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The development and use of artificial intelligence (AI) in dermatology: a narrative review

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ABSTRACT

Artificial intelligence (AI) is defined as a computer science involving program development aiming to reproduce human cognition to analyze complex data. Artificial intelligence has rapidly developed in the medical field. In dermatology, its development is relatively new and is generally used in the diagnostic, especially for skin imaging analysis and classification, and also for risk assessment. The greatest advances have been primarily in the diagnosis of melanoma, followed by the assessment of psoriasis, ulcers, and various other skin diseases. The use of AI has shown good accuracy and is comparable to dermatologists in various studies, especially related to melanoma and skin tumors. However, several obstacles exist in the application of AI to daily clinical practice, including generalizability, image standardization, the need for large data quantities, and legal and privacy aspects. In current developments, AI should be aimed at helping enhance the decision-making of clinicians.

ABSTRACT

Artificial intelligence (AI) adalah ilmu komputer yang terlibat dalam pembuatan program yang bertujuan untuk mereproduksi kognisi manusia dan menganalisis data yang kompleks. *Artifical intelligence* berkembang pesat, namun di bidang dermatologi masih tergolong baru dan umumnya digunakan untuk diagnostik yaitu analisis, klasifikasi gambar dan penilaian risiko. Kemajuan paling besar adalah pada penegakan diagnosis melanoma, diikuti penilaian psoriasis, ulkus dan berbagai penyakit kulit lainnya. Penggunaan AI telah menunjukkan akurasi yang baik dan sebanding dengan dokter spesialis dermatologi dalam berbagai studi, terutama terkait melanoma dan tumor kulit. Meskipun demikian, terdapat beberapa hambatan dalam penerapan AI, meliputi kemampuan generalisasi, standardisasi gambar, kebutuhan akan kuantitas data yang besar, aspek legal, privasi dan lainnya. Sebaiknya, AI digunakan untuk membantu pengambilan keputusan oleh klinisi.

***Keywords*:**
artificial intelligence;
deep learning;
dermatology;
machine learning;
machine learning

INTRODUCTION

Intelligence represents the mental ability to think, plan, solve problems, understand complex ideas, and learn from experiences.[1] Artificial intelligence (AI) is a scientific understanding of the underlying mechanisms of intelligent behavior and its embodiment in a machine. In other words, AI is defined as a branch of computer science involving program development aiming to reproduce human cognition to analyze complex data.[2] The term "augmented intelligence' was often used rather than artificial intelligence to emphasize systems that enhance and augment human decision-making rather than an attempt to replicate human intelligence.[3]

In the medical field, AI is well-acknowledged and supported by the rapid technological development. AI in dermatology is fast emerging, especially for image classification and

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risk assessment.[4] We are entering an era of AI for dermatology; hence, a proper understanding is needed regarding this automated system and how it should be implemented in future clinical settings to deliver better skin care. This review aimed to discuss the basic concept of AI, AI development, and AI applications in dermatology.

DISCUSSION

Basic concept

The term AI was first coined by John McCarthy during the Dartmouth College Conference in 1956, though the concept of human behavior simulating machine was proposed by Alan Turing in 1950.[5,6] In 1970, AI began to be applied in life science, yet the development was hindered by technological limitations.[2] Rapid technology development in the last two decades provides an opportunity to apply AI in medical practices.[7] Artificial intelligence is divided into strong AI and weak AI. The former refers to a machine with human-level intelligence, capable of learning independently and performing several different tasks. Meanwhile, the latter refers to a machine that learns to fulfill a single task, thus requiring several programs to run several different tasks.[2,8]

Machine learning

Machine learning (ML) differs from classic programming, in which a computer is supplied with a dataset and an algorithm. Classical programming uses an existing algorithm to process the dataset into outputs. In contrast to classical programming, ML uses the dataset and its output, allowing the model to learn and generate an algorithm linking the data and the output. The generated algorithm can be used to process the new dataset.[9] In other words, ML represents a model's learning ability to find the pattern in a large dataset.[1]

There are several methods of machine learning, including supervised, unsupervised, semi-supervised, and reinforcement learning.[9] The model generates an algorithm from the training dataset to predict the outputs of the new dataset. In supervised ML, the data and target output have been labeled, while in unsupervised ML, the model finds the pattern of the data and categorizes them into target output on its own. The semi-supervised ML is positioned between the supervised and unsupervised ML, in which some data have been labeled while others are not labeled. Reinforcement learning employs a system of “reward and punishment” to generate the problem-solving strategy.[9,10]

Deep learning

The deep learning (DL) term was coined by Geoffrey Hinton, known as the father of deep learning.[11] Deep learning is a part of ML that uses artificial neural networks (ANN). Figure 1 shows the interrelationship of terms related to AI. DL has several processing layers, and each layer possesses the ability to recognize and learn a specific feature of the given data. These processing layers are built sequentially and can be unlimited in number. The complexity of the layered structure allows the model to perform more complex tasks.[7,12] The ANN is inspired by human biological neurons. Each ANN has nodes (similar to nerve cell bodies) communicating with other nodes (similar to axons and dendrites).[7] The data are analyzed using an algorithm in each layer. The output of the first layer is analyzed by the algorithm of the next layer until generating the final output.[5] The most common training method used in DL is the supervised method, in which the dataset (e.g., skin lesion) has been labeled (e.g., benign or malignant). The reinforcement learning method can be used in the learning process that requires demonstration, e.g. robotic surgical assistant.[12]

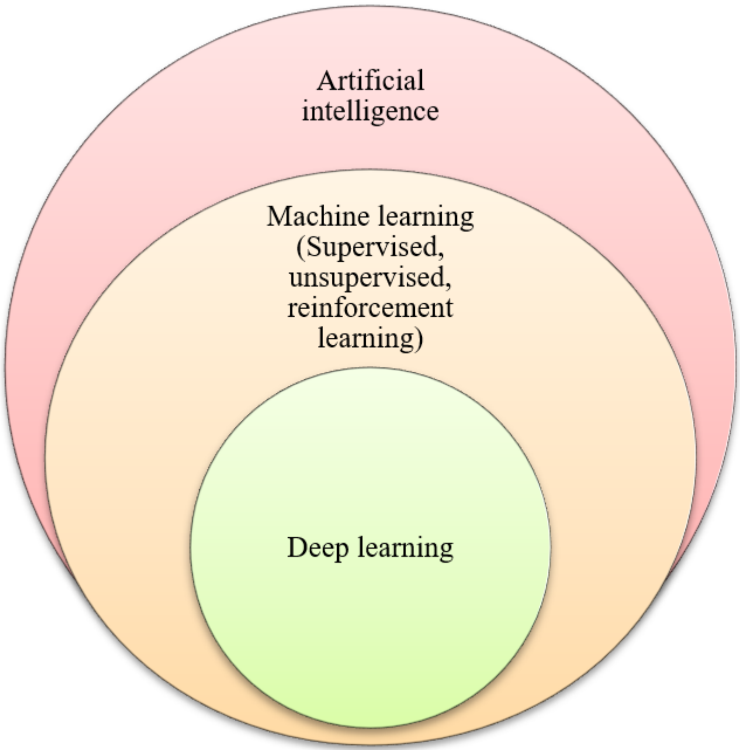

FIGURE 1. Diagram showing interrelationship of terms related to artificial intelligence.

A convolutional neural network (CNN) is a subtype of ANN that is commonly used to process grid-pattern data such as images. CNN is designed to recognize the spatial hierarchy of the image features. The CNN is composed of three types of layers: a convolutional layer and a pooling layer to extract features of an image, and fully connected layer that maps the extracted feature into final output such as image classification.[13] Thus, CNN is highly efficient for image processing since the feature could be anywhere in the image.

