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MINI-REVIEW ARTICLE

Potential Use of Artificial Intelligence in a Healthcare System

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Abstract: Artificial Intelligence (AI) is a swiftly evolving branch of technology that has been used to improve clinical practice, minimize errors, and boost safety and efficiency worldwide; in almost every field. AI is used for machine-learning algorithms and techniques to replicate human cognition in the assessment, display, and interpretation of complicated medical and healthcare data. AI is surfacing and producing a discernible shift in the healthcare system by expanding the availability of data in healthcare and speeding up the development of analysis tools. Additionally, AI and its applications in healthcare have evolved and proved to be a boon. The pharmaceutical business, health services, medical institutes, and patients, not only doctors use the applications but also dermatology, echocardiography, surgery, and angiography are only a few applications. AI can improve healthcare systems without hesitation. Automating time-consuming tasks can free up clinicians' schedules so they can encounter patients. It is causing a radical shift in healthcare, attributed to the increasing availability of healthcare data and the rapid advancement of advanced analytics. Screening, monitoring, and medical and clinical investigations are all made easier by AI. Despite some of the obstacles and limitations that AI faces, this new technology has enormous potential in the medical field. Regarding their reduced size, electronic devices have become more powerful as technology has progressed. Currently, the COVID – 19 pandemic is propelling the digital age to unprecedented heights. On multiple fronts, Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) are being employed to combat the pandemic.

Keywords: Artificial intelligence, healthcare, robotics, machine learning, deep learning, robot nurses, patients, device.

1. INTRODUCTION

Artificial intelligence (AI) is defined as machine intelligence rather than the intelligence of an individual or other living species [1]. Voice recognition, robotics, and biometric authentication are examples of AI-based technologies. AI is used in numerous fields, including healthcare. AI can help healthcare providers have a better experience by spending more time on direct patient care. Patients, doctors, and hospital executives' lives are simplified by artificial intelligence, which performs activities normally performed by people in a fraction of the time and at a fraction of the expenses. Electronic gadgets are becoming smaller in appearance as semiconductor technology advances, yet they are becoming more powerful in function. With the popularity of various wearable gadgets, more data is being gathered. As a result, we can create various applications, including behaviour recognition, motion sensors, and psychological pressure alert. While greater data volume and kind opens up more application possibilities, it also necessitates more data processing power. Traditional data processing technologies cannot meet the demands of new applications. A number of artificial intelligence technologies have been used to process data with wearable technology in this scenario. With the rise of deep learning in recent years, this has become increasingly important [2]. Increasingly artificial intelligence technologies, such as image recognition [3], audio processing [4], and traffic prediction [5], are beginning to play an essential role in numerous industries and have achieved favourable performance much beyond previous approaches. Artificial intelligence (AI), namely machine learning (ML) and deep learning (DL) is being utilised to assist medical professionals in battling the impacts of COVID-19 on numerous fronts. AI can recognise trends, forecast outcomes, assist with ethical decisions, and help find meaningful information from data given the right input and unique algorithmic design [6].

2. ARTIFICIAL INTELLIGENCE DEVICES

Artificial Intelligence (AI) is a rapidly changing and expanding branch of technology that has helped improve most in every field [7]. It indicates that AI devices are divided into two vital categories: The initial type has the Machine Learning (ML) technique that helps with analysing the structure of data for, *e.g.*, Imaging, Genetic, and Equivalence Partitioning (EP) data. ML methods are applied to use medical group patient features instead of estimating the likelihood of a virus's manifestation [8]. Deep learning (DL) is the new advancement of traditional neural network techniques. The basic structure of the neurons and synapses in the human neocortex inspired DL, a subset of ML. DL com-

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prises a multi-layered form of algorithms known as neural networks. Every layer consists of nodes or neurons. Many layers of neural networks act as filters, extracting features from the input (Fig. **1**).

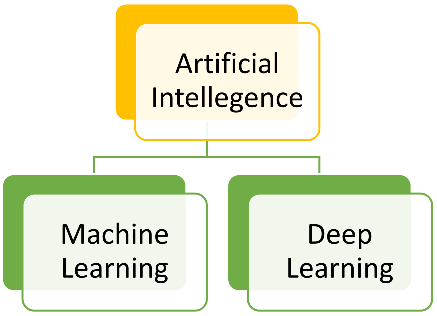

Fig. (1). Artificial Intelligence devices. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

2.1. The AI Devices: Machine Learning [ML] and Deep Learning (DL)

This section describes the Artificial Intelligence devices or techniques proven helpful for medical settings. They are classified into two types: traditional machine learning and deep learning techniques [9].

