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**Review Article**

# Impact of artificial intelligence on healthcare

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## ABSTRACT

Artificial intelligence (AI) is revolutionizing various medical practices, making them more affordable, efficient, and faster. Its uses range from diagnosis, management, monitoring, and outcome forecasting to individualized care. AI technology in psychotherapy can help conditions such as dementia, autism spectrum disorder, and schizophrenia, and due to its image processing, segmentation, and reconstruction capabilities, AI has found applications in a wide range of fields, including the diagnosis of cancer, the treatment of skin lesions, the prediction of metastasis of malignancies, the staging of lung nodules, the identification of COVID-19, and the classification of thyroid tissue. In addition to histopathology images, imaging techniques such as CT, MRI, mammography, fundus imaging, and even photographs can be used to diagnose patients. In this study, we tried to address the current status and future scope of AI to bring substantial upliftment to health care. It is anticipated that human intelligence and AI will coexist in the field of medicine in the future. Modern smart devices collect a huge amount of data that can be used for disease prevention, health promotion, monitoring, and diagnosis in medicine. AI will improve as long as we train them. With the development of sophisticated machinery, robotics, and virtual reality, the healthcare industry is likely to undergo revolutionary changes. AI has performance on par with that of human experts, with the added benefits of scalability and automation. Before becoming fully autonomous in nature, AI systems might need tight supervision due to their lack of training, limited knowledge, and limited flexibility in clinical settings.

**Keywords:** Artificial intelligence, Psychiatry, Cancer research, Cardiology, Dermatology, Ophthalmology, Surgery, Gastroenterology

## INTRODUCTION

Artificial intelligence (AI) is the ability of a machine to detect patterns and relationships in data and use this knowledge effectively for decision-making.[1] AI is currently a driving force in many facets of life and is expected to change medical practices like consultation, examination, and prescription and make them affordable and efficient. Replications of expert judgment and prediction of prognosis using support vector machines, decision trees, artificial neural networks, and machine learning are widely used. Because imaging in diagnosis is at the forefront of the use of AI, screening and prediction techniques are being developed especially for glaucoma, cataracts, age-related macular degeneration, and diabetic retinopathy.[2,3] Improvements in computing and deep learning architectures enabled us to improve cancer detection, classification, drug discovery, and patient treatment outcome predictions.[1] Beyond histopathology pictures, other imaging like CT, MRI, mammography, fundus imaging, and even photographs can be used for diagnosis and prediction of prognosis.[1] Studies have shown that radiology, ophthalmology, cardiology, orthopedics, and pathology AI promise in facilitating diagnosis and management, population-based surveillance, personalized care, reducing the burden of cost and work load, and making predictions that can help policymakers make plans.[4-9] Everyone has the rights to access health services. It is imperative to address the core problems like cost and the inadequacy of professionals. AI could provide a system for triage-like care that could provide least resource-utilizing care to most people first and more intensive care to patients that need it the most.[10] Machines are devoid of distraction, stress, and fatigue, are not susceptible to the individual inclinations of human therapists, and thus may have better results in treating patients.[11] Modern smartphones and smart gadgets capture a vast dataset that can be used for medical diagnosis, monitoring, follow-up, health promotion, and disease prevention. This article aims to provide an overview of the role of AI in relation to medical science, its current status, and its future prospects (Figure 1).

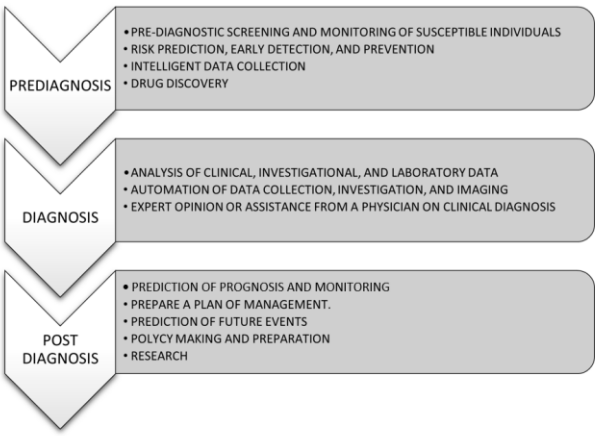


**Figure 1: An overview of artificial intelligence in the medical field.**

## LITERATURE RESEARCH

An extensive search on PubMed, Google Scholar, and other search engines was made by using keywords such as AI, psychotic disorder, cardiology, oncology, dermatology, diagnosis, and future. The relevant references were selected. In this study, we tried to address the current status and future of AI, which are discussed under different pre-defined medical specialties. Our study also tries to understand the scope of AI to bring substantial upliftment to health care.

## AI IN PSYCHIATRY

Clinical data on mental health is more subjective and qualitative. But still, mental health has a lot to gain from artificial intelligence.[11] Machine learning algorithms have successfully discriminated healthy patients from patients with psychotic disorders with an accuracy >70% and also conduct pre-diagnostic screening and work out risk models to determine an individual's possibility of developing mental illness.[12,13] EEG-based deep learning methods can identify depressive patients with an accuracy of more than 90%.[14] Psychotherapeutic devices like Tess and other chatbots that work with an interactive screen.[15] The Woebot helps patients identify their emotions, reduce anxiety, and reduce depressive symptoms.[16] Avatar therapy successfully improves medication adherence in schizophrenia, especially in treatment-resistant schizophrenia, and improves hallucinations, depressive symptoms, and overall quality of life.[17,18] Socially assistive robotics was designed to help children with autism spectrum disorder develop social skills, and their spontaneous language has improved during therapy sessions. Children seem to perform better with their robot partners compared to human therapists.[19] Companion bots are used to help patients with dementia and elderly or depressed patients and are helpful in reducing stress, agitation, and loneliness and improving mood and social connections.[20] Text-based psychoeducational conversations lead to higher program adherence compared to verbal presentations and reductions in substance use.[21,22]

## AI IN CANCER RESEARCH

The cancer data pools like Genome Atlas contain data including genomics, proteomics, histology, and radiology images, which helped in machine learning. On differentiating cancer and healthy cells using H and E-stained tissue with high prediction accuracy, a similar photographic and dermoscopic image of skin lesions model performed better than dermatologists.[23-25] In predicting occult peritoneal metastasis in gastric malignancies, DNNs have an improved AUC (0.92-0.94) when compared to using clinical and pathological characteristics.[26] MRI-based prostate cancer differentiation reported an AUC of 0.84.[27] Cancer risk scores from the mammograms show high accuracy in biopsy-confirmed cases.[28] Researchers showed increased absolute specificity and sensitivity of mammograms for cancer detection in comparison to an average radiograph. In order to predict the grade from the MRI scans of patients with liver cancer, Zhou et al constructed a deep learning strategy and reported an AUC of 0.83.[29] Prediction of drug properties and toxicity has been achieved using non-neural network-based approaches.[30] AI has been utilized to classify thyroid tissue by ultrasound imaging, detect COVID-19 from chest X-rays, and stage lung nodules from computed tomography (CT) images.[31-33] Convolutional neural networks have been used for automated detection of liver tumors on CT scans, and they have shown both high accuracy and precision of 93% and 67%, respectively.[34]

## AI IN CARDIOLOGY

Cardiac magnetic resonance is a recent development for AF, but quantitative data collection is a tedious process that is time-consuming, labor-intensive, and error-prone.[35] DL techniques are particularly well suited for segmentation, reconstruction, and image processing. It reduced processing time and improved accuracy.[36] ECG signal data similar to that from wearable smart devices is used to achieve an area under the ROC of 0.91 to identify these rhythms, and it outperformed cardiologists.[37,38] The Apple study evaluated the ability of an irregular pulse notification algorithm to identify atrial fibrillation, and a total of 34% of cases were clinically confirmed with a positive predictive value of 0.84.[38] Rogers et al analyzed 5796 intracardiac electrophysiological signals from 42 subjects with LVEF ≤ 40% and selected the most relevant input features using LR and avoiding coliniarities.[39] Predicting the long-term efficacy of rhythm control strategies is a critical step in the clinical decision-making process for patients with AF. In the AADGEN study, the potential of different ML algorithms to monitor the initiation of Dofetilide was demonstrated and predicted dosing decisions with 96.1% accuracy.[40] Radiofrequency ablation can be evaluated using computational simulation AF with an average sensitivity and specificity of 82% and 89%, respectively, and an AUC of 0.82 to predict the recurrence risk of AF.[41]

## AI IN OPHTHALMOLOGY

AI systems performance is comparable to that of human experts in diabetic retinopathy, glaucoma, age-related macular degeneration, cataracts, refractive error, retinopathy of prematurity, retinal detachment, choroidal disease, and ocular tumors.[42-48] In April 2018, the FDA approved the first AI-assisted DR detection device, IDx-DR.[49] For higher predictive performance, retinal images can be used.[50] AlexNet and VGG achieved 96.8% sensitivity, 87% specificity, and 98% area under the curve.[51] Tinget et al reported clinically acceptable diagnostic performance with an AUC of 93.6%, sensitivity of 90.5%, and specificity of 91.6%. Investigators from Aalto University trained a DL that could accurately separate DR and macular edema.[52] Li et al optimized the Inception-v4 to detect DR and DMO and achieved an AUC, sensitivity, and specificity of 99.2%, 92.5%, and 96.1%.[53] Ryu et al proposed a convolutional neural network (CNN) model for diagnosing DR based on optical coherence tomography angiography (OCTA) images, achieving 91-98% accuracy, 86-97% sensitivity, and 94-99% specificity.[54] A portable fundus photography device, which consists of a detector lens, smartphone, and fixed holder, allows users to take fundus photographs, which are then transmitted to a server for diagnostic analysis with an accuracy rate of 85%, which is comparable with that of ophthalmologists. The best DL model achieved an AUC of 0.91 in distinguishing GON eyes from healthy eyes, 0.97 in identifying GON eyes with moderate-to-severe functional loss, and 0.89 in identifying GON eyes with mild functional loss.[55] Yoon et al used convolutional neural networks developed for the diagnosis of CSC.[56]

## AI IN DERMATOLOGY

Computer-aided diagnosis of pigmented skin lesions, e.g., DANAOS and MoleAnalyser expert systems, are now available.[57] Smartphone-based apps like SkinVision and DermaAId are available for screening skin cancers, tracking changes in moles on the skin, and identifying basic skin lesions.[58] SkinVision scored 80% sensitivity and 78% specificity in detecting premalignant conditions.[59] With psoriasis treatment using biological agents, outcomes can be predicted, reducing the assessment gap.[60] Automated diagnosis of seborrheic dermatitis, atopic dermatitis, and pityriasis rubra pilaris has been studied using various clinical and histopathological features.[61,62] A study by Min et al. showed that with manual counting performed by an expert dermatologist, the sensitivity and positive predictive value of the lesion-counting program were greater than 70% for papules, nodules, pustules, and whitehead comedones.[63] Monitoring of autoimmune disorders like SLE, systemic sclerosis, and vitiligo has been developed.[64] Analysis of chronic wounds and providing an objective and quantitative assessment of healing rate during treatment are available, along with prediction of pressure injuries.[65-67] An automated skin biopsy system, a robot-assisted automatic laser hair removal system , and a robotic system for hair restoration have been developed.[68] Clinical and dermoscopic images using neural networks trained from images directly, using only pixels and disease labels as inputs, showed performance on par with that of dermatologists on biopsy-proven clinical images to differentiate between benign pigmentary skin lesions and melanoma.[69]

## AI IN SURGERY

All of the aspects of AI provide the basis for all the autonomous actions in surgeries.[70] Collective data on applications of AI in different spinal surgeries has been summarized by Chang et al.[71] The development of automation in surgeries has led to an increased use of AI. The surgeries can become completely AI-based and autonomous over time, from partial roles like image guidance to operations where no direct human involvement is required.[72] The Da Vinci Surgical System is one of the most well-known robotic-assisted surgery systems. The surgical system allows the doctors to perform surgery from a remote booth equipped with technology to control the arms of the robot.[73] This is a minimally invasive method and is usually trusted by most physicians due to its accuracy. Internet or mobile platforms, which are controlled by AI and can be used to provide surgical expertise remotely, even in spacecraft in space or in places with environmental disasters or war.[74] Even if AI doesn't seem to be directly involved in surgery due to individual variables in human anatomy and the need for spontaneous decision-making, surely AI is developing towards that goal.

## AI IN INTESTINAL DISEASES

ANNs trained on VCE images can identify non-obstructive stenosis and detect small bowel ulcerations with an accuracy of about 95%.[75] Barash et al developed an AI-ulcer detection system.[76] MES model with outstanding AuROC, sensitivity, and specificity of 0.970, 0.83, and 0.96, employing more than 16,000 pictures from roughly 3000 UC patients.[77] In a different study by Syed and coworkers, a convolutional neural network was capable of analyzing sets of duodenal biopsies and 93.4% accurately differentiating between celiac disease, environmental enteropathy, and normal tissue.[78] A neural network segmentation of the lumen, bowel wall, and backdrop agreed with manually segmented bowel pictures in research using 23 MREs in young CD patients in 75%, 81%, and 97% of the instances, respectively.[79] With an accuracy of 0.754 vs. 0.590. Human has more chance of error in interpretation of images may be limited the knowledge, experience, exposure, fatigue, distractions, large amount of image data, and the physical quality of the image itself.[80]

## ATTITUDE AND PERCEPTION OF HEALTH PROFESSIONALS TOWARDS AI

The future of medicine is expected to involve a mix of human intelligence and AI.[81] So for the changing healthcare system, we have to train our health care providers frequently to use, enrich, and develop AI, which we should validate with adequate research on the field. AI is posing threats to health workers jobs.[82] A survey of 791 psychiatrists revealed that 83% believed AI would not provide empathetic care and 3.8% felt it would make their jobs obsolete.[83] 89% of radiologists did not fear job loss, and similarly, pathologists showed openness to AI, with only 17.6% concerned about future job security.[84] Neurosurgeons reported using AI to predict outcomes.[85] AI can reduce the burden of work for health professionals, so physicians can focus on the interpersonal relationship with patients. In recent years researches published on topics connecting AI and medical fields are in increasing exponentially (Figure 2).

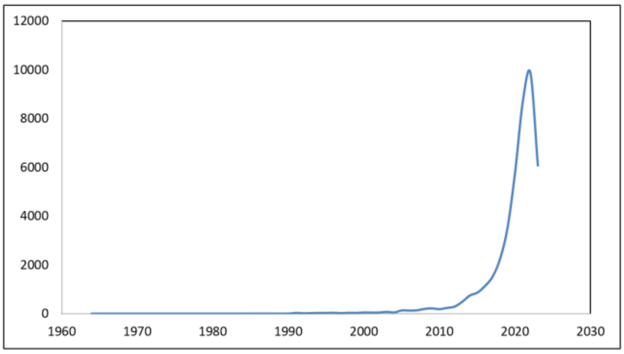


**Figure 2: Number of articles published in PubMed with key words AI and medical science from 1964 to 2023.**

## CONCLUSION

AI models are only as good as the data they are trained on to build trust in these systems, apart from research and development, transparency and reproducibility are necessary. Prevention rather than treatment may be the most compelling application of AI in healthcare. Knowing the prognosis of a disease can bring necessary changes to the action plan, and health care can be individualized, which reduces the adverse effects and brings the best of the existing management and meaningful changes to existing protocols. In the future, with the development of complex machinery, robotics, and virtual reality, we can expect a revolutionary change in health care. Advances in technology have enabled various means of collecting data at the individual patient level, which enables monitoring patients remotely and alerting clinicians if needed. AI systems have made significant contributions to health, with performance comparable to that of human experts and the added advantages of scalability and automation. However, AI systems may need supervision for years to gain confidence due to their inexperience, limited knowledge, and inflexibility in situations and clinical contexts. The future of medicine is expected to involve a mix of human intelligence and AI. We should prepare our existing health system to accept and develop AI -based medical care.

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