AI application in dermatology

Dermatology is a field involving high visual aspects with a large number of patients; hence, studies on medical image interpretation are highly required.[14] Image classification becomes the most frequent target of AI development in dermatology. Before 2016, most studies applied conventional computer assisted diagnosis (CAD) for automatic diagnosis based on the given medical images. CAD is composed of several tasks, including image quality enhancement, segmentation, feature extraction, and classification.[15]

Preprocessing

This process aims to enhance the image quality and eliminate noise and artifacts (hair, shadow, etc.) The frequently used methods include color transformation, illumination correction, contrast improvement, and artifact elimination. A proper preprocessing stage is important for facilitating the segmentation stage and improving classification accuracy.[16,17]

Segmentation

The segmentation process aims to determine the region of interest (ROI) in the images. This stage represents the most complex phase due to the numerous diagnoses of skin lesions.[15] The segmentation is continuously performed until the ROI is successfully isolated from the rest of the unimportant parts of the image.[18] Previous studies have compared or combined several image segmentation methods. Some of the frequently used methods include edge-based (using information from sudden changes at the lesion edge, such as discontinuity and pixel intensity changes), thresholding and region-based (using similarity criteria to identify the skin lesion), AI-based (neural network, k-means clustering, fuzzy logic, and evolutionary computation), active contour-based, etc.[16] The accuracy of the segmentation method is evaluated by comparing it to the ground truth established by manual segmentation.[17]

Feature extraction

After determining ROI, the feature extraction stage aims to identify the features with discriminating characteristics to classify the image into certain categories.[15] For instance, in melanoma diagnosis, the most frequently used feature extraction algorithm is the ABCDE criteria. Asymmetry (A) is measured by dividing the segmented area into two subregions based on the X and Y axes. Border (B) is classified into regular and irregular borders. Color (C) denotes the number of colors found in a lesion. Diameter (D) is determined by measuring the greatest distance between two edges.[19] Other extractable features include shapes (area, asymmetry, diameter, density), color, texture, and histogram color.[18]

Image detection and classification

This process classifies the image set into suitable categories. There are several types of classifiers. Some frequently used models include logistic regression, support vector machine (SVM), decision tree, random forest, Naive Bayes, and K-nearest neighbor. Proper classifier selection is pivotal to generating a satisfactory result.[15,20]

In conventional CAD, the process of determining and extracting features requires considerable time and resources. In contrast, when using DL, the learning model can independently determine the important features for image classification. As a result, a process that previously took years to complete can now be completed in a few months.[11] Some AI studies used dermoscopic and non-dermoscopic image sets to segment and classify melanocytic, keratinocyte tumors, ulcers, psoriasis, and other inflammatory diseases. Some models even exhibit diagnosis capacity comparable to dermatologists.[21]

AI application in skin malignancy classification

Artificial intelligence has been developed to classify melanoma and non-melanoma skin cancers using digital images.[22] The CNN model can be used for binary or multiclass classification.[23] Nasr-Esfahani *et al.*[24] used CNN to distinguish melanoma from the benign lesion with a sensitivity and specificity of 0.81 and 0.80, respectively. Fujisawa *et al.*[25] employed the deep convolutional neural network (DCNN) GoogleNet to classify skin tumor images into fourteen types of diagnosis and compared them to the diagnosis of certified dermatologists. Their study used 4,867 images from 1,842 skin tumor patients obtained from the institution's database with the three-level assessment. The first level aimed to differentiate benign from malignant lesions; the second level aimed to classify the images into certain tumor categories; and the third level aimed to classify lesions into specific diagnoses. The sensitivity and specificity of the model were 96.3% and 89.5%. The most accurate diagnosis was malignant epithelial tumor (95.7%), followed by benign melanocytic tumor (90.9%), malignant melanoma (72.6%), and benign epithelial tumor (62.8%). In the first level assessment, DCNN and dermatologist classification accuracy was 92.4 ± 2.1%, and 85.3 ± 3.7%; while in the third level, the accuracy was 74.5 ± 4.6% and 59.7 ± 7.1%. In general, a large number of labeled images is required to achieve high accuracy, yet this study used less than 5,000 training images.[25]