2.1.1. Classical ML

Machine Learning produces statistical tools that discover knowledge from the information gathered. Machine learning statistical tools are fed with clinical populations and, in some cases, clinical-related results. Diagnosing scans, protein expression, EP test results, physical assessment, clinical signs, pharmaceutics, and other disorder statistics and statistical information like period, sex, and clinical history, are very often shown in a client's features. Patients' health results, as well as their characteristics, are commonly collected in clinical studies. In those results are disorder indicators, improved survival times, and quantitative disorder tiers such as cancer cell diameter [10].

Unsupervised and supervised learning are two types of machine learning that differ in incorporated outcomes. Semi-supervised learning is ideal for extracting features but chaperoned learning outcomes are used for predictive analytics [11].

Modelling was performed by developing correlations between the patient's features as given data and the expected outcome as received data. In addition, the intended obtained results as received data. ML combines unguided and guided learning, showing as a boon for situations when the result of a particular topic is unravelled [12]. The different modes of supervised learning are shown in the diagram above (Fig. **2**).

2.1.2. Deep Learning: A New Era of ML

It can be stated as a multi-layered neural network (Fig. **3**). The rapid growth of current computing allows for creating human brains with many layers, which is impossible to achieve with traditional human brains. Therefore, deep learning may be able to delve more through information to find more complicated nonlinear patterns. Another factor driving deep learning's current popularity is the increased amount and severity of the information. In 2016, there was an upsurge in the usage of this approach in medical research [13].

Unlike typical neural networks, deep learning algorithms have more hidden layers, allowing them to handle complex data with various topologies [14]. Very frequently associated with DL algorithms in healthcare use are the Convolution Neural Network (CNN), recurrent neural network, deep belief network, and deep neural network.

Old ML algorithms have been unable to use or see the HD data information with many attributes; hence CNN was founded. Machine Learning algorithms are constructed to examine information on limited digits of attributes. The photographic information is essentially HD because almost every image comprises hundreds of illuminations on display screens as characteristics.

3. DISEASE FOCUS

Even though research in this healthcare field is rising, the majority is concentrated on fewer diseases: Cancer, nervous system disease, and cardiovascular disease (Fig **4**). We will go over a few examples below:

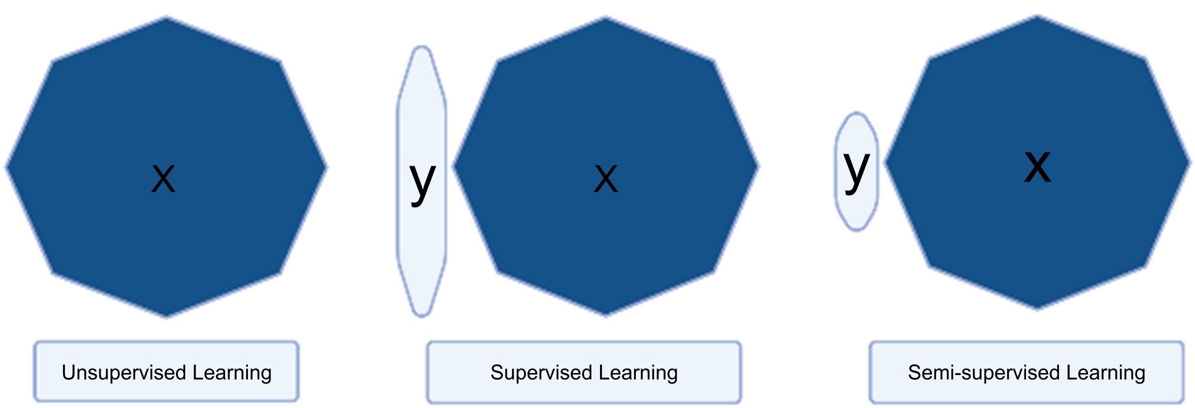

Fig. (2). Unsupervised, supervised, and semi-supervised learning is presented graphically. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

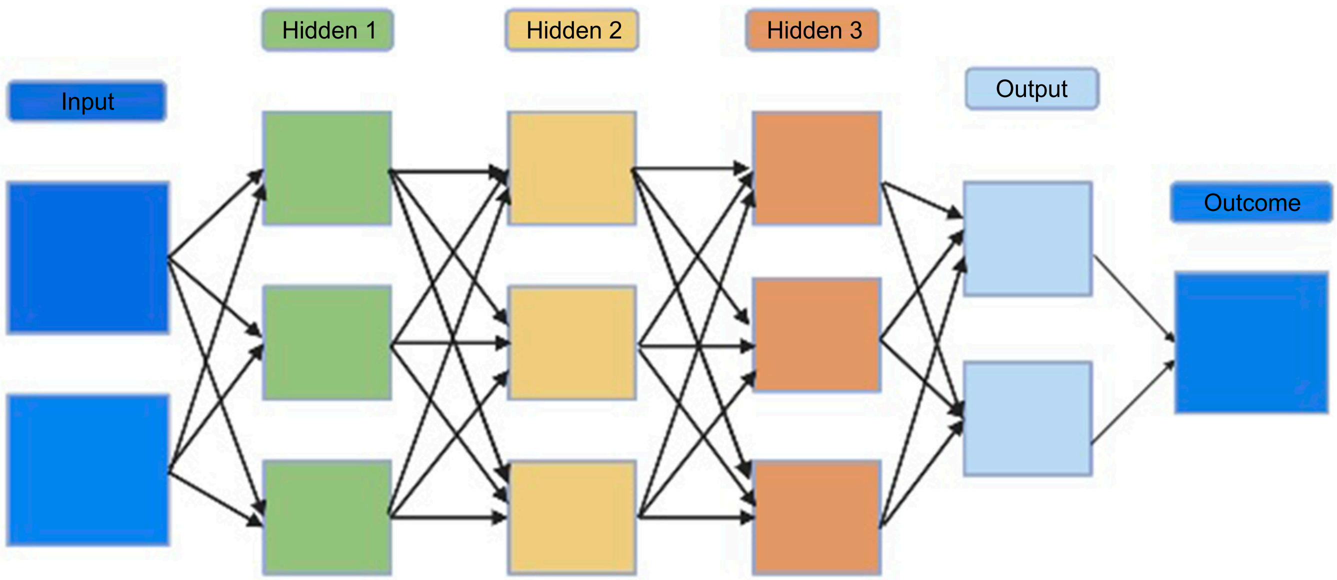

Fig. (3). An illustration of deep learning with multi hidden layers. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

3.1. Cancer

In a double-blind validation study, Somashekhar *et al*. IBM Watson for Cancer has been proven to be an effective method for treating tumour cells [15]. To identify skin cancer subgroups, Esteva *et al*. colleagues analysed clinical pictures.

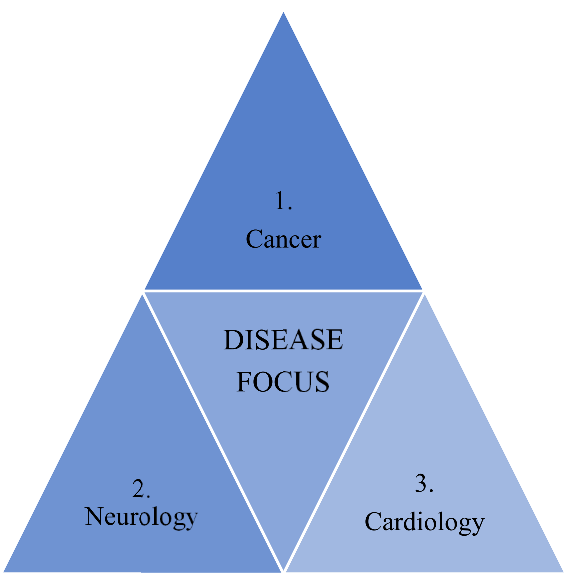

Fig. (4). Disease focus. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

3.2. Neurology

In Neurology, Bouton *et al*. developed an artificial intelligence method to help quadriplegic individuals regain control of their movements [16]. Farina *et al*. examined the efficiency of a physical man or machine link, which works according to the topmost implant release rates of lumbar neurons [17].

3.3. Cardiology

In Cardiology, Dilsizian and Siegel discussed how an AI system could diagnose heart illness using cardiac images. The US FDA lately gave Artery permission to market their Artery Cardio DL program; based on typical cardiac MRI data, AI is used to produce automatic, editable ventricular segmentation [18]. None of that is unexpected that these three ailments appear to be linked. Because these three illnesses are the biggest killers, getting treatment as early as feasible is critical to keeping the patient's condition from worsening. Additionally, by enhancing analytic methods on imaging, genomics, Equivalence Partitioning (EP), or Electronic Medical Records (EMR), which seems to be the strength of the Artificial Intelligence system, premature evaluation may be possible. AI has been primarily used to treat various conditions and the three primary disorders. Long *et al*. researchers diagnosed congenital cataract illness using ocular imaging data [19]. Also, Gulshan *et al*. used retinal fundus pictures to detect referable diabetic retinopathy, two recent examples [20].

4. AI APPLICATION FOR STROKE

Heart attack is a frequent and often fatal illness that causes not less than 500 million people worldwide. The highest cause of death in China was also sixth in North America. It has trolled the worldwide economy by $689 billion for healthcare bills, placing countries and families under threat [21, 22]. