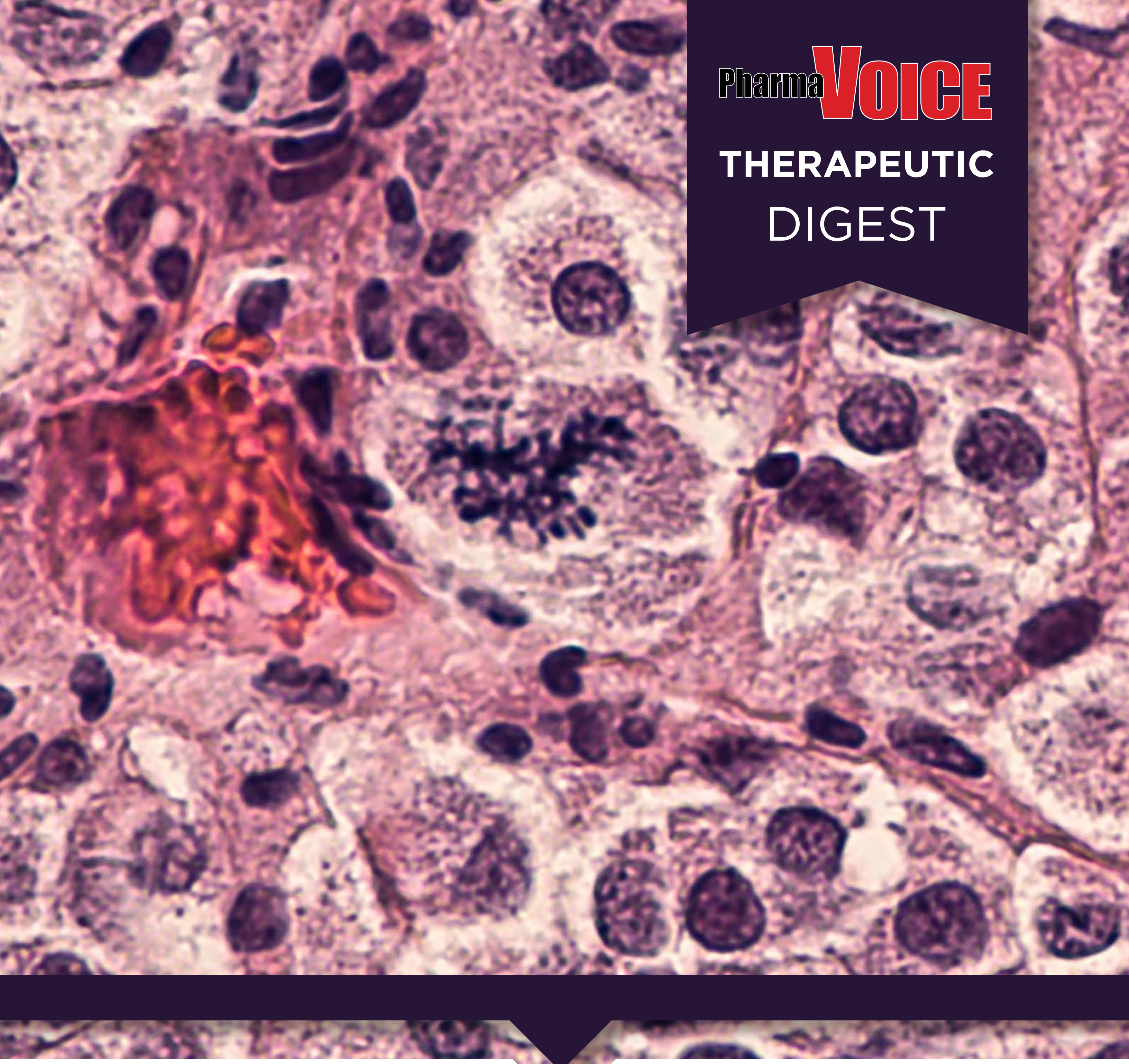

DERMATOLOGY

ARTIFICIAL INTELLIGENCE IN DERMATOLOGY

IN COLLABORATION WITH
thinkgen

JULY 2021

Clinical Ink®
Confident Decisions, Faster

Lunexis™

Dermatology Data You Can Depend On

Get the accurate, consistent assessment data you need with an application purpose-built for patient- and site-centric studies. With the Lunexis™ eSource Ecosystem you can:

- Save weeks by capturing patient-reported outcomes and clinical outcome assessments directly — no transcription required
- Improve consistency with rater-based interview and questionnaire support
- Make more informed decisions by reviewing audio, video, and photos in real-time

Power your next dermatology clinical trial with Lunexis — a unified platform tailor-made for complex data capture.

Schedule a Demo Today at ClinicalInk.com/therapeutic-focus

www.clinicalink.com

Table of Contents

thinkgen Editorial content provided by ThinkGen (www.think-gen.com)
Written by Kristina Erfe Pines

DERMATOLOGY

Artificial Intelligence in Dermatology

Although artificial intelligence has been available for some time, it has garnered significant interest recently and has been popularized by major companies with its applications in image identification, speech recognition and problem solving. Artificial intelligence is now being increasingly studied for its potential uses in medicine. A sound understanding of the concepts of this emerging field is essential for the dermatologist as dermatology has abundant medical data and images that can be used to train artificial intelligence for patient care. There are already a number of artificial intelligence studies focusing on skin disorders such as skin cancer, psoriasis, atopic dermatitis and onychomycosis. Dermatology is in a unique position to be an early contender for the implementation of AI because of its large clinical image databases for use and interpretation.

ARTIFICIAL INTELLIGENCE IN DERMATOLOGY

▶ Skin Cancer

Melanoma and non-melanoma skin cancer (NMSC) are the most common types of cancer in Caucasian populations[1,2]. Early screening and accurate diagnosis of skin cancers are integral to best patient outcomes[3]. Currently, screening by health professionals results in detection rates ranging between 1 and 9 per 1000 individuals screened[4]. Researchers have been exploring the potential for AI to improve or supplement current screening processes. This section explores and analyzes current research.

A number of studies have focused on producing classification programs. These studies primarily utilize convolutional neural networks (CNNs), which are a type of Artificial Neural Network (ANN), that have been demonstrated to be useful for image recognition and classification purposes[5,6]. In a 2016 article published in the Engineering in Medicine and Biology Society Membership, Dr. Nasr-Esfahani and team were the first to investigate a program that could detect melanoma[7]. They trained their CNN on 6120 images (170 were taken from images of melanoma and nevi; the remaining images were synthesized), and their proposed method had 0.81 and 0.80 sensitivity and specificity, respectively. Unfortunately, it is difficult to assess the external validity of their program as they did not include demographic information. In a separate study, researchers further demonstrated the potential of AI in skin disease classification when they created a program with dermatologist-level classification[8]. The CNN in this study achieved an overall accuracy of 72.1%, with an AUROC of > 0.91 for its classifications. The accuracy of the CNN was similar to that of two dermatologists, who achieved 65.6% and 66.0% accuracy on the same set[9].

Researchers aimed to build on this and created a deep learning program that was both sensitive and specific. This contrasts with other screening tools that trade-off specificity for higher sensitivity, particularly in the screening of melanoma skin cancers[10,11]. A 2018 study published in the British Journal of Dermatology, Dr. Fugisawa and team used a comparatively small dataset of 4867 clinical images to train a program to differentiate 14 different clinical conditions that included both malignant and benign conditions. The machine's performance was then compared against that of 13 dermatologists and nine dermatology trainees and tested on 1142 images distinct to those used for training. The over-all classification accuracy of this program was 76.5%, with a sensitivity and specificity of 96.3% and 89.5%, respectively, when classifying diseases as malignant or benign[12]. The CNN was more accurate than the dermatologists in this study. However, the classifications were based on single image analysis, and the dermatologists would have anticipated greater accuracy with additional history and examination findings.

In another study, researchers created a separate program using a CNN (subsequently made public for testing) that performed comparably to the performance of 16 dermatologists. They used 19,398 images to develop an automated classification system for 12 established skin disorders. When tested with the validation image set, the average sensitivity and specificity for all the conditions was 85.1% and 81.3%, respectively, with an AUROC of 0.89[13]. However, the external validity was potentially limited as patients examined were largely those of Caucasian descent. This is reflected in the findings of Navarrete-Dechent et al[14], who externally tested the program in a different patient population and found much lower sensitivity, with the correct histopathological diagnosis identified in only 29 of the 100 lesions. The AI programs in the Han and Fujisawa studies both outperformed the dermatologists. However, the performance of the dermatologists was lower than expected in both studies as they were required not only to correctly identify malignancy but also correctly subtype the malignancy in order to score a point. The dermatologists would likely have performed better if required only to identify malignancy or if they had access to contextual information[15].

