



Journal of Experimental Biology and Agricultural Sciences

<http://www.jebas.org>

ISSN No. 2320 – 8694

Applications of Artificial Intelligence in Healthcare

Shagufta Quazi, Rudra Prasad Saha*, Manoj Kumar Singh*

Department of Biotechnology, School of Life Science & Biotechnology, Adamas University, Kolkata 700126, India

Received – September 03, 2021; Revision – December 17, 2021; Accepted – January 08, 2022

Available Online – February 28, 2022

DOI: [http://dx.doi.org/10.18006/2022.10\(1\).211.226](http://dx.doi.org/10.18006/2022.10(1).211.226)

KEYWORDS

AI

Healthcare

COVID-19

Machine Learning

Artificial Neural Network

Medical diagnosis

ABSTRACT

Now in these days, artificial intelligence (AI) is playing a major role in healthcare. It has many applications in diagnosis, robotic surgeries, and research, powered by the growing availability of healthcare facts and brisk improvement of analytical techniques. AI is launched in such a way that it has similar knowledge as a human but is more efficient. A robot has the same expertise as a surgeon; even if it takes a longer time for surgery, its sutures, precision, and uniformity are far better than the surgeon, leading to fewer chances of failure. To make all these things possible, AI needs some sets of algorithms. In Artificial Intelligence, there are two key categories: machine learning (ML) and natural language processing (NLP), both of which are necessary to achieve practically any aim in healthcare. The goal of this study is to keep track of current advancements in science, understand technological availability, recognize the enormous power of AI in healthcare, and encourage scientists to use AI in their related fields of research. Discoveries and advancements will continue to push the AI frontier and expand the scope of its applications, with rapid developments expected in the future.

* Corresponding author

E-mail: manoj.k.singh@adamasuniversity.ac.in (Manoj Kumar Singh);
rudraprasad.saha@adamasuniversity.ac.in (Rudra Prasad Saha)

Peer review under responsibility of Journal of Experimental Biology and Agricultural Sciences.

Production and Hosting by Horizon Publisher India [HPI]
(<http://www.horizonpublisherindia.in/>).
All rights reserved.

All the articles published by [Journal of Experimental Biology and Agricultural Sciences](#) are licensed under a [Creative Commons Attribution-NonCommercial 4.0 International License](#) Based on a work at www.jebas.org.



1 Introduction

Artificial Intelligence (AI) is a technology that supports machines with similar intelligence as human beings, to perform some tasks given by a human, like facial recognition for identification of individuals and voice recognition with virtual assistants like Alexa and Siri. Driverless vehicles or self-driving cars are also assisting elderly or blind passengers. Google DeepMind has instructed machines to read retinal signals with the same precision as a skilled specialist. Babylon, the wellbeing application, claims its chatbot can breeze through General Practitioners tests (He et al. 2019).

AI in healthcare promises noble repayment to patients. To determine the best approach for the customization of medicine, researchers need to evaluate comprehensive patient data alongside broader aspects to track and recognize sick and relatively healthy people, contributing to a better understanding of biological indicators that can indicate a change in health (Ahmed et al. 2020). Various aspects of patient care and administrative procedures among suppliers, payers, and pharmaceutical corporations could be managed by AI. AI devices are already surpassing radiologists when it comes to diagnosing critical tumors and advising researchers on how to establish consortia for expensive clinical trials (Davenport and Kalakota 2019).

Machine learning can enhance clinical decision support (CDS) for clinicians and healthcare workers. This gives the means to increase revenue potential. Machine learning, a division of AI, categorizes

patterns, using algorithms and information to commit automated perceptivity to healthcare providers. AI uses advanced algorithms to ‘learn’ characters from a large section of healthcare data, followed by taking advantage of the obtained perspective to serve clinical practice (Jiang et al. 2017). Additionally, it can be equipped with the knowledge and self-correcting abilities to perk up its correctness based on feedback. An AI program supports doctors by supplying them with up-to-date health care knowledge from newspapers, journals, and professional procedures to alert them of appropriate treatment. AI uses tools to discover complex relationships that cannot be simplified to an equation. Neural networks, a part of AI, similarly interpret data to the human Central Nervous System (CNS) via an immense number of interconnected neurons. Such interpretation allows Machine learning (ML) structures to address difficult problem solving exactly as a clinician could, by deliberately evaluating facts to draw reasonable conclusions (Buch et al. 2018).

AI and robotics are already a part of our healthcare system. Rather than entirely replacing the work of physicians and other healthcare professionals, AI devices will support and enhance their jobs. Artificial intelligence can assist healthcare practitioners with a variety of jobs, such as administrative tasks, clinical documentation, patient outreach, and also in the areas like image analysis, medical device administration, and patient monitoring. Hence, we need to keep tabs on recent AI advancements (Ahmed et al. 2020). Figure 1 represents twelve major applications of AI in healthcare and these are (i) Medical Diagnosis, (ii) Robot-Assisted Surgery, (iii) Clinical Trial, (iv) Training, (v) Fraud Detection, (vi)

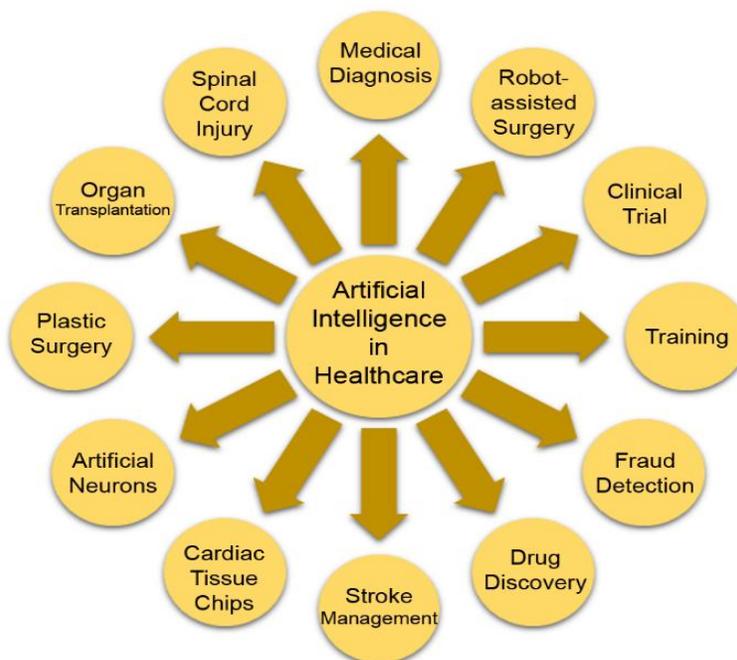


Figure 1 Twelve major applications of Artificial Intelligence in Healthcare.

Drug Discovery, (vii) Stroke management (viii) Cardiac Tissue Chips, (ix) Artificial Neurons, (x) Plastic surgery, (xi) Organ Transplantation and (xii) Spinal Cord Surgery. In this review article, we have discussed how Artificial Intelligence is being used in various healthcare and allied products or applications.

1.1 Artificial Neural Network and AI-Devices

The non-linear relationships between input and output variables are involved in artificial neural networks (ANN), which is comparable to how the human brain works (Park and Lek 2016). In 1958, the artificial neural network was introduced and became very popular due to the increase in capacity and complexity of data (Ravi et al. 2017). ANNs consist of an input layer, a hidden layer, and an output layer. Input data is obtained directly by the input layer by inserting a function into each node. The nodes in the hidden layer then receive a balanced linear combination as input from all the components in the input layer and use a non-linear transformation activation feature. The output layer does a similar function to the hidden layer. It receives signals from the hidden layer and generates an outcome with an activation function (Han et al. 2018).

AI devices involve two major categories – (a) Machine learning (ML), for analyzing organized facts such as genetics, electrophysiological, and imaging data. In therapeutic applications, ML methods evaluate a patient's attributes and infer the likelihood of disease outcomes. Precision medicine is the most prevalent application of conventional machine learning in healthcare, evaluating the therapy actions that are likely to be helpful in a patient based on the outcomes of prior patients (Lee et al. 2018). (b) Natural language processing (NLP) enhances and expands standardized medical data by extracting knowledge from unstructured data sources such as clinical notes or medical publications (Spasic and Nenadic 2020). The goal of NLP methods is to turn texts into structured computer-readable data that can be studied using ML approaches. Natural Language Processing primarily functions as human-computer interaction. The NLP systems can evaluate vast amounts of scientific data efficiently and help maintain inappropriate spam off the files. In healthcare, NLP helps to isolate complex data. The usage of Artificial Intelligence in NLP allows healthcare to collect critical data in real-time from trustworthy sources. The virtual healthcare assistants use models activated by medical terminology through interactions using NLP (Murff et al. 2011).

1.2 AI-Assisted Medical Diagnosis

AI is commonly used in medicine and can facilitate the advancement of therapy, taking care of chronically ill patients, recommend specific interventions for complicated diseases, and improve the quality of medical care. Furthermore, the improvement of various AI approaches has resulted in early

disease identification, diagnosis, and referral management (Shen et al. 2019). Tencent, a Chinese mobile services firm has launched two new AI-based medical imaging devices 'AI Medical Innovation System (AIMIS) Medical Image Cloud' and 'AIMIS Open Lab', which will help with medical data management and stimulate the development of medical AI applications. Patients can access their images created by CT scans, MRIs, and X-rays on the Tencent AIMIS Medical Image Cloud, which will allow comfortable and reliable sharing of patients' medical information. Tencent AIMIS Open Lab may create medical AI applications by sharing Tencent's medical AI abilities with external parties such as scientific research institutions, universities, and research and engineering innovation companies. Tencent's 'AIMIS Image Cloud' connects medical institutions at all levels in the Medical Treatment Combination via cloud-based Picture Archiving and Communication Systems (PACS), helping physicians to undergo examinations in primary medical centers and acquire professional diagnoses virtually. Physicians can use Tencent's real-time interactive multimedia facilities to conduct online consultations and concurrent collaborative image operations to communicate more effectively while dealing with complex cases (Hithaishi 2020). The team plays digital health platform's AI-powered augmented workflow solutions to help minimize the strain of fundamental repetitive chores and improve diagnostic precision while evaluating medical pictures. It allows users to quickly access solutions for operational, therapeutic, and strategic decision support while also assuring future-readiness through flexibility and scalability (Siemens Healthcare 2021). The AI-RAD Companion Chest CT is a computed tomography device assistant based on AI. Through AI-powered algorithms, the AI-RAD companion automates the post-processing of image datasets. Regular processes with repeated actions and high patient numbers can be automated to assist radiologists to focus on more relevant issues. This method can compute severity scores in about 10 seconds per case, compared to 30 minutes for hand comments. These findings can be utilized to quickly determine the severity of the pulmonary infection and track the course of irregularities in COVID-19 patients (Gouda and Yasin 2020). These advancements represent how AI has caught up with human intelligence, starting from the day it was founded and extending into the future. It is anticipated that AI may surpass human performance in specific activities in the future, which can become beneficial for humans (Hosny et al. 2018). AIRad companion helps in increasing the accuracy of diagnosis through AI-powered algorithms while rendering medical images thereby helping radiologists reduce workload and error rates.

1.3 Robot-Assisted Surgery

Robot-assisted surgical devices allow surgeons to perform different surgical procedures in a patient's body via incisions.

Compared to standard surgical approaches, this type of surgery can help to reduce pain, blood loss, scars, infection, and post-operative recovery time. While examining the surgical site in three dimensions, a computer and software program helps a surgeon efficiently operate surgical equipment connected to the robotic arms through small incisions (Lanfranco et al. 2004). A laparoscopic approach is a surgical process that includes making small incisions into the abdomen (less than one centimeter) to introduce short, thin tubes (trochars) through which long, slender equipment is inserted. These instruments are used by the surgeon to manipulate, cut, and suture tissue. Laparoscopic treatment is generally less painful for the patient, and recuperation is much faster. The growth of robotic technologies has revolutionized controlled access surgery by resolving some of the shortcomings of the laparoscopic technique (Garry 2006). Robotic systems do not substitute the surgeon or conduct duties individually, instead, these systems have the capabilities that boost flexibility and ergonomic performance. They are operated by the surgeon, which is why they are referred to as 'master-slave systems'. They include: (a) the master console involving the user port that allows the operator to see a 3D representation of the operating area, manipulators for monitoring instruments, and a monitor panel for adjusting camera position and focus; and (b) the slave unit is mounted on the side of the patient where the instruments and the camera are connected and operated with the robotic arms (Singh et al. 2018).

1.4 Virtual Nursing Assistant

Virtual nursing assistants support patients in hospitals for an illness or surgery. Sally and Walt, the virtual personal healthcare assistants from iCare Navigator, connect with empathy to enable patients to take an active role in their health and rehabilitation. They can be accessed through a tablet or hospital TV set (Sadhika 2019). Studies have shown that if the patient's healthcare assistant is not a human, they do not feel criticized for asking questions. Sally and Walt have as much patience as it takes to ensure that patients understand their recommended instructions and discharge details to take proper care of them upon discharge. As a result, patients participate honestly and fearlessly, and they are praised for their dedication (Barrett et al. 2019). TeleHealth services, which created iCare Navigator, claims that it leverages electronic health records from a patient and utilizes machine learning to create a customized connection. iCare Navigator is developed on cloud-based technologies and a sophisticated artificial intelligence system that constantly tracks and examines the patient's response, attitude, receptivity, sensitivity, and overall commitment to providing fully customized patient experiences (Raleigh 2017).

1.5 Clinical Trial Assistance

Because of regulatory uncertainty, risk avoidance, and apprehension about rapidly emerging technologies (machine

learning and wireless health monitoring tools and sensors) clinical drugs have largely stagnated during the past 30 years. Another significant obstacle in the drug research phase is the recording of the outcomes of most modern clinical trials with normal patient effects that do not readily turn into individualized medical decisions at the standard point of care (Shah et al. 2019).

The goal of artificial intelligence is to change clinical decision-making procedures. Since it can leverage the large quantities of genomic, biomarker, and phenotype data collected throughout the healthcare system, including patient records and guidance systems, to enhance the protection and quality of healthcare outcomes (Magrabi et al. 2018).

Research centers, biotechnology firms, and development companies examined the use of AI and ML, generally in three major areas are (i) machine-based learning to determine the therapeutic effects of molecular products and drug discovery targets; (ii) utilizing neural networks and optimization strategies on diagnostic images (e.g., retinal scans, autopsy samples and body surfaces, bones, and vital organs) to allow for quicker detection and monitoring of progression of diseases and dynamic algorithms for a numerical increase of current therapeutic and diagnostic data sets; (iii) working with deep-learning methods on integrative information sources such as the combination of genetic and therapeutic data to identify new prediction method (Shah et al. 2019).

1.6 Training

Improving ML models requires well-structured training data regarding a fairly stable process over time. Divergence from this results in over-fitting where AI puts undue emphasis on false associations in records (Buch et al. 2018). Along with reforming the traditional way doctors operate, two of the most awaited problems are the black box problem and liability issues. Mount Sinai Hospital's Black Box engineers have developed a deep learning algorithm that was tested on 700,000 patient results. This algorithm could predict with high precision, the onset of a condition such as schizophrenia. This is much more remarkable given that even for professionals, this disease is hard to diagnose. The main issue with this approach is that there is no way to tell how the machine generates this prediction or what variables are considered. This concept is called the Black Box phenomenon (Paranjape et al. 2019).

Recent advances in computing capacity and data collection have culminated in a new area requiring digital stored information processing to gain new knowledge. Whereas clinical trials and costly prospective research have mostly found the standard treatment and data science's inclusion into the medical sector, which has the potential to significantly increase the rate at which

information is generated and the range of issues that can be addressed (Celi et al. 2016). Through the accelerated digitalization of health care, electronic health records (EHRs) promote innovative ways of collecting and accessing useful knowledge, which can be used for better decision-making. Doctors have to use their knowledge and skills to handle evidence, monitor AI software and use AI apps to make educated decisions (Paranjape et al. 2019).

1.7 Fraud Detection

Healthcare fraud is classified into three categories: (a) People (e.g., doctors, dentists) or provider institutions (e.g., hospitals) that commit healthcare fraud; (b) often companies engage in unethical practices targeting other service providers (e.g., laboratory services) or suppliers of medication and medical products by collecting fees on payout; (c) fraudulent activities related to caregivers can often include certain classes, e.g., patients or insurers. Initiatives to counter fraud and abuse in the healthcare sector can be categorized into the 3 types of initiatives that aim to stop, track, and respond to fraud and abuse (Joudaki et al. 2015).

A few auditors manage thousands of healthcare reports through conventional techniques to prevent fraud. The problem is that they do not have much time for each claim; they focus on specific aspects of the claim instead of the overall picture of the provider's activity. Hence, this approach takes time and is inefficient. Electronic medical records and increased use of computer-based applications have provided new ways to help diagnose fraud and misconduct. Technologies in ML and AI technologies are bringing fraud detection solutions that are automatically generated to the forefront (Bauder and Khoshgoftaar 2018). The core aspect of 'knowledge discovery from databases (KDD) is data mining, which includes the application of techniques that analyze the data, establish specific models and find previously unknown trends within the data. Data mining can help third-party payers, like health insurance organizations, derive valuable information from numerous cases and classify a limited subset of cases or applicants for further review and inspection of fraud and abuse (Joudaki et al. 2015).

The data mining tools used in the analysis of healthcare fraud were classified into two basic strategies – Supervised and Unsupervised methods. Unsupervised techniques are deployed, where no previous collections of valid and fraudulent findings exist. Unsupervised techniques usually measure the characteristics of one claim in comparison to other claims to decide whether they relate to one another or vary from each other. This also explicit the order and correlation rules between records identify anomaly records or related records in classes. Supervised techniques involve a dataset of identified fraud / genuine cases to create a model that will allocate the observation to either fraudulent or non-fraudulent based on rating. They require trust in identifying the documents

accurately. They help identify previously identified trends of fraud and misconduct. Therefore, the models will be revised periodically to represent innovations in dishonest activities and regulatory and settings adjustments (Bolton and Hand 2002).

1.8 Drug Discovery and Other Research

Deep neural networks (DNN) and recurrent neural networks (RNN) are two types of artificial neural networks that help AI develop faster. Artificial Intelligence technologies generated broad attention in pharmaceutical science, as deep learning algorithms showed superior results in the prediction of properties. The application of AI for early drug development has been greatly expanded, e.g., the *de novo* development of chemical compounds and peptides and formulation preparation (Hessler and Baringhaus 2018).

Deep Neural Network (DNN) is composed of several stages of non-linear functions, such as several hidden layers of neural networks. Deep learning approaches focus on understanding feature hierarchies in which features are built at higher levels of hierarchy using features at lower levels. In deeper structures, even better outcomes may be obtained when each layer is retrained with an unsupervised learning program (Gudivada et al. 2016). The Tox21 challenge, which took place in 2014, was the scientific community's "largest" endeavor to test computational algorithms for predicting toxicity. Using specially devised assays, 12,000 pharmaceuticals and chemicals from the environment were tested for 12 different hazardous effects. As part of the "Tox21 Data Challenge" (Tox21 challenge), the efficiency of computational algorithms for preliminary assessment of toxicity had been analyzed to determine their potential to reduce in vitro research and animal testing (Mayr et al. 2016). DNNs demonstrate equal or better output than other machine learning strategies, for example, for various properties ranging from predicting biological behavior, ADMET (Absorption, Distribution, Metabolism, Excretion, and Toxicity) characteristics to physicochemical parameters. The lack or presence of identified toxicophores had been implemented as a descriptor in addition to physicochemical descriptors and extended connectivity fingerprinting (ECFP). The DNN can isolate molecular characteristics that are allegedly associated with recognized toxicophoric components. These networks tend to know more complex concepts in the different hidden layers (Hessler and Baringhaus 2018).

Researchers at TCS Innovation Labs in Hyderabad, India, are harnessing artificial intelligence (AI) to acquire novel compounds which could attack specific portions of the novel coronavirus (SARS-CoV-2). The researchers began by training the generative deep neural network model on a sample of approximately 1.6 million drug-like small compounds from the ChEMBL database and then they retrained the network with protease inhibitor

molecules and finally, they examined how strongly they bonded with chymotrypsin-like protease, which is the target protein (Lee et al. 2014). They found 31 candidate molecules out of which two molecules were extremely similar to aurantiamide, an antiviral compound that exists naturally (Desikan 2020).

Since AI is increasingly changing the medical world, specialization on the subject has also significantly increased in recent years; emphasizing the need for a systematic analysis of study findings and developments of Artificial Intelligence in Medicine (AIM). IBM Watson-Oncology has occupied medicine for treating people with cancer with comparable or greater effectiveness than human specialists. Microsoft's Hanover Project at Oregon has examined scientific evidence to customize the care choice for a person's cancer. The National Health Service of the United Kingdom (NHS) used Google's DeepMind tool to identify health threats by examining smartphone application data and diagnostic photos obtained from NHS patients (Bali et al. 2019).

Introducing such high-throughput methods to biology and disease provides the pharmaceutical industry with both obstacles and prospects to discover possible therapeutic strategies. Recent improvements have contributed to an increase in participation in utilizing machine learning (ML) technologies in the pharmaceutical industry. The eminent drug development strategy aims to produce medications (small molecules, antibodies or peptides or newer techniques such as short RNAs or cell therapies) to improve the disease condition by amplifying the function of a molecular target (Liu et al. 2019). Despite a recent revival in phenotypic tests, launching a product development plan demands - the target modulation which will lead to modulation of the disease status. Based on the available data, target recognition and prioritizing refers to the process of selecting the target. The subsequent phase requires validating the function of an identified target for disease utilizing physiologically relevant *ex vivo* and *in vivo* approaches (target validation). As an example machine learning can be used to evaluate broad datasets with knowledge of a putative target's function to form assumptions about possible cause and effect based on known genuine targets. To identify morbidity-related genes that are also druggable, a tree-based meta-classifier that specializes in the topological network of transcriptional, protein-protein, metabolic interactions, along with tissue expression and subcellular localization, has been developed (Costa et al. 2010). Jeon et al. (2014) developed a support vector machine (SVM) classifier for breast, pancreatic and ovarian cancers using different sets of genomic data to identify proteins as drug targets or non-drug targets.

1.9 AI Application for Stroke Management

Stroke is a widespread and consistently-occurring disease due to which over 140,000 people dies in the US. Hence, studies on

stroke prevention and care are of considerable significance. AI methods have been used in an increasing number of stroke-related trials in recent years, especially in the three key fields of stroke care – early disease prediction, diagnosis, and treatment (Astrakas et al. 2012).

Scientists from the UK and USA claim the AI system will forecast heart attacks and strokes accurately. Kristopher Knott, a British Heart Foundation research associate, and his colleagues performed the largest yet cardiovascular magnetic resonance imaging (CMR) and AI study. CMR is a procedure that tests blood circulation to the heart by measuring how much of a single cardiac muscle contrast product takes up; the greater the blood flow, the less probable obstructions may exist in the cardiac arteries. Interpreting the reports is laborious and time-consuming; it is often more qualitative than quantitative. To build a more insightful strategy, they created an AI system that reviewed images and learned to identify symptoms of impeded blood flow. Researchers discovered that the AI model performed well when the device was tested on scans of over 1,000 patients who wanted CMR because they were either at risk of developing cardiac failure or had already been diagnosed, in determining which individuals were more likely to suffer from a heart attack or stroke.

Machine learning programs may be able to distinguish an ischemic stroke from a hemorrhagic or any other type of stroke, reducing the risk of ignoring cases such as meningitis, coma, encephalitis, acute demyelination, abscess, and subdural hematoma. In 2018 the FDA allowed an AI algorithm to be used in triage support for clinical decision-making, called Viz. AI Contact can interpret CT scans to identify symptoms of stroke in visual videos, allowing a tentative diagnosis. The device can alert a neurovascular specialist via smartphone or laptop upon detecting a stroke case, allowing the specialist to focus on the most critical cases while the radiologist can study less urgent photos. This AI-enabled system management will provide timely treatment for patients who might not take the regular examination protocol without endangering their health or even their life (Liebeskind 2018).

With scientifically validated, data-driven technologies, Rapid AI allows physicians to make quicker, more precise diagnosis and recovery decisions for stroke patients. Clinicians globally are enhancing patient safety and outcomes every day with a proven, respected network built by stroke experts and are used in more than 1300 hospitals worldwide. NeuroView, a medical technology startup, also aims to automate the prediction of stroke defects in the area. A common goal shared by many of today's more well-known professional organizations, healthcare infrastructure firms, and even hospitals that are increasingly partnering together to solve common challenges, developing their own departmental and consumer-friendly AI practices. Nonetheless, researchers'

achievements during the last decade should not be underestimated. It casts a largely positive forecast for what healthcare practitioners, patients, and businesses assume to see in the future of AI in healthcare (Tran et al. 2019).

1.10 Cardiac Tissue Chips (CTCs)

The heart has usually been one of the most challenging organs to imitate in artificial organ and organ-on-a-chip technology studies. Research teams at Birmingham's University of Alabama have created biomimetic cardiac tissue chips (CTC)–cell culture systems, which can reliably simulate complicated blood flow pressures involved with shifts in the pressure volume of the heart. Researchers hope that by detecting harmful medications before they reach clinical trials, these tissue chips will speed up research into medicines and medical devices and enhance health. The cardiac tissue chip (CTC) prototype consists of entrapped cardiac cells which could be grown in three-dimensional (3-D) fibres and exposed to hemodynamic loading for simulating shifts in the pressure-volume relationship of the left ventricle. Several parameters related to cardiac function, heart rate, peak-systolic pressure, end-diastolic pressure-volume, as well as systolic and diastolic length proportion, can be monitored accurately, causing cardiac cell cultures under developmental, normal, and pathological conditions (Rogers et al. 2019).

The CTC can replicate the pressures involved with an overload of both pressure and volume (Kong et al. 2019). The experiments with cardiomyogenic cell line-derived H9c2 cells, showed that under pathological hemodynamic pressure, the culture inside the CTC generates changes in morphology and gene expression that are comparable to those reported with hypertrophic and dilated cardiomyopathy (Rogers et al. 2019). The cells inside the CTC undergo accelerated cardiac hypertrophy remodeling and fibrosis under pressure overload, whereas the cells susceptible to prolonged volume overload, encounter major adjustments in the cellular size due to thinning and elongation of the designed tissue. According to these findings, CTC is capable of being utilized to build significant designs in which hemodynamic loading and unloading could be replicated correctly to simulate heart illnesses. However, platforms like Organ-on-chip and CTC produces a huge amount of data (related to shape, size, structure, interaction, and composition) that needs to be analyzed. This can be very complex to analyze using traditional computational methods. In such cases, AI and ML can do the job more efficiently. Since CTCs can offer a clearer picture of the course of illness and medication toxicity, scientists expect to find more about these problems sooner (Fermini et al. 2016). Now the researchers are focusing on combining the CTCs with chips describing other organs and tissue coupled with AI. Since these broader tissue chips may replicate human physiology more precisely for science and drug testing (Mencattini et al. 2019; Rogers et al. 2019).

