Abstract
Artificial intelligence (AI) has emerged as a major frontier in computer science research. Although AI has been available for some time and found its application in many fields of medicine, its use in dermatology is comparatively new and limited. A sound understanding of the concepts of AI is essential for dermatologists as skin conditions with their abundant clinical and dermatoscopic data and images can potentially be the next big thing in the application of AI in medicine. There are already a number of artificial intelligence studies focusing on skin disorders, such as skin cancer, psoriasis, atopic dermatitis, and onychomycosis. This article presents an overview of AI and new developments relevant to dermatology, examining both its current applications and future potential.

Key Words: Artificial intelligence, artificial neural network, deep learning, machine learning

Introduction
Medicine is on the verge of an exciting new age with the advent of potentially disruptive technologies, which range from virtual reality, genomic prediction of disease, data analytics, personalized medicine, stem cell therapy, 3-D printing to nanorobotics.

The practice of dermatology is also evolving rapidly. The approach to the diagnosis and management of dermatological conditions has considerably changed with the advent of newer technology and invention. Computer algorithms have found their application in aiding dermatologists with disease diagnosis especially in conditions like malignant melanoma. Machine learning is a subset of artificial intelligence (AI) in which computer programs learn automatically from experience without explicit programming instructions.

Dermatology has taken the pole position for the implementation of AI in medical field because of its large clinical, dermatoscopical, and dermatopathological image database. A basic understanding of AI will therefore be a prerequisite to design and interpret medical studies in this area. So, it is important to consider the potential role of AI in the practice of dermatology. Therefore, in this review, we will try to provide a basic understanding and the use of dermatology in the present and recent future.

Definition
AI is defined as “the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines” by the association for the advancement of artificial intelligence. In simpler words, AI is a computer science that involves creating programs that aim to reproduce human cognition and processes involved in the analysis of complex data.

History of Artificial Intelligence
Mathematician Alan Turing published a paper titled “On Computable Numbers, With an Application to the Entscheidungs problem”. This paper is often considered as the founding document of the computer age. Turing and his Princeton colleague, Alonzo Church, used calculus to define the concept of “effective calculability”, which became the basis of computational model called “algorithm”.

AI was first coined at a famous Dartmouth College conference in 1956. In the early 1970s, medical
However, at present, we are far from being the first to train a neural machine. This was quite a landmark in technology. However, the limitation in technology also restricted the application of AI in the last two decades because of improved hardware and software technologies, made us recognize the potential for AI to improve current medical practices, and AI research is already being conducted in numerous medical fields, including dermatology. However, the beginning of dermatological AI lags far behind the more advanced medical AI uses, like in radiology. With changing scenario, and much more researches in dermatological AI, one can expect the application of AI in the field of dermatology will greatly shorten the gap between doctors at the different levels of hospitals and improve the accuracy of diagnosis.

**Terminologies of Artificial Intelligence**

**Classification of AI**

AI can broadly be classified into either strong AI or weak AI. Strong AI or “artificial general intelligence” confers a machine with human-level intelligence. This complex machine should have the ability to learn by itself to conduct several different tasks. Within this broad category are machines with the capacity for consciousness, ethical cognition, and multi-tasking capabilities. However, at present, we are far from having such complex machines in reality.

At present we have only access to weak or narrow AI where a machine learns to complete a single goal. With weak AI, different programs must be created to perform different tasks.

**Analytics, training, confidence**

Artificial neural networks are flexible mathematical models or algorithms to identify complex nonlinear relationships within large datasets (analytics). Machines learn when errors encountered in response to minor algorithm modifications are corrected (training), progressively improving predictive model accuracy (confidence).

**Machine learning**

Machine learning is a subfield of artificial intelligence (AI) in which computer programs learn automatically from experience without explicit programming instructions.

This learning of machines can be supervised, semi-supervised, or unsupervised. In supervised setup, the machine is fed with datasets of problems with the answers. Machines learn to pick up the correct answer through trial and error. In unsupervised learning, machine analyze input data with no defined answer. The semi-supervised is a hybrid approach that involves both labeled and unlabeled data.

**Artificial neural network**

Artificial neural networks are flexible mathematical models that use multiple algorithms to identify complex nonlinear relationships within large datasets (analytics). Information enters the artificial neural network through the input layer, which is then fed through the multiple layers of hidden algorithmic processes. These processes are applied according to the weights learned in the machine learning processes. Finally, the processed data come out of the output layer. Artificial neural networks help the machine for deep learning [Figure 1].

**Deep learning**

As we know, machine learning is the ability of the machine to automate a learning process, deep learning is defined as a particular type of machine learning that uses artificial neural networks. In deep learning, the machine uses an infinite number of layers where every layer within the neural network can recognize and learn different features specific to the dataset. This complex multiple-layered structure helps the machine to perform complex tasks.

**Current Status of AI Application in Dermatology**

In the last decade or so, AI is gradually finding its relevance in different fields of dermatology including skin cancer, eczema, and psoriasis.

**Application of AI in skin cancer**

Researchers have been exploring the usefulness of AI to improve or supplement current screening processes in melanoma and nonmelanoma skin cancer (NMSC). Nasr-Esfahani et al. were the first to train a neural network for detecting melanoma and their proposed method had 0.81 and 0.80 sensitivity and specificity, respectively. In 2017, Stanford University published a study on deep learning of skin tumors. They demonstrated classification of skin lesions using a single convolutional neural network, trained end-to-end from images directly, using only pixels and disease labels as inputs. They trained a convolutional neural network using a dataset of 129,450 clinical images of 2,032 different diseases. They tested its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification of cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represented the identification of the most common cancers; the second represented the identification of the deadliest skin cancer. It was found that the machine had a competence comparable to board-certified dermatologists in identifying and classifying skin cancer. This was quite a landmark paper in the use of AI in dermatology. However, the external validity of their work is uncertain, as they did...
not include demographic information. Another limitation of the study was that, though it was understood that the application of deep-learning technology to skin cancer classification could potentially improve the sensitivity and specificity of skin cancer screening, it was generally accepted that the number of training images required for such a system would be extremely large.

Fujisawa et al. published a paper recently (2019) where they carried out a study to determine whether deep-learning technology could be used to develop an efficient skin cancer classification system with a relatively small dataset of clinical images. They trained a deep convolutional neural network (DCNN) using a dataset of 4867 clinical images obtained from 1842 patients diagnosed with skin tumors at the University of Tsukuba Hospital from 2003 to 2016. The images consisted of 14 diagnoses, including both malignant and benign conditions. Its performance was tested against 13 board-certified dermatologists and nine dermatology trainees. The overall classification accuracy of the trained DCNN was 76.5%. The DCNN achieved 96.3% sensitivity and 89.5% specificity. Although the accuracy of malignant or benign classification by the board-certified dermatologists was statistically higher than that of the dermatology trainees (85.3% ± 3.7% and 74.4% ± 6.8%, P < 0.01), the DCNN achieved even greater accuracy, as high as 92.4% ± 2.1% (P < 0.001).

A year earlier in China, Han et al. tested the use of a deep learning algorithm to classify the clinical images of 12 skin diseases including melanoma. 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 area under the receiver operating characteristic (AUROC) of 0.89. The tested algorithm performance was found to be comparable to that of 16 dermatologists. However, external validity of this program is still limited, as Navarrete–Dechent et al. who externally tested the program in a different patient population, found much lower sensitivity, with the correct histopathological diagnosis identified in only 29 of the 100 lesions.