Han *et al.*[26] used pretrained CNN MicrosoftResNet-152 to classify medical images into 12 types of skin tumor diagnosis. The validation results showed sensitivity and specificity of 85.1% and 81.3% on the Caucasian dataset, and 85.4% and 85.5% on the Asian dataset respectively.[26] Brinker *et al.*[27] evaluated the CNN ResNet50 to distinguish between melanoma and nevus based on dermoscopic images using histopathology as the gold standard. Their study used 4,204 training images and 804 test images. The sensitivity and specificity of certified and junior dermatologists were 67.2% (95% CI: 62.6-71.1%) and 62.2% (95% CI: 57.6-66.9%), respectively, while the sensitivity and specificity of the CNN model were 82.3% (95% CI: 78.3-85.7%) and 77.9% (95% CI: 73.8-81.8%), respectively.[27]

Haenssle *et al.*[28] used pre-trained CNN Google's Inception v4 model to classify 100 dermoscopic images into melanoma and benign nevus, with dermatologists' diagnoses were used as the reference standard. Dermatologists were given two-level of assessment. In the first level, they were only given dermoscopic images, while in the second level, they were given dermoscopic images, clinical data, and clinical images. The study reported the sensitivity, specificity, and area under the curve (AUC) of dermatologists in the first level was 86.6 ± 9.3%, 71.3 ± 11.2%, and 71.3%, respectively, while in the second level, they was 88.9 ± 9.6%, 75.7 ± 11.7%, and 75.7%, respectively. Meanwhile, those of CNN were 63.8%, 86%, and 95%, respectively. This study showed that additional clinical information improves dermatologists' diagnosis accuracy. However, the specificity and AUC of dermatologists in this study were inferior compared to those of the CNN.[28]

AI application in classifying non-neoplastic skin disease

Gustafson *et al.*[29] developed natural language processing (NLP) to build a registry of atopic dermatitis from the electronic medical record. The data included coding of diagnosis (ICD9 and ICD10) and the narrative data from medical history. A group of keywords was determined based on Hanifin Rajka and The United Kingdom Working Party's (UKWP) criteria to build a dictionary concept. The concept found in the medical history was then extracted and converted into a group of features which will be analyzed using Lasso logistic regression. The model's sensitivity in this study was 75.0%, with a positive predictive value of 84.0%.[29]

A systematic review conducted by Yu *et al.*[14] evaluates the use of ML for psoriasis. It has been used in many studies to identify psoriasis lesions, calculate psoriasis area and severity, and predict outcomes.[14] Shrivastava *et al.*[30] developed a psoriasis risk assessment system (pRAS) to classify 670 skin lesion images into five categories: healthy skin, mild, moderate, severe, and very severe psoriasis. The support vector machine (SVM) and Fisher discriminant ratio (FDR) classifications exhibited 99.84% accuracy and 99.99% reliability.[30]

Zhao *et al.*[31] developed a CNN to diagnose psoriasis from more than 8,000 images consisting of nine diagnoses (four diagnoses that mimic psoriasis and five diseases significantly different from psoriasis) into binary classification, psoriasis, and non-psoriasis. The CNN model was reported to exhibit an AUC of 0.981 ± 0.015 with 96% accuracy, higher than the accuracy of 25 dermatologists (87%).[31] The severity of psoriasis was clinically measured by the psoriasis area and severity index (PASI), consisting of erythema, scales, and induration criteria. Some studies have implemented ML to automatically assess the psoriasis severity from medical images. George reported the model accuracy to assess the degree of erythema and scales to be 70.1% and 80.81%.[32,33]

Several recent studies developed AI for multiclass image classification. Liu *et al.*[34] used a deep learning system (DLS) to distinguish the twenty-six most common skin conditions in primary care, with the reference standard was a panel consisting of three certified dermatologists. The DLS provided three differential diagnoses and achieved top-1 and top-3 accuracies of 0.71 and 0.93, respectively.[34] Meanwhile, Zhu *et al.*[21] applied CNN Google's Efficient Net-b4 model to classify dermoscopic images into fourteen diagnosis categories and reported an overall accuracy of 94.8%, a sensitivity of 93.4%, and a specificity of 95%.[21]