1.11 Artificial Neurons

Alzheimer's disease is a neurodegenerative condition that entails gradual destruction of neurons with emotional, behavioral, and motor implications, losing the afflicted person's spirit, and is traumatic not just for patients but also for their families (Oboudiyat et al. 2013). However, experts are pursuing potential approaches in nanotechnology that may greatly improve the wellbeing of sufferers. The World Health Organization (WHO) designated dementia as a priority condition in 2008 in a part of its campaign called the mental health gap action program (mhGAP). In 2010, the global dementia population was estimated to be around 35.6 million individuals, and it is anticipated to nearly double every 20 years, surpassing 65.7 million in 2030 and 115.4 million in 2050. Every year, over 7.7 million new incidences of dementia are discovered around the world, or once every four seconds (Tanna 2013). A recent study showed an unusual immunoglobulin (Ig) accumulation in the brain parenchyma of AD tissues, along with the distinct neurons that demonstrated such vascular-derived antibodies to be degenerative and apoptotic. Later studies found that these Ig-positive neurons possessed classical complementary elements, C1q and C5b-9, that were more often spatially aligned to Ig-negative neurons with reactive microglia. As a result, the mere existence of anti-neuronal autoantibodies in previously rejected serum can have no pathogenic implications, given no Blood-Brain Barrier (BBB) defect is prevalent that would allow the harmful effects of such autoantibodies to reach their targets (D'Andrea 2005).

A multinational research team has created artificial neurons that could be inserted into the brain to repair damage sustained by neurodegenerative diseases including Alzheimer's disease. The chips developed by the team are silicon-based miniature machines, built on biological ion channels that simulate the function of actual neurons (Abu-Hassan et al. 2019). The aim is to make such chips to reverse the harm done by autoimmune reactions, repairing the nervous circuit's key functions. In reality, they reflect linking bridges that disrupt a neural canal. The silicon chips, which functions like biological neurons, need just 140 nanoWatts of electricity, which is one-billionth of the power supplied by the microprocessors used to create artificial neurons, rendering the silicon chips ideal for use as medical implants or in other bioelectronic devices. The next target for scientists is to investigate the least intrusive and non-surgical approaches for administering deep brain stimulation to promote access to this care for people with Alzheimer's disease, making it possible to endorse the application of artificial intelligence (University of Bath, 2019).

1.12 Plastic Surgery

Cosmetic surgeons are creative and are always on the frontlines of modern scientific developments. Starting from the development of

skin grafts through transplantation, the profession of plastic and reconstructive surgery has ever advanced immensely, due to our ability to integrate innovations quickly and effectively. Snapchat's AI technology has indeed begun to affect the world of plastic surgery. Using AI processing technology to discern facial expressions, Snapchat puts filters on people's faces to dramatically change its portrayal (Ameer et al. 2013). Snapchat is a smartphone app available for both Android and iOS devices, built for communication purposes. Evan Spiegel, one of the company's co-founders, is in charge of designing this mobile application. The app's basic feature is that any picture, video, or message you share is viewable to the receiver for a short time before being unavailable (Velten et al. 2007). People seeking plastic surgery to look like their filtered selfies have become known as "Snapchat dysmorphia" as a result of AI advancements (Ameer et al. 2013).

Data-driven surgical modelling applications that can define empirical asymmetries in pre-operative photographs can offer feedback on the finest tactic towards attaining a favored cosmetic result. Picture modifying software that promotes such abilities raise unrealistic expectations and are incapable of compensating for the constraints of cosmetic operation reality. In terms of surgical screening, AI systems have now been created to categorize patients upon whom certain therapies are too dangerous and to exclude them from the pre-operative environment. Both depend on unintuitive risk factors concealed in previous surgery mishaps data, and both have significant health and economic contributions (Kim et al. 2019). Through the creation of plastic surgery monitoring operations and results (TOPS), the General Register of Autologous Fat Transfer (GRAFT), the Regional Surgical Quality Improvement Plan (NSQIP), Cosmet Assure, and ASAPS CLOUD databases, the cosmetic surgery group has recently shown their ability to integrate massive data. This reflects the willingness that requires processing data from plastic surgery systematically, as well as a forthrightness to artificial intelligence upheaval. Finally, the American Society for Cosmetic Plastic Surgery (ASAPS) initiated the Aesthetic Neural Network (ANN), which is a preliminary method for refining treatments and modelling economics (Chandawarkar et al. 2020).

Health decisions about wound treatment are based on an assessment of wound features, such as dimensions and location, as well as patient-related parameters, such as skin texture, genetic details, and living environment. The seriousness of certain casualties meets the human eye clearly which signifies the emergence of artificial intelligence to render assessment easy and more effective (Yeong et al. 2005). By matching wound pictures against explicit measures of the patient's body, a thinking machine may estimate the magnitude of infected/damaged tissues (Kim et al. 2019).

In addition to other smart imaging techniques, angiograms from computed tomography (CT) based on AI-assisted analysis may help surgeons develop surgical flaps. The new equipment allows doctors to view three-dimensional (3D) photographs as strips, thereby saving lapse of time and improving reliability in their ability to see the human body's inner framework. While radiologists must divide CT angiography images into 64 slices for precise diagnosis, a computer can evaluate all slices of a 3D imaging specimen at the same time. While conducting a separate flap procedure, cosmetic surgeons very often choose the same configuration of flaps. Nevertheless, AI's fast, integrative thought capabilities may assist surgeons in developing a strategy that can be customized to each particular patient.

Cutaneous wound infections may extend into osteocytes, causing gradual swelling and osteomyelitis. During the diagnosis phase, there are many problems raised for osteomyelitis because of the time it takes to display some sort of osseous lesion for simple radiographic images. AI-assisted radiographic image assessment may reduce the amount of time required for osteomyelitis to become detected on a radiographic photograph. Radiologists, in a similar manner, have used temporal subtraction, a function of computer-assisted diagnosis, for strengthening the differences in intervals between two radiological images (Kim et al. 2019).

Amongst the most serious craniofacial deformities that cosmetic surgeons have come across is craniosynostosis (Johnson and Wilkie 2011). Both genetic and environmental factors contribute to the epidemiology of craniosynostosis. The chief drawback seems to be the lack of further evidence on the results of craniosynostosis cases. Researchers and surgeons are now capable of understanding both the genetic and environmental causes of this abnormality. Today, AI technologies are applied to combine the various pictures to support and enhance surgical preparation. This seems to be especially true in syndromic illnesses, where due to the pathophysiology of osteogenesis, recurring deformities may be more likely. Cosmetic surgeons can now employ artificial neural networks (ANNs) to anticipate postoperative difficulties following craniofacial surgery. Syndromic craniosynostosis may result in repeated cranial defects, and after corrective surgery, the bone may begin to develop abnormally. In many cases, AI and precision medicine may be used to boost surgical changes to maximize postoperative outcomes. Furthermore, Big Data picture processing can help configure cranial remodeling to better fit individual children (Kim et al. 2019).

1.13 Organ Transplantation

More than 100,000 organs are transplanted globally every day and yet more around the world are waiting for an organ transplant (Healio 2019). To tackle this challenge an AI-powered application

OrganSecure has been introduced, which seeks to connect organ donors with individuals who needs real-time organ transplantation. OrganSecure is now undergoing alpha testing and intends to overcome the two main problems in the organ donation ecosystem, i.e., having more people to become organ donors and providing the organs at the right time for those in need. The application starts by providing people with organ donation-related knowledge and allows them to sign up to become a patient, make them realize what organs they should donate depending on their medical records, and help them understand local regulations (Pradhan et al. 2020). Organ recipients would benefit from an AI-powered real-time rating on the donor list, and the timeframe required to move to the top of the list. Patients and their relatives will now be able to prepare themselves properly for the procedure with facts about anticipated prices, nearby organ banks, and other important data. Given the various criteria regulating organ donation, such as blood group and form of antigen, the software uses Azure Machine Learning to determine an organ match and approximate the rank and time needed for an expecting recipient (Pahl et al. 2020). If a potential donor has an injury or passes away, there is no convenient way to search the records to efficiently preserve the organs. Hospitals can check the donor's identification with OrganSecure before commencing the extraction process.

1.14 AI in Spinal Cord Injury

A 28 years old participant, Ian Burkhart, sustained a spinal cord injury from the diving incident (2010) and is still collaborating with researchers since 2014 on a program named NeuroLife (Cell Press 2020), aimed at returning sense to his right arm. The Ohio State University Wexner Medical Center and Battelle's research team announced that after spinal cord injury (SCI), paralyzed muscles can be resuscitated with a brain-computer interface (BCI) to improve motor control by itself. More importantly, the touching sensation is a central feature of motor activity (Ganzer et al. 2020). The device they created works with an electrode system on his skin and a silicon chip inserted in his motor cortex. The system fuses and improves synaptic impulses that are so tiny that they cannot be detected by artificial sensory input transmitted back to the user, resulting in extremely enhanced motor activity. According to Patrick Ganzer, a principal research scientist from Battelle, in patients with a "clinically complete" spinal cord injury, there are still some preserved flecks of the nerve fiber. Using haptic feedback, the sub-perceptual touch impulses are selectively brought back towards the participant. Mobile phone or gaming controller vibrations alert the user that it is working are the common examples of haptic feedback. The researchers are developing a next-generation sleeve that comprises the necessary electrodes and sensors and can be swiftly applied and withdrawn (Ganzer et al. 2020).

2 AI in COVID-19

In December 2019, some people were hospitalized with pneumonia of unknown origin, exhibiting symptoms such as fever, dry coughs, weariness, and some were also experiencing nasal congestion, runny nose, sore throat, pain, and diarrhea, resulting in the death of many in Wuhan, China. On the 31st of December, China reported this remorseless pneumonia to the WHO country office, and the outbreak was eventually declared a Public Health Emergency of International Concern (PHEIC) on January 31, 2020. On February 11, 2020, the International Committee on Taxonomy of Viruses (ICTV) labeled the virus causing pneumonia as "Severe Acute Respiratory Syndrome Coronavirus 2" (SARS-Cov-2), and the World Health Organization (WHO) called the condition "COVID-19".

One of the ways to deal with infectious diseases, particularly those that spread quickly, such as COVID-19, is to quickly identify the infection and ensure proper isolation. Although detecting a viral infection is time-consuming and needs perplexing techniques that are often performed in specialized laboratories. Diagnosis can take hours or days so, the time taken to determine the presence of an infectious agent can promote further spread of disease and delay the patient's care. For this reason, researchers in the United Kingdom are putting a new mobile diagnostic system to the test: a portable laboratory with chip devices that connect to the cloud via a smartphone. Studies show that even in remote areas, this can detect the early onset of infectious diseases. The connected smartphone application helps the user to undergo testing and diagnostics of the patient (Mashamba-Thompson and Crayton 2020). Sample from the patient is taken in a disposable cartridge that contains electrochemical sensors. After that, the cartridge is inserted into a portable device, which amplifies the sample by regulating the temperature until RNA and DNA are identified, which requires roughly 30 minutes. The device consists of a microcontroller that sends patient data to a smartphone application via Bluetooth. When the results are positive, location reports and related data are sent to the cloud for viewing on the Internet. New cartridges for new pathogens, such as the SARS-CoV-2 virus that causes COVID-19, can be developed in a week after the new DNA sequence is presented to the public. The cartridge can then be used to provide quick and easy access to the detection and controlling the outbreak. The Deep Learning Classifier examines the image for anomalies before segmenting it and applying large-scale texture extraction. AI can rapidly distinguish lungs from patients with frequent viral pneumonia or COVID-19 by counting the number and size of lesions and determining the severity of each case (McCall 2020; Santosh 2020; NYU 2020).

AI uses natural language processing which is capable to answer any questions related to COVID-19 (Cury et al. 2021), by providing authentic and true information, giving clear

recommendations, and offer multilingual virtual assistance, monitoring symptoms, and also recommending whether any people need to get hospitalized or self-quarantine at home. Apple Siri and Amazon Alexa respond at an advanced level to two out of seven questions related to “coronavirus” or “COVID-19” (Mehta et al. 2020).

Web scraping and data mining are technologies that play a significant role in collecting facts and minimizing the flow of erroneous information. This data helps medical practitioners to evaluate the success or failure and adjust policies according to that. Tools such as Healthmap and Johns Hopkins University dashboard are currently some of the most popular sources of information about the epidemic. They use network erosion, data mining, machine learning, and geographic information technology to gather information from a variety of sources, including local and national government hospitals and medical centers, news, chat rooms, forums, and more (Rennie et al. 2020).

Due to a new generation of uncooled infrared (IR) thermal sensors based on microbolometers, thermal infrared sensing technology has advanced dramatically during the last few decades. These detectors generate massive 2D arrays using microelectromechanical system (MEMS) techniques, which reduce costs while maintaining excellent sensitivity and image quality. To assess psychophysiological and emotional states, behavioral analysis and several Autonomic Nervous System (ANS) factors, such as skin conductance, the temperature of a hand palm, modulations of heartbeat, and peripheral vascular tone, have been measured (Cardone and Merla 2017). Thermal cameras are used to identify people with fever, but the disadvantage of the technology is that it requires an operator. Hence, AI-based multi-sensor cameras (Health Cam) are now used in airports, hospitals, and nursing homes. The Kogniz Health Cam is equipped with an installed optical camera, a thermal camera, and a high-resolution display screen that can be placed on a desk, or a wall. People's temperatures are measured in actual time whether they walk alone or in a crowd with high-precision infrared technology, allowing the image of anyone with a high temperature to be spotted. The Health Cam uses the latest AI to measure the temperature of a human close to his eyes to get the most precise reading. Real-time updates are forwarded via SMS and Slack™. The live footage, including the temperature of an individual, is displayed on the Kogniz Health Cam monitor and is accessible via the Kogniz central smartphone app (Jiang et al. 2020).

AI can incur the costs of developing antibodies and vaccines against new coronaviruses that have been completely developed from scratch or by drug repurposing strategies. For example, Google DeepMind uses the AlphaFold system to create a

structural model of virus-related proteins for a better understanding of the virus in the scientific community (Drori et al. 2019). However, the results have not been verified experimentally, and this is a positive step. A variety of research was done using AI to classify medications that have been created to fight certain diseases, but that may now be retrofitted to combat COVID-19. After analyzing the molecular structure of current drugs with AI, companies want to recognize which ones may compete with the manner COVID-19 works. Benevolent AI, a drug research company in London, is focusing on the issue of the COVID-19 pandemic utilizing its AI-powered information graph, which can store a large quantity of scientific literature and biomedical research to identify connections among disease genetic and biological characteristics and drug structure and behavior. An example is baricitinib, a drug introduced by Benevolent AI that prevents viral entrance by blocking endocytosis and is used to treat arthritis (Ghose et al. 2020). Researchers can use the knowledge they gain from other viruses with familiar qualities, check their functions, and then figure out whether the medications can be used to stop the virus.

The main areas in which robots can help are clinical, logistics, and information management, which solve tasks such as identifying infected people or adhering to quarantine or social distance requirements. In addition to the medical field, robots can preserve the economy and infrastructure by working for employees of important companies such as factories or waste management, or power generation. Robot nurses are available to give medicines and food to patients who have tested positive for the coronavirus, allowing doctors and nurses to restrict direct contact with the patient and reduce the risk of infection. An Indian startup Invento Robotics, Bengaluru, has developed a robot named “Mitra” for assisting patients to communicate with their relatives (Singh et al. 2021).

Authorities use drones to combat the deadly epidemic of coronavirus. The drones are used to spray disinfectants into areas such as hospitals, offices, and government buildings.

Wenzhou Central Hospital, New York University, and Cangnan People's Hospital scientists collaborated on designing Artificial Intelligence-based early warning systems, which can anticipate whether a patient will display SARS-Cov-2 symptoms later or not, especially senior citizens. The AI system measures various changes in three conditions – alanine rates of aminotransferase, recorded myalgia, and hemoglobin levels – which are the most reliable predictors of eventual extreme disease and may potentially determine the risk of SARS-Cov-2 virus. In Wenzhou, China, 53 patients were tested with this system, which proves that this system is around 80% accurate (Jiang et al. 2020). Another advantage is that AI-based test kits do not need blood or genetic material as it is

linked with the CT scan machines in Indonesia's government hospitals, and it can evaluate the test in just 10 seconds.

Presently, whoever is showing symptoms or whoever has encountered with novel coronavirus or has been hospitalized are required to be diagnosed first, the standard laboratory testing involves "RT-PCR", "molecular point-of-care", "paper-based tests", and "testing for antibodies in the blood", but all these required much time to give results with good accuracy. However, the specificity is good, but sensitivity differs greatly depending on different countries. So, an AI-based CT scan can be employed to reduce the workload on physicians. Research groups are exhibiting an AI-based algorithm that can help by detecting, quantifying, and tracking COVID-19 on chest CT scans (Li et al. 2020). Researchers are aiming to change and adapt current AI systems with basic clinical knowledge to quickly build AI-based methods to resolve the problem of COVID-19. The proposed program incorporates deep learning systems and clinical knowledge of 2D and 3D modeling and has been based on data from accessible foreign databases, as well as from infected areas in China. This can also help in distinguishing between pneumonia and coronavirus disease.