In a recent study (2019) Brinker et al. showed for the very first time, automated dermoscopic melanoma image classification was significantly superior to both junior and board-certified dermatologists (P < 0.001). For the experiment, an additional 804 biopsy-proven dermoscopic images of melanoma and nevi (1:1) were randomly presented to the dermatologists of nine German university hospitals who evaluated the quality of each image and stated their recommended treatment (19,296 recommendations in total). Three McNemar’s tests comparing the results of CNN’s test run in terms of sensitivity, specificity, and overall correctness were predefined as the main outcome. The respective sensitivity and specificity of lesion classification by the dermatologists were 67.2% (95% confidence interval [CI]: 62.6%–71.7%) and 62.2% (95% CI: 57.6%–66.9%). In comparison, the trained CNN achieved a higher sensitivity of 82.3% (95% CI: 78.3%–85.7%) and higher specificity of 77.9% (95% CI: 73.8%–81.8%). The three McNemar’s tests in 2 × 2 tables all reached a significance level of P < 0.001. This significance level was sustained for both subgroups. They had similar findings in two earlier studies in 2019.

In another report, Brinker et al. also advocated for a melanoma classification benchmark, which they derived from their result for future comparisons. Their benchmark found that dermatologists had an overall sensitivity of 89.4% and specificity of 64.4% in detecting melanoma.

In recent years, smartphone applications are readily available and readily accessible for diagnosis of melanoma. If effective, they potentially offer an instant risk assessment of the likelihood of malignancy so that the right people seek further medical attention from a clinician for a more detailed assessment of the lesion. There is, however, a risk that melanomas will be missed and treatment delayed if the application reassures the user that their lesion is of low risk. Chuchu et al. assessed the diagnostic accuracy of smartphone applications to rule out cutaneous invasive melanoma and atypical intra-epidermal melanocytic variants in adults with concerns about suspicious skin lesions found four AI smartphone apps that classified skin lesions as melanoma (one app) or high-risk or “problematic” lesions (three apps).

Sensitivities for these apps ranged from 7% to 73%, and specificities ranged from 37% to 94%. They concluded, in the current state these apps might potentially miss melanomas and were potentially dangerous as they could instill a false sense of security in the user.

Another application of AI in skin cancer diagnosis can be at the histopathological level. Hekler et al. studied a total of 695 lesions, classified by an expert histopathologist in accordance with current guidelines (350 nevi/345 melanoma). A total of 595 of the resulting images were used to train a convolutional neural network (CNN). The additional 100 H and E section images were used to test the results of the CNN in comparison to 11 histopathologists. Three combined McNemar tests comparing the results of the CNNs test runs in terms of sensitivity, specificity, and accuracy were predefined to test for significance (P < 0.05). The CNN achieved a mean sensitivity/specificity/accuracy of 76%/60%/68% over 11 test runs. In comparison, the 11 pathologists achieved a mean sensitivity/specificity/accuracy of 51.8%/66.5%/59.2%, respectively. Thus, they concluded
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CNN was able to outperform 11 histopathologists in the classification of histopathological melanoma images and thus showed promise to assist human melanoma diagnosis. In general, though the use of artificial intelligence in the diagnosis of skin cancer, through clinical images, dermatoscopic images, and histopathologic images, is in the very initial days of evolution, it shows considerable promise.

**Atopic dermatitis**

In 2017, Gustafson et al. aimed to identify patients with atopic dermatitis for inclusion in genome-wide association studies. They described a machine learning-based phenotype algorithm. Using the electronic health record (EHR), they combined coded information with information extracted from encounter notes as features in a lasso logistic regression. Their algorithm achieved high positive predictive value and sensitivity, improving on previous algorithms with low sensitivity. These results demonstrate the utility of natural language processing and machine learning for EHR-based phenotyping.

De Guzman et al. designed an artificial neural network (ANN) for detecting atopic dermatitis 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 the discovery of the most appropriate AI processes. To improve the accuracy of current research, contextual information could be added for consideration by AI programs.