AI application in ulcer assessment

A wound analysis system is frequently implemented to capture high-quality images, determine the wound border and area, classify wound tissue, and assess wound recovery.[35] Mukherjee *et al.*,[36] employed Bayesian and SVM classification to recognize different tissues in chronic wounds, such as granulation tissue, slough, and necrotic tissues compared to clinicians' assessment. The accuracy of SVM was reported to be 87.84, 90.90, and 79.78% in classifying granulation tissue, slough, and necrotic tissue, respectively, with the overall accuracy of 86.13%.[36] Wang *et al.*[35] used SVM to determine the wound border of 100 leg ulcer images taken using smartphones. The study reported sensitivity of 73.3% and and and specificity of 94.6%.[35] Dhane *et al.*[37] applied AI to determine the area of ulcers with an unclear border and reported a sensitivity of 87.3% and specificity of 95.7%.[37] Another study used ML to predict the risk of developing pressure injuries in postoperative patients based on data extracted from electronic medical records. The prediction model was reported to exhibit an AUC of 0.79.[38]

AI application in dermatopathology

Deep learning (DL) has been implemented to improve the precision of breast and lung cancer diagnosis. Hekler *et al.*[39] used a pre-trained CNN RestNet50 model to identify melanoma or benign nevus from histopathological images and compared it to the classification of a certified histopathologist. The study reported that the discordance of melanoma and nevus classification were 18% (95% CI: 7.4-28.6%) and 20% (95% CI: 8.9-31.1%), respectively.[39] The discordance between expert histopathologists in the classification of melanoma and nevi, as described in the literature, is 25%.[40] This is on par with the discordance between CNN and the histopathologists in this study. Digital pathology has the potential to enhance the accuracy of melanoma histopathological diagnosis.

Other applications of AI in dermatology

Artificial intelligence has also been used for diagnosing onychomycosis. Even though the evidence is limited, AI has the potential to assist clinicians in deciding whether further tests should be performed. Artificial intelligence can also be used to help patients evaluate their nails and to seek further assessment for nails that are suspicious for onychomycosis.[41] It can be used to monitor and predict disease outcomes.

Veredas *et al.*[42] used neural networks, random forest decision trees, and SVM to classify the types of wound tissue to monitor wound improvement. Their study reported an average accuracy of 81.87% (95% CI: 80.03-83.61%); 87.37% (95% CI: 85.76-88.86%); 88.08% (95% CI: 86.51-89.53%), respectively. Zang *et al.*[43] used ML to classify the risk of skin sensitization of some substances based on their chemical structure and reported the prediction accuracy was 78% in animal trials and 75% in humans.[43]

In cosmetic dermatology, AI is used to provide skin and hair care recommendations, analyze skin conditions, and assist cosmetic procedures. One examples of an AI applications is the VISIA® skin analysis system, which can analyze skin parameters, such as wrinkles, texture, pores, spots, and redness using face images. In the most recent VISIA® model, the TruSkin age feature provides information on wrinkle degree, UV damage, and discoloration based on the patients' age and compares them to a range of variables in the database.[44] Another skin analysis system is Janus-III, which uses high-resolution images to analyze pores, wrinkles, sebum, porphyrin, skin pigmentation, and skin color. The skin pigmentation parameter was found to be associated with dermatologist assessment (Pearson correlation coefficient = 0.869).[45] Another application is FotoFinder, which facilitates total body photography, dermoscopy, and trichoscopy. This system is equipped with AI to quantify hair falls, density, and anagen hair proportion.[44]

During the Covid-19 pandemic, research that focused on utilizing AI increased. Computational techniques, information and communication technologies, AI, and big data can handle a huge amount of data from public health surveillance, real-time epidemic outbreaks monitoring, trend forecasting, updating from governmental institutions, and others.[46] Big data is defined by three Vs: velocity (the unprecedented speed of data acquisition, processing, and manipulation), volume (the high amount of information), and variety (the number of different sources and channels releasing big data). It is a massive dataset that exceeds the computational capacity of conventional database systems to capture, store, manage, and analyze.[46,47]