2.1 AI-based Voice Tool

In Mumbai, a team of three students and a professor from DY Patil Institute of Biotechnology and Bioinformatics have designed an Artificial Intelligence (AI)-based tool to diagnose COVID-19 via voice-based diagnosis on a smartphone. This Indian AI speech gadget is fully functioning and is already being used in Italy to identify COVID-19 patients. The students get access to a complete working platform that includes a huge patient database and safe samples. The University of Rome is presently using this technology to detect COVID-19 patients with 98 percent of precision. Each of our internal organs is a resonator, and it's expressed by our voice whenever we are having an issue with our heart or our lungs (The Hindu 2020). When they are healthy, the same person has one voice, and when they have a condition, the voice changes. Since this virus is destroying the lungs and airwaves, it impacts speech. To identify infected individuals, the subject should speak to the microphone, and the device will break down the speech into several attributes such as volume and amplification of the sound. These readings are compared to those of an ordinary person, and the patient's positive or negative status is determined using this technique (Almada and Maranhão 2021).

Conclusion

The medicine training with AI is evolving with the advancement of the Machine Learning algorithm. An effective AI system must have the ML component for handling databases such as EMR data, scanning images, genetic information, as well as the NLP

component for unstructured text mining. Then, the advanced programs have to be tested by health care records which can help doctors with the diagnosis of illness and recommendations for treatment. These AI-based tools paired with advanced data science, are enhancing the validity and accuracy of the treatment and diagnosis among a wide range of professions. One noetic function is to build a powerful AI program. Such a program can be algorithmically built and can leave the human intellect far behind. The additional knowledge will help us eliminate illness, conflict, and misery with this creative data, and a strong AI can be developed that will be the biggest event in human history.

Here, we have discussed the role of AI and ML, and NLP in various fields of healthcare. Table 1 depicts some Artificial Intelligence applications deployed in the field of diagnosis, robotic surgeries, research, drug discovery, and disease management. As a result, we can conclude that AI can aid in the detection of abnormalities in various organs (colon, heart, brain, etc.) and surgeries (plastic surgery, spine surgery, retinal surgery, etc.). We also have virtual nursing assistants to answer any queries related to diseases and assist in finding a fair solution. Health records, genetic profiles, prescriptions, and environmental parameters are all examples of the information that AI may collect and evaluate, allowing more medical information to be retained, accessed, and analyzed.

The novel outbreak of coronavirus (COVID-19) was discovered in December of 2019 and requires special attention owing to its possible epidemics and worldwide threats. Since Artificial Intelligence (AI) proposes a modern technology for healthcare, it is utilized to understand data and make decisions. In addition to pharmaceuticals and clinical practices, numerous AI approaches and AI devices based on Machine Learning (ML) algorithms are used. This suggests that AI-based technologies would help doctors, and the existing physician-patient partnership would become stronger in the future. AI can help in decreasing the workload of healthcare professionals and provide better service to the people.

The limitation is the network's usage of multiple parameters to build its recommendation. If circumstances arise in which clinical characteristics are considered equally essential as all other variables, it may result in overfitting and overrepresentation of particular parameters. Since AI has been used to perform previously unimaginable tasks, awareness of the current revolution has yet to spread throughout the health sector for a variety of reasons, including a lack of evidence about the effectiveness, consistency, and safety of these tools, health sectors lacking AI regulations, and the ascription of liability in the event of an error. In any case, the outcome of ongoing machine-learning research will undoubtedly have an impact on longstanding disputes in cognitive science about the form and function of minds.

Table 1 Applications of AI deployed in the field of diagnosis, robotic surgeries, research, drug discovery & disease management

Domain	Sub-domain	Application	Reference/s
Diagnosis	Radiology	Colonoscopy	Hosny et al. 2018; Ciuti et al. 2020; Mori 2019
		Oncology	Esteva et al. 2017; Albarqouni et al. 2016
		Brain Imaging	Zaharchuk et al. 2018
	Pathology	Cardiology	Pavlou et al. 2015; Kolek et al. 2016; Narula et al. 2016; Johnson et al. 2018
		Lymphocyte morphology/cancer detection	Al-Kofahi et al. 2010; Ehteshami et al. 2017; Mohlman et al. 2020
		Cancer prognosis	Saltz et al. 2018; Corredor et al. 2019
Robot-Assisted Surgery	Cardiac Surgery	Mitral valve repair	Gillinov et al. 2018
	Orthopaedics	Hip arthroplasty and Spine Surgery	Lang et al. 2011; Hernandez et al. 2017
	Ophthalmic Surgery	Retinal surgery	Jensen et al. 1997; Dogangil et al. 2010; Urias et al. 2019
		Corneal surgery	Tsirbas et al. 2007; Pandey and Sharma 2019
	Plastic surgery	Prediction and clinical care	Ameer et al. 2013; Kim et al. 2019
Drug Discovery	Development	Identification and screening	Costa et al. 2010; Vamathevan et al. 2019
	Clinical Trial	Prediction of drug efficacy	Ferrero et al. 2017; Rouillard et al. 2018
Disease Management	Nursing	Virtual Nursing Assistant	Barrett et al. 2019
	Organ Transplantation	Finding organ match, rank and time	Pradhan et al. 2020
	Stroke management	Post stroke rehabilitation	Linder et al. 2015
		Clinical care	Krittanawong et al. 2017
	Training	Medical education	Paranjape et al. 2019

Conflict of Interest

The authors have no conflict of interest to declare.

References

- Abu-Hassan, K., Taylor, J. D., Morris, P. G., et al. (2019). Optimal solid-state neurons. *Nature communications*, 10(1), 5309.
- Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database: the journal of biological databases and curation*, 2020:baaa010. doi: 10.1093/database/baaa010.
- Albarqouni, S., Baur, C., Achilles, F., et al. (2016). AggNet: Deep Learning From Crowds for Mitosis Detection in Breast Cancer Histology Images. *IEEE transactions on medical imaging*, 35(5), 1313–1321.
- Al-Kofahi, Y., Lassoued, W., Lee, W., & Roysam, B. (2010). Improved automatic detection and segmentation of cell nuclei in histopathology images. *IEEE transactions on bio-medical engineering*, 57(4), 841–852.
- Almada, M., & Maranhão, J. (2021). Voice-based diagnosis of covid-19: ethical and legal challenges. *International Data Privacy Law*, ipab004. DOI:10.1093/IDPL/IPAB004.
- Ameer, F., Singh, A. K., & Kumar, S. (2013). Evolution of instruments for harvest of the skin grafts. *Indian journal of plastic surgery : official publication of the Association of Plastic Surgeons of India*, 46(1), 28–35.
- Astrakas, L. G., Naqvi, S. H., Kateb, B., & Tzika, A. A. (2012). Functional MRI using robotic MRI compatible devices for monitoring rehabilitation from chronic stroke in the molecular medicine era (Review). *International Journal of Molecular Medicine*, 29(6), 963–973.
- Bali, J., Garg, R., & Bali, R. T. (2019). Artificial intelligence (AI) in healthcare and biomedical research: Why a strong computational/AI bioethics framework is required?. *Indian Journal of Ophthalmology*, 67(1), 3–6.

- Barrett, M., Boyne, J., Brandts, J., Brunner-La Rocca, H.P., et al. (2019). Artificial intelligence supported patient self-care in chronic heart failure: a paradigm shift from reactive to predictive, preventive and personalised care. *The EPMA Journal*, *10*(4), 445-464.
- Bauder, R. A., & Khoshgoftaar, T. M. (2018). The effects of varying class distribution on learner behavior for medicare fraud detection with imbalanced big data. *Health information science and systems*, *6*(1), 9.
- Bolton, R.J., & Hand, D.J. (2002). Statistical fraud detection: a review. *Statistical Science*, *17*, 235-255.
- Buch, V. H., Ahmed, I., & Maruthappu, M. (2018). Artificial intelligence in medicine: current trends and future possibilities. *The British journal of general practice : the journal of the Royal College of General Practitioners*, *68*(668), 143-144.
- Cardone, D., & Merla, A. (2017). New Frontiers for Applications of Thermal Infrared Imaging Devices: Computational Psychophysiology in the Neurosciences. *Sensors (Basel, Switzerland)*, *17*(5), 1042.
- Celi, L.A., Davidzon, G., Johnson, A.E., et al. (2016). Bridging the Health Data Divide. *Journal of medical Internet research*, *18*(12), 325. doi: 10.2196/jmir.6400.
- Cell Press. (2020) Researchers restore injured man's sense of touch using brain-computer interface technology. *ScienceDaily*. Retrieved from <https://www.sciencedaily.com/releases/2020/04/200423130508.htm>
- Chandawarkar, A., Chartier, C., Kanevsky, J., & Cress, P. E. (2020). A Practical Approach to Artificial Intelligence in Plastic Surgery. *Aesthetic surgery journal. Open forum*, *2*(1), ojaa001.
- Ciuti, G., Skonieczna-Żydecka, K., Marlicz, W., et al. (2020). Frontiers of Robotic Colonoscopy: A Comprehensive Review of Robotic Colonoscopes and Technologies. *Journal of clinical medicine*, *9*(6), 1648.
- Corredor, G., Wang, X., Zhou, Y., et al. (2019). Spatial Architecture and Arrangement of Tumor-Infiltrating Lymphocytes for Predicting Likelihood of Recurrence in Early-Stage Non-Small Cell Lung Cancer. *Clinical cancer research : an official journal of the American Association for Cancer Research*, *25*(5), 1526-1534.
- Costa, P. R., Acencio, M. L., & Lemke, N. (2010). A machine learning approach for genome-wide prediction of morbid and druggable human genes based on systems-level data. *BMC genomics*, *11 Suppl 5*(5), S9.
- Cury, R. C., Megyeri, I., Lindsey, T., et al. (2021). Natural Language Processing and Machine Learning for Detection of Respiratory Illness by Chest CT Imaging and Tracking of COVID-19 Pandemic in the US. *Radiology. Cardiothoracic imaging*, *3*(1), e200596.
- D'Andrea M. R. (2005). Add Alzheimer's disease to the list of autoimmune diseases. *Medical Hypotheses*, *64*(3), 458-463.
- Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94-98.
- Desikan, S. (2020). Coronavirus: TCS uses AI for drug discovery. *The Hindu*. Retrieved from <https://cdn.splissons.com/wp-content/uploads/2020/04/april-5-articles-science-and-technology-the-hindu-splissons.pdf>
- Dogangil, G., Davies, B. L., & Rodriguez y Baena, F. (2010). A review of medical robotics for minimally invasive soft tissue surgery. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, *224*(5), 653-679.
- Drori, I., Thaker, D. D., Srivatsa, A., et al. (2019). Accurate Protein Structure Prediction by Embeddings and Deep Learning Representations. Retrieved from <https://arxiv.org/abs/1911.05531>
- Ehteshami Bejnordi, B., Veta, M., Johannes van Diest, P., et al. (2017). Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer. *JAMA*, *318*(22), 2199-2210.
- Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., et al. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115-118.
- Fermini, B., Hancox, J. C., Abi-Gerges, N., et al. (2016). A New Perspective in the Field of Cardiac Safety Testing through the Comprehensive In Vitro Proarrhythmia Assay Paradigm. *Journal of Biomolecular Screening*, *21*(1), 1-11.
- Ferrero, E., Dunham, I., & Sanseau, P. (2017). In silico prediction of novel therapeutic targets using gene-disease association data. *Journal of Translational Medicine*, *15*(1), 182.
- Ganzer, P. D., Colachis, S. C., 4th Schwemmer, M. A. et al. (2020). Restoring the Sense of Touch Using a Sensorimotor Demultiplexing Neural Interface. *Cell*, *181*(4), 763-773.
- Garry R. (2006). Laparoscopic surgery. *Best practice & research. Clinical obstetrics & gynaecology*, *20*(1), 89-104.
- Ghose, A., Roy, S., Vasdev, N., Olsburgh, J., & Dasgupta, P. (2020). The Emerging Role of Artificial Intelligence in the Fight Against COVID-19. *European Urology*, *78*(6), 775-776.

- Gillinov, A. M., Mihaljevic, T., Javadikasgari, H., et al. (2018). Early results of robotically assisted mitral valve surgery: Analysis of the first 1000 cases. *The Journal of Thoracic and Cardiovascular Surgery*, 155(1), 82–91.e2.
- Gouda, W., & Yasin, R. (2020). COVID-19 disease: CT Pneumonia Analysis prototype by using artificial intelligence, predicting the disease severity. *The Egyptian Journal of Radiology and Nuclear Medicine*, 51(1), 196.
- Gudivada, V. N., Raghavan, V. V., Govindaraju, V., Rao, C. R. (2016) *Cognitive Computing: Theory and Applications, in Handbook of Statistics*, pp. 301-340.
- Han, S. H., Kim, K. W., Kim, S., & Youn, Y. C. (2018). Artificial Neural Network: Understanding the Basic Concepts without Mathematics. *Dementia and Neurocognitive Disorders*, 17(3), 83–89.
- He, J., Baxter, S. L., Xu, J., et al. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine*, 25(1), 30–36.
- Healio. (2019). Transplant tourism: A ‘pervasive’ and dangerous ‘shadow world of medicine’, Infectious disease news. Retrieved from <https://www.healio.com/news/infectious-disease/20190416/transplant-tourism-a-pervasive-and-dangerous-shadow-world-of-medicine>
- Hernandez, D., Garimella, R., Eltorai, A., & Daniels, A. H. (2017). Computer-assisted Orthopaedic Surgery. *Orthopaedic Surgery*, 9(2), 152–158.
- Hessler, G., & Baringhaus, K. H. (2018). Artificial Intelligence in Drug Design. *Molecules (Basel, Switzerland)*, 23(10), 2520.
- Hithaishi, C. B. (2020). Tencent launches AI-powered medical imaging and data management devices. *Biospectrum*. Retrieved from <https://www.biospectrumasia.com/article/pdf/16966>
- Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. (2018). Artificial intelligence in radiology. *Nature reviews Cancer*, 18(8), 500–510.
- Jensen, P. S., Grace, K. W., Attariwala, R., Colgate, J. E., & Glucksberg, M. R. (1997). Toward robot-assisted vascular microsurgery in the retina. *Graefe's Archive for Clinical and Experimental Ophthalmology*, 235(11), 696–701.
- Jeon, J., Nim, S., Teyra, J., et al. (2014). A systematic approach to identify novel cancer drug targets using machine learning, inhibitor design and high-throughput screening. *Genome Medicine*, 6(7), 57.
- Jiang, F., Jiang, Y., Zhi, H., et al. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology*, 2(4), 230–243.
- Jiang, X., Coffee, M., Bari, A., et al. (2020). Towards an artificial intelligence framework for data-driven prediction of coronavirus clinical severity. *Computers, Materials & Continua* 63: 537–551.
- Johnson, D., & Wilkie, A. O. (2011). Craniosynostosis. *European Journal of Human Genetics* 19(4), 369–376.
- Johnson, K. W., Torres Soto, J., Glicksberg, B. S., et al. (2018). Artificial Intelligence in Cardiology. *Journal of the American College of Cardiology*, 71(23), 2668–2679.
- Joudaki, H., Rashidian, A., Minaei-Bidgoli, B., et al. (2015). Improving Fraud and Abuse Detection in General Physician Claims: A Data Mining Study. *International Journal of Health Policy and Management*, 5(3), 165–172.
- Kim, Y. J., Kelley, B. P., Nasser, J. S., & Chung, K. C. (2019). Implementing Precision Medicine and Artificial Intelligence in Plastic Surgery: Concepts and Future Prospects. *Plastic and Reconstructive Surgery. Global open*, 7(3), e2113.
- Kolek, M. J., Graves, A. J., Xu, M., et al. (2016). Evaluation of a Prediction Model for the Development of Atrial Fibrillation in a Repository of Electronic Medical Records. *JAMA Cardiology*, 1(9), 1007–1013.
- Kong, M., Lee, J., Yazdi, I. K., et al. (2019). Cardiac Fibrotic Remodeling on a Chip with Dynamic Mechanical Stimulation. *Advanced Healthcare Materials*, 8(3), e1801146.
- Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial Intelligence in Precision Cardiovascular Medicine. *Journal of the American College of Cardiology*, 69(21), 2657–2664. <https://doi.org/10.1016/j.jacc.2017.03.571>
- Lanfranco, A. R., Castellanos, A. E., Desai, J. P., & Meyers, W. C. (2004). Robotic surgery: a current perspective. *Annals of Surgery*, 239(1), 14–21.
- Lang, J. E., Mannava, S., Floyd, A. J., et al. (2011). Robotic systems in orthopaedic surgery. *The Journal of Bone and Joint Surgery*, 93(10), 1296–1299.
- Lee, H., Mittal, A., Patel, K., et al. (2014). Identification of novel drug scaffolds for inhibition of SARS-CoV 3-Chymotrypsin-like protease using virtual and high-throughput screenings. *Bioorganic & Medicinal Chemistry*, 22(1), 167–177.

- Lee, S. I., Celik, S., Logsdon, B. A., et al. (2018). A machine learning approach to integrate big data for precision medicine in acute myeloid leukemia. *Nature Communications*, 9(1), 42.
- Li, L., Qin, L., Xu, Z., et al. (2020). Using Artificial Intelligence to Detect COVID-19 and Community-acquired Pneumonia Based on Pulmonary CT: Evaluation of the Diagnostic Accuracy. *Radiology*, 296(2), E65–E71.
- Liebeskind D. S. (2018). Artificial intelligence in stroke care: Deep learning or superficial insight?. *EBioMedicine*, 35, 14–15.
- Linder, S. M., Rosenfeldt, A.B., Bay, R.C., et al. (2015). Improving Quality of Life and Depression After Stroke Through Telerehabilitation. *The American journal of occupational therapy*, 69(2), 6902290020p1–6902290020p10.
- Liu, B., He, H., Luo, H., Zhang, T., & Jiang, J. (2019). Artificial intelligence and big data facilitated targeted drug discovery. *Stroke and Vascular Neurology*, 4(4), 206–213.
- Magrabi, F., Ammenwerth, E., McNair, J. B., et al. (2019). Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications. *Yearbook of Medical Informatics*, 28(1), 128–134.
- Mashamba-Thompson, T. P., & Crayton, E. D. (2020). Blockchain and Artificial Intelligence Technology for Novel Coronavirus Disease-19 Self-Testing. *Diagnostics (Basel, Switzerland)*, 10(4), 198.
- Mayr, A., Klambauer, G., Unterthiner, T., & Hochreiter, S. (2016). DeepTox: Toxicity Prediction using Deep Learning. *Frontiers in Environmental Science*, 3, 80.
- McCall, B. (2020). COVID-19 and artificial intelligence: protecting health-care workers and curbing the spread. *Lancet Digit Health*, 2, 166-167.
- Mehta, V., Rammohan, R., Sanivarapu, R., Sayedy, N., & Akella, J. (2020). The role of virtual assistants with coronavirus diagnosis and treatment. *Chest*, 158(4), A1176.
- Mencattini, A., Mattei, F., Schiavoni, G., et al. (2019). From Petri Dishes to Organ on Chip Platform: The Increasing Importance of Machine Learning and Image Analysis. *Frontiers in pharmacology*, 10, 100.
- Mohlman, J. S., Leventhal, S. D., Hansen, T., et al. (2020). Improving Augmented Human Intelligence to Distinguish Burkitt Lymphoma From Diffuse Large B-Cell Lymphoma Cases. *American Journal of Clinical Pathology*, 153(6), 743–759.
- Mori, Y. (2019). Artificial intelligence and colonoscopy: the time is ripe to begin clinical trials. *Endoscopy*, 51, 219-220.
- Murff, H. J., FitzHenry, F., Matheny, M. E., et al. (2011). Automated identification of postoperative complications within an electronic medical record using natural language processing. *JAMA*, 306(8), 848–855.
- Narula, S., Shameer, K., Salem Omar, A. M., Dudley, J. T., & Sengupta, P. P. (2016). Machine-Learning Algorithms to Automate Morphological and Functional Assessments in 2D Echocardiography. *Journal of the American College of Cardiology*, 68(21), 2287–2295.
- Oboudiyat, C., Glazer, H., Seifan, A., Greer, C., & Isaacson, R. S. (2013). Alzheimer's disease. *Seminars in Neurology*, 33(4), 313–329.
- Pahl, E., Emery, R. W., Noce, M., et al. (2020). Mobile Application for Communication Increases the Efficiency of Organ Procurement and Transplantation. *Progress in transplantation (Aliso Viejo, Calif.)*, 30(2), 172–176.
- Pandey, S. K., & Sharma, V. (2019). Robotics and ophthalmology: Are we there yet?. *Indian Journal of Ophthalmology*, 67(7), 988–994.
- Paranjape, K., Schinkel, M., Nannan Panday, R., Car, J., & Nanayakkara, P. (2019). Introducing Artificial Intelligence Training in Medical Education. *JMIR Medical Education*, 5(2), e16048.
- Park, Y. S., & Lek, S. (2016). Artificial Neural Networks: Multilayer Perceptron for Ecological Modeling. In *Developments in Environmental Modelling*, 28, 123-140.
- Pavlou, M., Ambler, G., Seaman, S. R., et al. (2015). How to develop a more accurate risk prediction model when there are few events. *BMJ (Clinical research ed.)*, 351, h3868.
- Pradhan, P., Mishra, A. S., & Habeebullah, H. (2020). Organ donation-an android application. *SSRN Electronic Journal*, 7(12), 85-89.
- Raleigh. (2017). TeleHealth Services Redefines Patient Engagement, Launches iCare Navigator with AI-Driven Virtual Health Coach. *TeleHealth Press Release*. Retrieved from https://www.telehealthservices.com/sites/default/files/TeleHealth_Press_Release_iCN_10-11-17.pdf
- Ravi, D., Wong, C., Deligianni, F., et al. (2017) Deep Learning for Health Informatics. *IEEE Journal of Biomedical and Health Informatics*, 21(1), 4-21.

- Rennie, S., Buchbinder, M., Juengst, E., et al. (2020). Scraping the Web for Public Health Gains: Ethical Considerations from a 'Big Data' Research Project on HIV and Incarceration. *Public Health Ethics, 13*(1), 111–121.
- Rogers, A. J., Miller, J. M., Kannappan, R., & Sethu, P. (2019). Cardiac Tissue Chips (CTCs) for Modeling Cardiovascular Disease. *IEEE Transactions on Bio-medical Engineering, 66*(12), 3436–3443.
- Rouillard, A. D., Hurlle, M. R., & Agarwal, P. (2018). Systematic interrogation of diverse Omic data reveals interpretable, robust, and generalizable transcriptomic features of clinically successful therapeutic targets. *PLoS Computational Biology, 14*(5), e1006142.
- Sadhika. (2019). Fintalk. *Bank of Baroda*. Retrieved from https://www.bankofbaroda.in/writereaddata/Portal/Fintalk/466_1_Fintalk-05-02-19.pdf
- Saltz, J., Gupta, R., Hou, L., et al. (2018). Spatial Organization and Molecular Correlation of Tumor-Infiltrating Lymphocytes Using Deep Learning on Pathology Images. *Cell Reports, 23*(1), 181–193.
- Santosh, K. C. (2020). AI-Driven Tools for Coronavirus Outbreak: Need of Active Learning and Cross-Population Train/Test Models on Multitudinal/Multimodal Data. *Journal of Medical Systems, 44*(5), 93.
- Shah, P., Kendall, F., Khozin, S., et al. (2019). Artificial intelligence and machine learning in clinical development: a translational perspective. *NPJ Digital Medicine, 2*, 69.
- Shen, J., Zhang, C., Jiang, B., et al. (2019) Artificial Intelligence Versus Clinicians in Disease Diagnosis: Systematic Review. *JMIR Medical Informatics, 7*(3), e10010.
- Siemens Healthcare GmbH. (2021). Siemens Healthineers Digital Marketplace Online Help – Online Guide. Retrieved from https://marketplace.teampay.siemens.com/api/download/media/digital_marketplace_user_guide.pdf
- Singh, H., Modi, H. N., Ranjan, S., et al. (2018). Robotic Surgery Improves Technical Performance and Enhances Prefrontal Activation During High Temporal Demand. *Annals of Biomedical Engineering, 46*(10), 1621–1636.
- Singh, S., Dalla, V. K., & Shrivastava, A. (2021). Combating COVID-19: Study of robotic solutions for COVID-19, *AIP Conference Proceedings*. Retrieved from <https://aip.scitation.org/doi/pdf/10.1063/5.0050148>
- Spasic, I., & Nenadic, G. (2020). Clinical Text Data in Machine Learning: Systematic Review. *JMIR Medical Informatics, 8*(3), e17984
- Tanna, S. (2013). Alzheimer's Disease (AD). *Priority Medicines*. Retrieved from https://www.who.int/medicines/areas/priority_medicines/BP6_11Alzheimer.pdf
- The Hindu. (2020). Mumbai students develop AI-based voice tool to detect COVID-19. *Sci-tech*. Retrieved from <https://www.thehindu.com/sci-tech/technology/mumbai-students-develop-ai-based-voice-tool-to-detect-covid-19/article31360091.ece>
- Tran, B. X., Latkin, C. A., Vu, G. T., et al. (2019). The Current Research Landscape of the Application of Artificial Intelligence in Managing Cerebrovascular and Heart Diseases: A Bibliometric and Content Analysis. *International Journal of Environmental Research and Public Health, 16* (15), 2699.
- Tsirbas, A., Mango, C., & Dutton, E. (2007). Robotic ocular surgery. *The British Journal of Ophthalmology, 91*(1), 18-21.
- University of Bath. (2019). World first as artificial neurons developed to cure chronic diseases. *Press release*. Retrieved from <https://www.bath.ac.uk/announcements/world-first-as-artificial-neurons-developed-to-cure-chronic-diseases/>
- Urias, M. G., Patel, N., He, C., et al. (2019). Artificial intelligence, robotics and eye surgery: are we overfitted?. *International Journal of Retina and Vitreous, 5*, 52.
- Vamathevan, J., Clark, D., Czodrowski, P., et al. (2019). Applications of machine learning in drug discovery and development. *Nature reviews. Drug discovery, 18*(6), 463-477.
- Velten, J. C., Arif, R., & Moehring, D. (2007). Managing Disclosure through Social Media: How Snapchat is Shaking Boundaries of Privacy Perceptions. *Core*. Retrieved from <https://core.ac.uk/download/pdf/276236099.pdf>
- NYU Langone Health / NYU School of Medicine. (2020). Experimental AI tool predicts which COVID-19 patients develop respiratory disease. *ScienceDaily*. Retrieved from www.sciencedaily.com/releases/2020/03/200330152135.htm
- Yeong, E. K., Hsiao, T. C., Chiang, H. K., & Lin, C. W. (2005). Prediction of burn healing time using artificial neural networks and reflectance spectrometer. *Burns : Journal of the International Society for Burn Injuries, 31*(4), 415–420.
- Zaharchuk, G., Gong, E., Wintermark, M., Rubin, D., & Langlotz, C. P. (2018). Deep Learning in Neuroradiology. *AJNR. American Journal of Neuroradiology, 39*(10), 1776–1784.