A couple of recent studies compared dermatologist performance against a new CNN Machine Learning (ML) classifier [16,17]. One study designed a digital melanoma classifier using 12,378 open source dermoscopic images and found similar or better sensitivity and specificity to that with dermatologists[18]. This study also advocated for a melanoma classification benchmark, which they derived from their results for future comparisons. Their benchmark found that dermatologists had an overall sensitivity of 89.4% and specificity of 64.4% at detecting melanoma[19].

Finally, some ML classifiers have been translated onto smartphone applications (apps) for use by individuals in the community setting. One study found four AI smartphone apps that classified skin lesions as melanoma (one app) or high-risk or ‘problematic’ lesions (three apps)[20]. Sensitivities for these apps ranged from 7 to 73%, and specificities ranged from 37 to 94%. In their current state, these apps may potentially miss melanomas and are potentially dangerous as they can instill a false sense of security in the user.

▶ Psoriasis

Psoriasis is common and estimated to affect approximately 125 million people worldwide[21]. Although not curable, it can be well-managed. AI may not only serve as a tool in clinical assessment but also help develop personalized treatment protocols and outcome predictions.

AI programs for diagnosing and monitoring psoriasis are still being refined. A study led by Guo et al first designed an AI program in 2014 that aimed to predict psoriasis[22]. Three featured selection algorithms were applied to the data to screen for 21 psoriasis-associated features, which were then used to create the classifier. The resultant binary classifier achieved an average overall accuracy of 99.81%.

Another study proposed an AI program to assist in the assessment of psoriasis severity and have reported several attempts to develop this program[23,24]. This study adopted three different standard classifiers (support vector machine, decision tree and ANN) for risk stratification in assessing three main attributes: color, texture and high-order spectra. The researchers used 670 images of psoriasis to train the classifier. The classifiers worked towards lesion segmentation and classified lesions into healthy and lesional classes at a pixel level. The model achieved 99.84% accuracy, with sensitivity and specificity of 99.76% and 99.99%, respectively.

▶ Atopic Dermatitis

AI for atopic dermatitis (AD) holds potential as an adjunct for clinical diagnosis, individualized patient care and personalized treatment outcome prediction. It could help standardize and reduce assessment times for AD, which may increase efficiency. However, the research regarding AI in AD is in its infancy. The two studies found in this area were published in computer science journals and reported measures not used in medical evaluation. Dr. Gustafson and team designed an ML algorithm that identified AD from electronic health records. This included structured coded data such as demographic data as well as unstructured clinical narratives. To incorporate unstructured data, AI for natural language processing was required. A total of 562 case notes were included in the ML process. Gustafson et al achieved a positive predictive value of 84.0% and a sensitivity of 75.0%[25]. Alternatively, Dr. De Guzman et al designed an ANN for detecting AD versus unaffected skin, using information directly from images. They discovered that multiple hidden node level models would be more stable and more resistant to overfitting. However, relatively small sample sizes were used because this model was designed to be experimental for discovery of the most appropriate AI processes. To improve the accuracy of current research, contextual information could be added for consideration by AI programs[26].

Onychomycosis

AI research has been conducted in onychomycosis. A recent study compared dermatologists and a CNN for detecting onychomycosis, using a training set of 49,567 images to train their classifier to differentiate between onychomycosis and normal nails[27]. The AUROC, a performance model used to evaluate classification models, was reported as 0.82–0.98. The capacity of the classifier to differentiate onychomycosis from normal nail was statistically significantly better than the performance of dermatologists in this study.

CONCLUSION

Several investigators are likely to be interested in creating AI programs requiring data, with data sources for AI training likely coming from the following four sources. First, there are phenotypic clinical patient data including demographics, comorbidities, skin lesion characteristics, and laboratory and imaging findings. Second, there are molecular profiles derived from biopsy data, including proteomic analysis. A third source is data from available published literature, and, finally, images can be used for analysis and classification[28]. Publicly available benchmarking image datasets are available for training AI. Examples are the International Skin Imaging Collaboration and PH2 dermoscopic archives[29]. Most of the lesions in these databases have been confirmed by pathology, others by follow-up, expert consensus or in vivo confocal microscopy.

Although some physicians may perceive AI as a potential threat to their livelihood, it is unlikely to become more than an adjunct to clinical practice for the foreseeable future. AI is fast emerging in dermatology. It holds great potential for patient care, particularly in improving the sensitivity and accuracy of screening of skin lesions, but is also susceptible to the same flaws as classical statistics, and there are important ethical and governance considerations in its use. An understanding of AI concepts, benefits and potential pitfalls will enable the dermatologist to better discern its place in clinical practice and to subsequently optimize its use in patient care.

NOTES

[1] Leiter U, et al. “Epidemiology of skin cancer.” Advances in Experimental Medicine and Biology. 2014.
[2] Lomas A, et al. “A systematic review of worldwide incidence of nonmelanoma skin cancer.” British Journal of Dermatology. 2012.
[3] Rat C, et al. “Use of smartphones for early detection of melanoma: systematic review.” Journal of Medical Internet Research. 2018.
[4] Australian Cancer Network, New England Guidelines Group. Clinical Practice Guidelines for the Management of Melanoma in Australia and New Zealand. New Zealand Guidelines Group. 2008.
[5] Han SS, et al. “Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm.” Journal of Investigative Dermatology. 2018.
[6] Krizhevsky A, et al. “ImageNet classification with deep convolutional neural networks.” Advances in neural information processing systems. 2012.
[7] Nasr-Esfahani E, et al. “Melanoma detection by analysis of clinical images using convolutional neural network.” Engineering in Medicine and Biology Society. 2016.
[8] Nasr-Esfahani E, et al. “Melanoma detection by analysis of clinical images using convolutional neural network.” Engineering in Medicine and Biology Society. 2016.
[9] Esteva A, et al. “Dermatology-level classification of skin cancer with deep neural networks.” Nature. 2017.
[10] Malvehy J, et al. “Clinical performance of the Nevisense system in cutaneous melanoma detection: an international, multicentre, prospective and blinded clinical trial on efficacy and safety.” British Journal of Dermatology. 2014.
[11] Cukras AR. “On the comparison of diagnosis and management of melanoma between dermatologists and Melafind.” JAMA Dermatology. 2013.
[12] Fujisawa Y, et al. “Deep learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis.” British Journal of Dermatology. 2018.
[13] Han SS, et al. “Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm.” Journal of Investigative Dermatology. 2018.
[14] Navarette-Dechent C, et al. “Automated dermatological diagnosis: hype or reality.” Journal of Investigative Dermatology. 2018.
[15] Han SS, et al. “Interpretation of the outputs of deep learning model trained with skin cancer dataset.” Journal of Investigative Dermatology. 2018.
[16] Brinker TJ, et al. “A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task.” European Journal of Cancer. 2019.
[17] Brinker TJ, et al. “Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task.” European Journal of Cancer. 2019.
[18] Brinker TJ, et al. “Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task.” European Journal of Cancer. 2019.
[19] Brinker TJ, et al. “Comparing artificial intelligence algorithms to 157 German dermatologists: the melanoma classification benchmark.” European Journal of Cancer. 2019.
[20] Chuchu N, et al. “Smartphones. Applications for triaging adults with skin lesions that are suspicious for melanoma.” Cochrane Database System Review. 2018.
[21] Shrivastava VK, et al. “Computer-aided diagnosis of psoriasis skin images with HOS, texture, and color features: a first comparative study of its kind.” Computer Methods and Programs in Biomedicine. 2016.
[22] Guo P, et al. “Gene expression profile based classification models of psoriasis.” Genomics. 2014.
[23] Shrivastava VK, et al. “Computer-aided diagnosis of psoriasis skin images with HOS, texture, and color features: a first comparative study of its kind.” Computer Methods and Programs in Biomedicine. 2016.
[24] Shrivastave VK, et al. “A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification.” Computer Methods and Programs in Biomedicine. 2017.
[25] Gustafson E, et al. “A machine learning algorithm for identifying atopic dermatitis in adults from electronic health records.” IEEE International Conference on Healthcare Informatics. 2017.
[26] De Guzman LCD, et al. “Design and evaluation of a multi-model, multi-level artificial neural network for eczema skin lesion detection.” AIMS. 2015.
[27] Han SS, et al. “Deep neural networks show an equivalent and often superior performance to dermatologists in onychomycosis diagnosis: automatic construction of onychomycosis datasets by region-based convolutional deep neural network.” PloS One. 2018.
[28] Esteva A, et al. “Dermatology-level classification of skin cancer with deep neural networks.” Nature. 2017.
[29] Mendonca T, et al. “PH2 – a dermoscopic image database for research and benchmarking.” Engineering in Medicine and Biology Society. 2013.

RESOURCES

Australian Cancer Network, New England Guidelines Group. Clinical Practice Guidelines for the Management of Melanoma in Australia and New Zealand. New Zealand Guidelines Group. 2008.

Brinker TJ, et al. "A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task." European Journal of Cancer. 2019.

Brinker TJ, et al. "Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task." European Journal of Cancer. 2019.

Brinker TJ, et al. "Comparing artificial intelligence algorithms to 157 German dermatologists: the melanoma classification benchmark." European Journal of Cancer. 2019.

Chuchu N, et al. "Smartphones. Applications for triaging adults with skin lesions that are suspicious for melanoma." Cochrane Database System Review. 2018.

Cukras AR. "On the comparison of diagnosis and management of melanoma between dermatologists and Melafind." JAMA Dermatology. 2013.

De Guzman LCD, et al. "Design and evaluation of a multi-model, multi-level artificial neural network for eczema skin lesion detection." AIMS. 2015.

Esteva A, et al. "Dermatology-level classification of skin cancer with deep neural networks." Nature. 2017.

Fujisawa Y, et al. "Deep learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis." British Journal of Dermatology. 2018.

Guo P, et al. "Gene expression profile-based classification models of psoriasis." Genomics. 2014.

Gustafson E, et al. "A machine learning algorithm for identifying atopic dermatitis in adults from electronic health records." IEEE International Conference on Healthcare Informatics. 2017.

Han SS, et al. "Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm." Journal of Investigative Dermatology. 2018.

Han SS, et al. "Interpretation of the outputs of deep learning model trained with skin cancer dataset." Journal of Investigative Dermatology. 2018.

Han SS, et al. "Deep neural networks show an equivalent and often superior performance to dermatologists in onychomycosis diagnosis: automatic construction of onychomycosis datasets by region-based convolutional deep neural network." PloS One. 2018.

Hogarty D, et al. "Dermatology — Where we are and the way to the future: a review." American Journal of Clinical Dermatology. 2020.

Krizhevsky A, et al. "ImageNet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

Leiter U, et al. "Epidemiology of skin cancer." Advances in Experimental Medicine and Biology. 2014.

Lomas A, et al. "A systematic review of worldwide incidence of nonmelanoma skin cancer." British Journal of Dermatology. 2012.

Malvehy J, et al. "Clinical performance of the Nevisense system in cutaneous melanoma detection: an international, multicentre, prospective and blinded clinical trial on efficacy and safety." British Journal of Dermatology. 2014.

Mendonca T, et al. "PH2 – a dermoscopic image database for research and benchmarking." Engineering in Medicine and Biology Society. 2013.

Nasr-Esfahani E, et al. "Melanoma detection by analysis of clinical images using convolutional neural network." Engineering in Medicine and Biology Society. 2016.

Navarette-Dechent C, et al. "Automated dermatological diagnosis: hype or reality." Journal of Investigative Dermatology. 2018.

Rat C, et al. "Use of smartphones for early detection of melanoma: systematic review." Journal of Medical Internet Research. 2018.

Shrivastava VK, et al. "Computer-aided diagnosis of psoriasis skin images with HOS, texture, and color features: a first comparative study of its kind." Computer Methods and Programs in Biomedicine. 2016.

Shrivastave VK, et al. "A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification." Computer Methods and Programs in Biomedicine. 2017.

PharmaVOICE

THERAPEUTIC DIGESTS

2021 THERAPEUTIC TOPICS:

Diabetes

Digital Therapeutics

Endocrinology

Vaccines

Cardiology

Oncology

Dermatology

Inflammatory Diseases

Rare Disorders

Neurology

Infectious Disease

Pulmonology

Copyright 2021 by PharmaLinx LLC