AI has been immensely helpful in telemedicine, such as in providing systems to analyze medical information and assist in diagnosis. During the Covid-19 outbreak, AI was implemented in telemedicine for various diseases. AI can be used to make early diagnosis and contact tracing, monitoring symptoms and treatment, clinical management, and virtual and remote treatment.[48] Artificial intelligence in telemedicine can also be used as a method of triaging patients with potential skin cancer who require in-person evaluation by dermatologists.[49] Medical professionals need to adapt to AI advances to provide better healthcare delivery.[48]

AI implementation and interpretation in dermatology

Although some previous studies have reported the superiority of machine learning over dermatologists, it is necessary to highlight the presence of bias commonly found in the study design and bias that puts clinicians at a disadvantages.[50] Machine learning is trained and tested using the same data sources, thereby limiting their generalizability. Model learning is basically a reflection of the training data. Bias in the training data is likely to affect the model's performances and will be apparent when they are tested on a completely different dataset.[50]

In previously published studies, most learning models used binary classification, which does not reflect clinical practice, where numerous differential diagnoses are taken into account.[27] Moreover, AI models are often tested by comparing them to dermatologists without considering the clinical context and the limitation of diagnosis based on images alone.[12] Automated diagnosis using AI is beneficial as a tool to assist and enhance dermatologists' diagnosis, but not as an independent decision-maker without clinicians' supervision.[27]

Limitation in the development and application of AI

Despite its significant development in dermatology, AI still faces several limitations. Artificial intelligence development requires solid multidisciplinary collaborations, such as computer science, biomedical, and medical staff. Massive skin image resources are extremely important. Currently, skin disease images data is still inadequate, information-sharing among hospitals is low, and the quality of skin images varies.[51] The most critical factor in developing a predictive model is the dataset. A supervised DL model requires a large and labeled dataset. Obtaining a few labeled datasets is possibly easy but may result in poor performance on a new dataset. Meanwhile, an unlabeled dataset can only be useful for semi-supervised or unsupervised model.[12] Small datasets potentially lead to bias and lower accuracy, especially for neural networks.

The uneven proportion of certain disease categories in the training dataset also results in bias and affects the model's generalizability.[34] Navarrete-Dechent *et al.*[52] conducted external validation on the learning model developed by Han *et al.*[26] on a Caucasian population dataset. The study reported that Han's algorithm sensitivity was lower when tested on a different population. This result indicates that developing and training the DL model requires a large dataset covering the full spectrum of the human population and clinical variation. Detection of skin lesion is also affected by several factors, including skin color variation, redness level, severity, etc.[53]

Another challenge in dermatology comes from image standardization, including variability in technology (camera type), and image-capturing technique (lighting, angle, body position, etc.). Unlike in radiology, there is no standardization for taking images in dermatology.[54] Navarrete-Dechent *et al.*[52] attempted to manipulate medical images by changing the magnification, contrast, brightness, and rotation from a previous dataset, which resulted in some different diagnoses. Although AI can enhance medical service accuracy, access, and efficiency, it carries a risk of misdiagnosis. This risk increases if the AI system is provided directly to patients.[52]

The current AI diagnosis also involves legal, ethical, and patient privacy aspects that have not yet been fully resolved. Certain data may violate patients' privacy and in the case of an adverse event, the matter of accountability is yet to be addressed.[55] Furthermore, establishing a diagnosis requires various clinical information in addition to clinical images or photographs. These data should be integrated to determine the patient's working diagnosis, treatment, and prognosis. Future research integrating AI diagnosis and clinical data will provide better information on how to implement them in clinical settings. Lastly, the development of AI in medicine does not aim to substitute doctor-patient communication, holistic approach, and other humanistic care.[51]

CONCLUSION

Artificial intelligence can significantly contribute to medical clinical practice, including dermatology.

Existing studies have shown that AI-assisted diagnosis has comparable accuracy to dermatologist, especially in skin cancer screening. However, the models need to be trained on a large dataset with the full spectrum of the human population and clinical manifestations to obtain better generalizability, and further study integrating AI diagnosis and clinical data is necessary. Artificial intelligence is a beneficial tool to assist clinicians' decision-making processes and improve health services in the future healthcare system.

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