**Psoriasis**

The use of AI in psoriasis can help in clinical assessment and in the choice of personalized treatment protocols and outcome predictions. One of the most interesting and early use of AI in psoriasis was by Guo et al. who used an AI program to predict psoriasis. This system utilized microarray-based gene expression profiles from two datasets: GSE14905 and GSE13355. This study integrated the knowledge of three feature selection algorithms that revealed 21 features belonging to 18 genes as candidate markers. The final psoriasis classification model was established using the novel Incremental Feature Selection algorithm that utilizes only 3 features from 2 unique genes, IGFL1 and C10orf99. This model has demonstrated highly stable prediction accuracy (averaged at 99.81%) over three independent validation strategies.

In another study, Shrivastava et al. built nine kinds of psoriasis risk assessment system (pRAS) utilizing different combinations of the key blocks. These nine pRAS systems use three classifiers [Support Vector Machine (SVM), Decision Tree (DT), and Neural Network (NN)] and three feature selection techniques [principal component analysis (PCA), Fisher discriminant ratio (FDR), and mutual information (MI)]. The two major experiments conducted using these nine systems were: (i) selection of best system combination based on classification accuracy and (ii) understanding the reliability of the system. This leads us to the computation of key systems performance parameters, such as feature retaining power, aggregated feature effect, and reliability index besides conventional attributes like accuracy, sensitivity, and specificity. Using the database used in this study consisted of 670 psoriasis images, the combination of SVM and FDR was revealed as the optimal pRAS system and yielded a classification accuracy of 99.84% using cross-validation protocol. Further, SVM-FDR system provides the reliability of 99.99% using cross-validation protocol. They validated the pRAS system with automatically segmented lesions against manually segmented lesions showing comparable performance.

**Onychomycosis**

In a 2018 study, Han et al. by training with a dataset comprising of 49,567 images, could achieve a diagnostic accuracy for onychomycosis using deep learning that was superior to that of most of the dermatologists who participated in this study. On the validation datasets, they achieved sensitivity and specificity ranges of 82.7%–96.7% and 69.3%–96.7%, respectively. The AUROC was reported as 0.82–0.98.

**The Future of Dermatology AI: Opportunities and Challenges**

Many countries in the world have adopted strategic plans for the development of AI. The United States has released the National AI Research and Development Strategic Plan. The United Kingdom has released Growing the AI industry in the UK. The EU has issued The Age of AI: Towards a European Strategy for Human-Centric Machines.

However, there are challenges of AI in the field of dermatology, which also need to be addressed:

1. At present, image data of different skin diseases are insufficient, the degree of information sharing between sources is low, and the quality of skin images are not uniform.
2. Medical and AI researchers come from different fields and a multidisciplinary approach in computer science, biomedical, and medical sciences is essential.
3. Dermatological AI can only recognize a few specific skin diseases, whereas the dermatological condition is extremely varied. To make AI identify and classify a long and vast list of dermatological disorders with various clinical presentations will be a challenge.
4. AI diagnosis also involves legal issues, ethical issues, and data privacy issues, which need to be sorted out.
The diagnosis and classification of skin diseases require comprehensive consideration of patient history, gender, age, and other information beyond photographs. So in future there needs an integration of clinical data with this information.

We are entering an exciting era of AI for dermatology, especially for melanoma diagnosis. Thoughtful questions about how to better understand these automated systems, how to best use those in practice, and how to implement them widely into different clinical settings will all be critical next steps. Prospective studies in clinician’s hands would provide exciting information about how to best use and interpret these novel tools to better help our patients.

**Conclusion**

AI is fast emerging in the field of dermatology. It can revolutionize patient care, particularly in improving the sensitivity and accuracy of screening of skin lesions including malignancies. However, AI research needs clinical and photographic data of all skin types and the data needs to be generated through better international skin imaging collaboration for elaborate researches.

In an endnote, physicians should not perceive AI as a potential threat to their skills, rather it can be an adjunct to clinical practice in the coming years. An understanding of AI concepts will help practicing dermatologists to deliver better skin care.

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**Conflicts of interest**

There are no conflicts of interest.

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