Artificial intelligence in dermatology and healthcare: An overview

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Abstract

Many aspects of our life are affected by technology. One of the most discussed advancements of modern technologies is artificial intelligence. It involves computational methods which in some way mimic the human thought process. Just like other branches, the medical field also has come under the ambit of artificial intelligence. Almost every field in medicine has been touched by its effect in one way or the other. Prominent among them are medical diagnosis, medical statistics, robotics, and human biology. Medical imaging is one of the foremost specialties with artificial intelligence applications, wherein deep learning methods like artificial neural networks are commonly used. artificial intelligence application in dermatology was initially restricted to the analysis of melanoma and pigmentary skin lesions, has now expanded and covers many dermatoses. Though the applications of artificial intelligence are ever increasing, large data requirements, interpretation of data and ethical concerns are some of its limitations in the present day.

Key words: Artificial intelligence, deep learning, dermatology, machine learning, medical imaging

Introduction

Machines have been used by man from time immemorial in his pursuit to survive and make life easier. The evolution of machines runs parallel to human spirit and enterprise, and has evolved from simple tools to modern-day computers. Dependence on machines has penetrated almost every aspect of human life including medicine. While the advent of modern medicine noted a reliance on subjective human skill, it has been gradually progressing towards a more objective approach with newer technological innovations.[1] One of the most discussed advancements of modern technologies in recent times is artificial intelligence and the implication of its application in various domains.[2] Artificial intelligence experts in medicine consider artificial intelligence to be the stethoscope of the 21st century.[1]

John McCarthy coined the term artificial intelligence in 1956 and defined it as "the science and engineering of making intelligent machines, especially intelligent computer programs."[3,4] The term applies to a broad range of items in medicine such as robotics, medical diagnosis, medical statistics, and human biology.[5]

History of Artificial Intelligence

The history of artificial intelligence can be believed to have begun in antiquity, with myths and stories of artificial beings designed by master craftsmen endowed with intelligence or consciousness.[6] In the first millennium Before the common era, Indian, Chinese and Greek philosophers developed structured methods of formal deduction like syllogisms (three-part deductive reasoning), described in the 'Nyaya school of thought' and Aristotle's work, which later moved towards Ramon Llull's theory of a reasoning machine in 1300 Common era.[2,7]

In 1950, Alan Turing, one of the founders of modern computer science, propounded the idea of artificial intelligence and devised the Turing test, which is a machine's ability to exhibit intelligent behaviour equivalent to, or indistinguishable from that of a human.[8] Over the next few decades, algorithms were generated for mathematical problems and geometrical equations. With exponential gains in computer processing power and storage ability, software giants used artificial intelligence algorithms to understand consumer behaviour,

How to cite this article: Pai VV, Pai RB. Artificial intelligence in dermatology and healthcare: An overview. Indian J Dermatol Venereol Leprol 2021;87:457-67.

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Received: June, 2019 Accepted: December, 2020 Published: June, 2021

DOI: 10.25259/IJDVL_518_19 **PMID:** ***

to develop computer vision, natural language processing and robotics.[6] Recently Google developed artificial intelligence programs namely Alpha Go and Alpha Zero, which were able to master the rules of an ancient Chinese game Go and chess by only playing against itself and then were able to defeat the best players in that sport.[9,10] Artificial intelligence ended the human domination over scientific discoveries when a robot called Adam in 2007 was used to identify the function of a yeast gene.[11]

History of the Use of Artificial Intelligence in Healthcare

Artificial intelligence in medicine coincides with the advent of artificial intelligence in the modern era.[2] Artificial intelligence has been applied in the field of medicine since as early as the 1950s when physicians made the first attempts to improve their diagnosis using computer-aided programs.[11,12] The application of artificial intelligence technology in the field of surgery was first successfully investigated by Gunn in 1976 when he explored the possibility of diagnosing acute abdominal pain with computer analysis.[7]

The last few decades have seen a surge in the interest in both the virtual and physical branches of artificial intelligence in medicine. The virtual branch includes electronic health records, medical imaging and active guidance of physicians in their treatment decisions. The physical branch is best represented by robots used to assist the patient or the doctor.[5,7] The market value of artificial intelligence in medicine is projected to reach $ 6.6 billion by 2021.[13]

The predominant fields of artificial intelligence with applications in medicine include: a) Machine learning including deep learning, b) natural language processing which includes content extraction, machine translation, question answering and text generation, c) visual applications which includes image recognition and machine vision, d) speech, and e) robotics.[3,14,15]

Artificial Intelligence, Machine Learning and Deep Learning

Arthur Samuel coined the term ‘machine learning’ defining it as, “the ability to learn without being explicitly programmed.” [Figure 1] In machine learning, instead of coding software with specific instructions to accomplish a particular task, the algorithm self-trains so that it can learn patterns by studying data directly.[16,17] Machine learning technology powers many aspects of modern society: from email spam filters, search suggestions, online shopping suggestions, and speech recognition in smartphones, etc.[18] Its ability to perform comprehensive analysis even with massive amounts of non-linear data makes it favourable in medical decision-making.[17,19]

Machine learning tasks are classified into two broad categories, depending on the type of task: supervised and unsupervised. Supervised learning involves an algorithm working with labelled training data. It involves the categorisation of data and programming of the relationship between input and output data. In unsupervised learning, the algorithm identifies hidden patterns in a stack of data and the various outcomes.[2,20,21] The difference between them is given in Table 1.

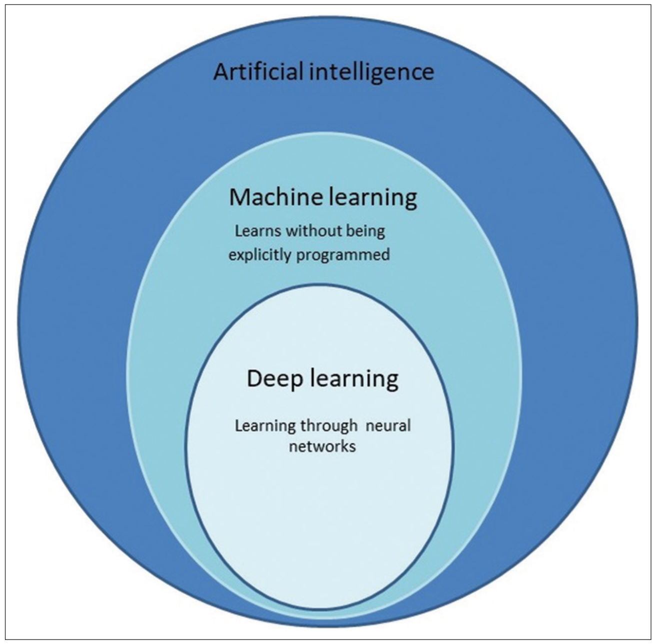

Figure 1: Artificial intelligence is an all-encompassing term which includes machine learning and deep learning as one of it types and subtypes respectively

Table 1: Differences between supervised and unsupervised learning

Supervised learning	Unsupervised learning
Input data is labelled	Input data is unlabelled
Uses training dataset	Uses only input dataset
Learns known pattern	Learns unknown pattern
Used for prediction	Used for analysis
Eg., Algorithm for classification include decision trees network, support vector machines, bayesian network Algorithm for regression include logistic regression, neural network	Eg., Cluster analysis, dimension reduction, association
Input » training » output	Input » output

In medicine, supervised learning is often performed in medical imaging and when observations have labels and these observations are paired to associated features such as age, sex, or clinical variables.[22,]

Algorithms

In image analysis through machine learning, several types of classification methods or algorithms are mentioned in literature. Commonly used among these methods are the artificial neural network, support vector machine, decision trees, k-nearest neighbour, regression analysis classifiers, Bayesian network, random forest, discriminant analysis, etc.[23] The neural network and support vector machines are the most common machine learning algorithms used in medical literature for image analysis. In data analysis of electronic health records, natural language processing is used.[24]

Neural networks

Artificial neural networks are a subset of machine learning, based on algorithms that are designed to recognize patterns that are inspired by the human neural network [Figure 2].[25] An artificial neural network is structured as one input layer of neurons, one or more "hidden layers" and one output layer. The input data is processed through a large number of highly interconnected elements, which are called neurons or nodes.[20] Deep learning is a subset of artificial neural network with stacked neural networks composed of one input and one output layer, and more than one hidden layer [Figure 3]. Deep learning algorithms require advanced computation and very large data.[25,26]

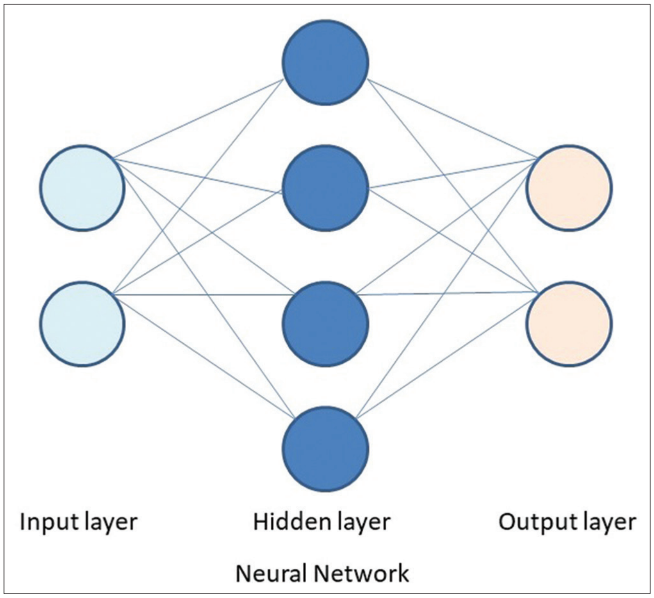

Figure 2: Basic structure of a neural network with a input layer, hidden layer and output layer

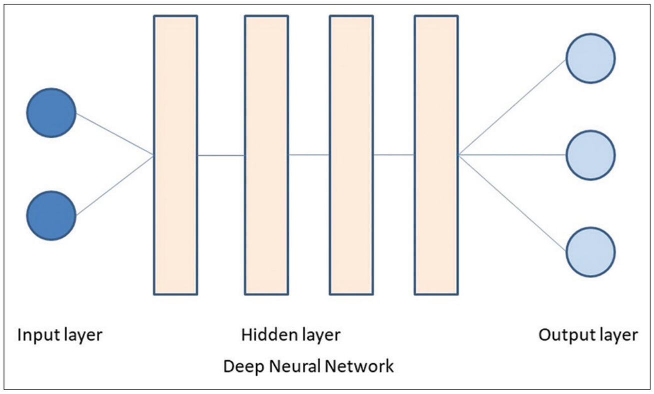

Figure 3: The deep neural network differs from a basic neural network in having more than one hidden layers

Deep neural networks can be divided into normal (one dimensional) or convoluted (two or three dimensions). Convolutional neural network has gained importance in medical image analysis for extracting patterns from images.[20] Convolutions are mathematic operations that are applied to pixel data in finding or filtering patterns.[20,21] Convolutional neural network is typically composed of three types of layers (or building blocks): convolution, pooling, and fully connected layers. The convolution and pooling layers perform feature extraction, whereas the fully connected layer maps the extracted features into final output, such as classification [Figure 4].[27]

Each input image will pass it through a series of convolution layers with filters.- Each layer learns to recognize a specific feature. For example: Once the first layer has successfully recognized a feature like an edge, it is fed to the next layer which trains itself to recognize more complex patterns like a corner in an image.The pooling (or down sampling) layer is used to reduce the spatial dimensions to gain computational performance As the model is repeatedly trained, individual convolutions begin to identify a specific portion of the image. Hundreds of these classifiers can be linked together to identify more complex structures within each image.[20,21,27]

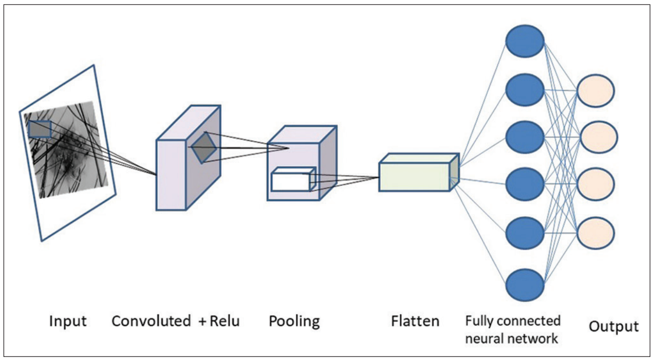

Figure 4: Processing of image through a convoluted neural network

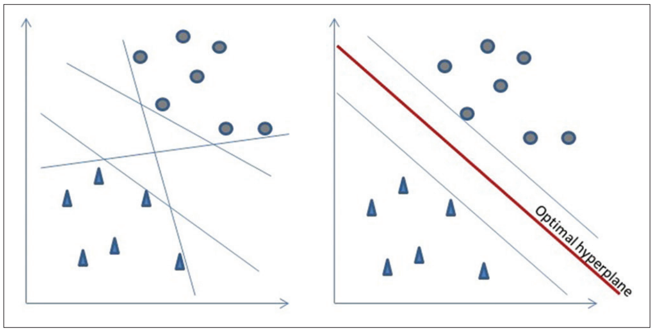

Figure 5: Support vector machine algorithm

Support vector machine

Support vector machine is a classification and regression algorithm for data classification in two classes that uses machine learning to maximize predictive accuracy while avoiding overfitting of data. It gives accuracy comparable to sophisticated neural networks when it is used in image analysis.[28,29] The support vector machine classifier is constructed by projecting training data into a higher dimensional space known as a hyperplane, which maximizes the separation between the classes [Figure 5].[30]

Natural language processing

Natural language processing is a machine learning program concerned with the use of software programming to understand and manipulate natural language text or speech for practical purposes.[2] It is used to extract information from unstructured data such as electronic health records electronic health records, which includes physical examination, clinical laboratory reports, operative notes and discharge summaries or medical journals. Data entry tasks of electronic health records takes time away from patient care and is contributing largely to physician burnout. The natural language processing procedures target at turning texts to machine-readable structured data, which can then be analysed by other machine learning techniques.[26,31,32]

Computer vision

Computer vision is a field in imaging which aims at designing systems mimicking the human sense of sight. This field involves areas such as artificial intelligence, digital image processing, machine learning, deep learning, pattern recognition, and scientific computing. The applications of computer vision include medical uses like lesion or cells classification and tumor detection, 2D/3D segmentation, 3D human organ reconstruction (MRI or ultrasound), vision-guided robotics surgery or robotics: for localisation, navigation, manipulation and human robot interactions.[33,34,35]

Artificial Intelligence in Medicine

An exponential increase in the use of artificial intelligence in clinical settings has been seen in recent years. Artificial intelligence is used for medical tasks like diagnosis, prognosis, and therapy. The difference between traditional statistical analysis and artificial intelligence is that the latter utilises data-mining and pattern recognition capabilities to analyse structured and unstructured data.[2]

Structured data such as imaging, genetics, electrophysiological data are analysed using machine learning algorithms and unstructured data like electronic health records are evaluated using natural language processing techniques.[24,36]

From 2008 to 2015, the use of basic electronic health records systems among hospitals in the US has increased from 9.4% to 83.8 %.[37] Analysis of electronic health records through artificial intelligence is supposed to enhance knowledge dissemination among clinicians and also empower patients to play an active role.[36]

Research on artificial intelligence in medicine, which was earlier limited to a few specialities like oncology, neurology, and cardiology, is at present encompassing every aspect of health care including surgical robots.[24]

Various fields of medicine influenced by artificial intelligence are briefly discussed in Table 2. [20,26,30,38-77]

Artificial intelligence in dermatology

Computer-based analysis of image assists in overcoming the subjective inter-observer and intra-observer variation thereby allowing an objective evaluation of parameters.[78] There is an upward trend in the use of artificial intelligence as a diagnostic aid in dermatology. The application of computational methods is being used in dermatology for faster data processing to give better and more reliable diagnoses.[79,80]

This development began in the 1980s, when a greater public awareness was noted following an increased incidence of malignant melanoma, resulting in newer diagnostic modalities for early detection of lesions. Around the same time, Wilhelm Stolz and others in the Munich imaging group developed a hand-held dermatoscope for cutaneous surface microscopy.[81] Later automated diagnosis of melanomas was tested using computer-aided diagnosis to reproduce the decision of the dermatologist when observing images of pigmented skin lesions either by photography, dermoscopy, and spectrophotometry.[82]

Several image processing software in the C programming language were written with the involvement of the dermatology digital imaging group. The focus was on automatic detection of lesional borders, malignant feature detection, detection of lesion changes, and algorithmic separation of benign from malignant lesions.[81,82] In 1987, Cascinelli *et al*. studied the automated classification of pigmented skin lesions based on images.[79,83] Over the last three decades, there is extensive literature on the use of machine learning models for analysing and classifying the data from skin lesions.[84] It is also believed that an exponential expansion of smartphone technology worldwide will provide low-cost universal access to this vital diagnostic care.[26]

The general steps involved in computer-aided diagnosis include:

i. Image acquisition:
   The two predominant dermatological image types are clinical and dermoscopic images with the increased use of the latter[23]
ii Image pre-processing: The term pre-processing in image diagnostic procedures usually encompasses artefact removal and lesion image enhancement.[25] Good performance at this stage ensures the correct behaviour of the algorithms in the following stages of analysis.[82]
   Artefact correction involves algorithms for removal of hair artefacts, dermoscopic gels, thin blood vessels,

Table 2: Various fields of medicine influenced by artificial intelligence

Speciality	Role of Machine learning
Oncology	Detection and classification of lung cancers, skin lesions and breast cancer metastases[26,38,39] Analyse the side effects of polypharmacy, radiotherapy, drug-drug and drug-protein interactions [40,41] Many CDSS, which are computer programs, are available that apply AI and provide clinicians/oncologist with evidence-based treatment recommendations for a variety of cancer diagnoses. Eg. CancerLinq, IBM's WFO.[42,43] CDSS show varying degree of concordance with the treatment recommendations of the expert group with ovarian cancer showing highest concordance (96%)[42,44] Newer frontiers of AI in oncology include predicting protein structure, classifying cells based on its cell cycle and drug development[40,45,46]
Neurosurgery	Machine learning algorithms have been increasingly used for diagnosis, presurgical planning like tumour segmentation or epileptogenic zone localization, and outcome prediction[47] Application in biomechanics and gait research[48,49]
Radiology	AI is used in various radiological imaging tasks, such as risk assessment, detection, diagnosis, prognosis, and therapy response[50] Machine learning models have been used in many aspects of radiology like detection of pulmonary lesions, fractures, organ laceration, mammography, malignancies and stroke.[20] The steps are similar to the image interpretation in dermatology given below
Drug development	Machine learning algorithms have been used in various stages of drug development, such as identification and validation of drug targets, designing of new drugs, drug repurposing, improving the R and D efficiency etc.[51-53] AI can predict with high accuracy the likelihood of failure of a drug clinical trial, to determine the cancer cell sensitivity to therapeutics, or the peptide-major histocompatibility complex binding for oncologic immunotherapy development[53-56]
Obstetrics	Machine learning algorithms are trained using features extracted from raw Cardiotocography foetal heart rate traces contained in the dataset to distinguish between caesarean section and vaginal delivery types[57] Neural network model have been developed to detect epithelial ovarian cancer using noncoding RNAs and also used to improve the performance of assisted reproductive technology[58,59]
Ophthalmology	Machine learning has been applied to ocular imaging like fundus photographs, optical coherence tomography and for ophthalmic diseases like diabetic retinopathy, glaucoma, age-related macular degeneration, retinopathy of prematurity and congenital cataracts[60-62]
Cardiology	Machine learning models are able to identify different wave morphologies (QRS complexes, P and T waves) with high precision[30] Machine learning models have also been used in cardiology for prediction of acute myocardial infarction by using proteomic measurements and clinical variables, estimation of in-stent restenosis from plasma metabolites, estimation of cardiovascular risks from electronic health records[63-65]
Anaesthesiology	Machine learning in anaesthesiology has been studied to predict bispectral index using controlled infusion rates of propofol and remifentanil, to estimate hypotension using leverage data available during induction of anaesthesia and high-fidelity arterial line waveforms, to predict postoperative mortality from electronic health record data[66-70] Robotics in anaesthesiology involved the introduction of McSleepy as a pharmacological robot to administer general anaesthesia using a closed loop system.[71] SEDASYS® was the first computer-assisted personalized sedation system to receive US FDA approval in 2013. It was developed to allow mild-to-moderate propofol sedation to be delivered by non-anaesthesiologists for upper endoscopy and colonoscopy in healthy adults. It was discontinued from the market after 3 years[72-74]
Psychiatry	Machine learning techniques have been used in psychiatry for the classification of dementia, attention deficit hyperactive disorder, schizophrenia[75,76] Advancements in ML have also resulted in the creation of artificial intelligent agents in the form of highly realistic simulated psychotherapists, counsellors, and therapeutic coaches[77]

CDSS: Clinical decision-support computing system, AI: Artificial intelligence, WFO: Watson for Oncology, CAD: Computer-aided diagnosis, FDA: Food and Drug administration, MRI: Magnetic resonance imaging

shadows, ruler markings, specular reflections and air bubbles, which can confuse diagnosis and impede the achievement of better accuracy in the automated diagnosis process.[23,82,85] Out of these, hair shafts and ruler markings are the most commonly reported artefacts.[23,85,86] Various machine learning models are used for this purpose. Filtering is a popular method to smooth a lesion image before detecting artefacts.[23]

Under image enhancement, the most important operation is colour calibration. This operation consists of recovering real colours of a photographed lesion, illumination correction, and contrast and edge enhancement.[82] Commonly used colour spaces include red-green-blue and International Commission on Illumination among others.[23,82]

iii Image segmentation: Precise border detection (segmentation) is one of the most important and crucial areas in the automated analysis of pigmented skin lesions. It is also believed to be the most difficult task due to low-contrasts surrounding the skin, fuzzy borders, the existence of artefacts and irregular structures characterizing lesional images[23,82]

Various machine learning approaches have been described for the segmentation of lesions. They are based on the colour information of the lesion, luminance, and texture. They can be broadly classified as thresholding, edge-based, fuzzy c-means, gradient vector flow snakes or region-based methods. Thresholding method is the most commonly used one and achieves good results when there is good contrast between the lesion and the skin.[23,82,87]

iv Feature extraction: The extraction of specific features in a given lesion image is an essential step towards effective automated lesion image classification. The primary objective of feature extraction is to quantify the image by a set of finite numerical features.[23] The various feature descriptors studied in the algorithm for melanoma analysis are based on dermoscopic (ABCD or pattern analysis) or clinical findings (ABCDE)[88,89] A combination of photometric features like colour, islands of colour, colour homogeneity, colour histogram etc. and textural aspects yield good results in identifying pigmented skin lesions.[23,90] The challenges in this process lie in the vast variety of images, body location, subject parameters (age), imaging parameters (lightening or camera), and the direction from which the lesion image is viewed.[23]

v Classification of lesions: Lesion classification is the last step in the process for the computerized analysis of images. Image classification involves using selected features of an image to classify pixels of the image into one of the several classes depending on specific knowledge domain.

The two main classification types as reported in the literature in relation to medical imaging are supervised classification and unsupervised classification (already discussed). The literature has reported the application of several classification methods for lesion images. Frequently used among these methods are the artificial neural network, support vector machine, decision trees, k-nearest neighbour, regression analysis classifiers, bayesian classifiers and fuzzy logic.[20,21,23,82]

Artificial Intelligence Applications in Dermatological Conditions

Automated detection of skin lesion using images has extended beyond melanoma to encompass pigmentary skin lesions, non-melanocytic skin cancers, psoriasis, skin rash, and onychomycosis among other skin diseases.[26, 91-95]

Pigmentary skin lesions and malignancy

Many research articles have been published classifying non-melanoma skin cancers vs. benign and pre-malignant lesions with varying efficacy between different artificial intelligence systems.[96,97] Many systems are commercially available for computer-aided diagnosis of pigmented skin lesions which are mainly based on dermoscopy. e.g. DANAOS expert systems, DBDermo-Mips, MoleAnalyser expert systems.[82] Multiple smartphone based apps like SkinVision, DermaAId, Skin 10, MoleScope are available for screening skin cancers, tracking changes in moles on the skin and identification of basic skin lesions.[98] Studies done on the SkinVision app scored an 80% sensitivity and 78% specificity in detecting premalignant conditions.[99]

Psoriasis

Artificial intelligence has been working on many aspects of psoriasis. Various computer aided diagnostic systems have been designed for image classification and psoriasis risk stratification.[91,100] Also machine learning prediction models have been designed to determine the treatment response of psoriasis to biologics and to differentiate psoriasis from psoriatic arthritis using genetic markers.[101,102] Correa da Rosa *et al*. showed that the gene-expression profiles of psoriasis skin lesions, taken in the first 4 weeks on patients who are on treatment with a biological agent, can be used to accurately predict (>80% area under the ROC curve) the clinical endpoint at 12 weeks using machine learning techniques thereby reducing the assessment gap by 2 months.[103]

Emam *et al*. studied whether machine learning could aid in predicting long-term responses to biologics in psoriasis through analysis of data of 681 psoriasis patients from the Danish registry cohort using various modelling techniques. Patients with early diagnosis and early initiation of treatment, without psoriatic arthritis, had 90% chance of continuing treatment as per the study.[104] Foulkes *et al*. noted that signals of response to therapy in patients with severe psoriasis treated with the etanercept may be systemically detectable in lesional skin, non lesional skin, and blood at baseline, before the commencement of therapy.[105] Automated diagnosis of other erythemato-squamous diseases such as seborrheic dermatitis, atopic dermatitis, lichen planus, pityriasis rosea and pityriasis rubra pilaris has been studied using various clinical and histopathological features.[106,107]

Acne

New technologies in imaging and software solutions have been developed in acne and rosacea evaluation. A study by Min *et al*. showed that compared with manual counting performed by an expert dermatologist, the sensitivity and positive predictive value of the lesion-counting program was greater than 70% for papules, nodules, pustules, and whitehead comedones.[108,109]

Autoimmune disorders

Machine learning has been used in various aspects of patient identification, risk prediction, diagnosis, disease subtype classification, disease progression and outcome and monitoring and management of autoimmune disorders like systemic lupus erythematosus, systemic sclerosis, vitiligo, psoriatic arthritis, rheumatoid arthritis, and systemic vasculitis.[110]

Also, machine learning techniques have been used for automated or semi-automated classification of myositis using ultrasound images. The study differentiated between normal muscle, dermatomyositis, polymyositis, and inclusion body myositis with accuracies above 70%.[97,111]

Allergic contact dermatitis

Contact dermatitis is a common immunological reaction to sensitizers. The predictive screenings for the sensitizing chemicals have been usually performed using animal models such as the murine local lymph node assay. Animal models for sensitization assessment are being replaced by non-animal testing methods like Genomic Allergen Rapid Detection assay, which is based on measurements of transcriptional levels of genomic biomarkers. Artificial intelligence algorithms were used to study the changes induced in these genomic biomarkers as compared to profiles of reference chemicals on cellular stimulation with unknown sensitizers.[112,113]

Ulcer evaluation and prediction

The common risk factors for chronic wounds in India are diabetes, tuberculosis, leprosy, vascular disorders, pressure ulcer, and trauma. Automated analysis has been used in various aspects of ulcer assessment like analysis of wound perimeter, surface, depth, area determination, wound delineation and composition thereby providing an objective and quantitative assessment of healing rate during treatment.[114-117] Artificial intelligence applications are also used in predicting the development of pressure injuries among surgical critical care patients.[118]

Robotics

Robots represent the physical aspect of artificial intelligence. In healthcare, Robot-assisted biopsies were one of the first uses of surgical robots and have been used for prostate, lung, breast and stereotactic brain biopsies.[119-122] Automated device for performing skin biopsies has been developed by scientists. Wherein the biopsy can be performed with fewer instruments within a shorter duration of time without the necessity of local anaesthesia.[123,124] Robot-assisted automatic laser hair removal system has been developed to automatically detect any arbitrary shape of the desired treatment area and to provide uniform laser irradiation to the designated skin area.[125] Studies on the laser hair removal system system provides consistent irradiation not only in terms of uniform distance and also the number of irradiation shots.[126] A robotic system for hair restoration (the ARTAS system) has been developed for the follicular unit extraction type of hair restoration surgery. It consists of a robotic system with a stereoscopic camera with high resolution to identify hair follicles for harvesting and implantation.[127,128]

Human versus Artificial Intelligence

Human interpretation of images may be limited by the presence of structure noise, incomplete visual search patterns, fatigue, distractions, vast amounts of image data, and the physical quality of the image itself.[50] With the evolution of machine learning techniques, the question among artificial intelligence experts is when, rather than whether, artificial intelligence models will outsmart their human counterparts. They believe in the next decade that artificial intelligence will outperform humans in many activities such as translation of languages and driving a vehicle. Also, in another 50 years, artificial intelligence may surpass the brainpower equivalent to that of all human beings combined i.e. attain singularity and probably be writing bestsellers, doing maths research and even perform surgeries.[4,129-131] Time will tell whether these predictions will fructify.

At present, in dermatology, many studies using varied algorithms have shown results ranging from equal or better efficacy. Comparison of human and deep learning systems for the management of small pigmentary skin lesions have demonstrated that for small lesions, the computer-vision system had significantly higher sensitivity and in a few studies outperformed dermoscopists.[130,132] A study by Esteva *et al*. analysed clinical and dermoscopic images using a single convolutional neural network, trained from images directly, using only pixels and disease labels as inputs. This is unlike other techniques which required extensive pre-processing, lesion segmentation and extraction of specific features before classification. The convolutional neural network was trained using a dataset of 129,450 clinical images consisting of 2032 different diseases. Its performance was tested against board-certified dermatologists on biopsy-proven clinical images to differentiate between benign pigmentary skin lesions and melanoma. The convolutional neural network demonstrated performance on par with tested experts across both tasks.[26] MacLellan *et al*. analysed artificial intelligence in the diagnosis of melanomas in clinical settings, which was not done in many of the previous studies and found an increased sensitivity of the local dermatologist (96.6%) as compared to the computer-based algorithm (88.1%). The study concluded that these tools would aid in better diagnosis but will not replace clinical decision making.[133]

Deep learning algorithms achieved better diagnostic performance than pathologists in identifying malignant tumours and detecting lymph node metastases in tissue sections of women with breast cancer.[4,39] In the field of radiology too, artificial intelligence systems have been on par with, and sometimes outperformed radiologists. Rajpurkar *et al*. found that deep learning models detected clinically important abnormalities (e.g., oedema, fibrosis, mass, pneumonia, and pneumothorax) on chest radiography, at a performance level comparable to practicing radiologists.[39,131,134,135]

Artificial Intelligence Limitations

Data

Artificial intelligence applications are only as robust as the data on which they are trained. Deep learning neural networks require large amounts of data. This can be a drawback when artificial intelligence is attempted on a disease with low prevalence or when data is generalised across different populations. The heterogeneity of medical data across institutions and the complexity of the neural networks can lead to over fitting models.[4,37,40] In addition, the quality of the information extracted, is still dependent on the accuracy of the input data being entered and the infrastructure available for data sharing. Also, algorithms can underperform in conditions where there is no precedence like new side effects of drugs or treatment resistance.[1,40,]

Acceptance

Detailed history and thorough clinical examination complemented by relevant investigations is the basis of diagnosis in most dermatoses. Histopathology still remains the gold standard diagnostic investigation as compared to other noninvasive investigations including artificial intelligence. Also patient care is not restricted to diagnosis but requires a holistic approach with human touch which cannot be replaced by algorithm. All these factors may challenge the acceptance of artificial intelligence in dermatology.[136,137]

Reasoning (the black box problem)

In medical practice, it has traditionally been essential in clinical decision-making to know the rationale for each decision. In contrast, DL utilizes unstructured input data, and the bulk of output generation occurs within the hidden layers. It thus becomes difficult to determine which specific feature or calculation of the input data contributed to the resultant output.[40,137]

Legal liability and ethics

The efficacy of the algorithms depends on large data and certain data may infringe on patients' privacy. Therefore, it is important to create standard ethical guidelines wherein artificial intelligence can be applied and where they are mandatory. Also, in the case of an adverse event, accountability is still a grey area that has to be addressed.[4,137,138]

Bias

Algorithms may also inherit the bias of the programmer or the self-learning algorithms may learn to be biased due to lack of diversity in the training material. As most machine learning programs are based on patient data which are collected from fair skinned populations, they may underperform on images of lesions in the skin of colour.[4,13,139]

Job threat

There is a huge debate among experts whether or not artificial intelligence will result in large scale job losses. Some believe that Artificial Intelligence is set to take over 47% of the U.S. employment market within 20 years across all sections.[140,141] Since medical imaging is an important field associated with artificial intelligence, some experts fear a job threat for these sub-specialities, while others believe that there is no immediate threat of job loss, but working with artificial intelligence systems will enhance diagnostic efficacy and benefit patient care.[131,142,143]

Limitations of the article

The article focuses on a basic understanding of artificial intelligence in healthcare and its applications in dermatology and is limited by the lack of in-depth computer knowledge of the authors. Furthermore, the applications and implications of artificial intelligence in healthcare are vast and ever-expanding. Therefore, these cannot be entirely covered in such a brief review.

Conclusion

Any new technology has its inherent advantages and disadvantages. The success of such technology in dermatology will depend on the benefits it provides to the vast majority of the general population and also to the treating doctor. Though artificial intelligence technology is not intended to replace medical professionals, their role is going to undergo change in the era of artificial intelligence. The limitations of applications of artificial intelligence in dermatology are very stark, but considering the rapid increase in efficiency of artificial intelligence models on one hand, and the ever demanding workload of doctors, the integration of artificial intelligence into healthcare may become the essential feature of medical care in the future. Medical personnel will then be able to give more focus on human emotional components like care and compassion with renewed vigour, which are important aspects of the doctor-patient relationship in medical care.

Acknowledgement

Authors would like to acknowledge the help of Mr Arvind Shenoy, principal consultant, Infosys for the technical inputs.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

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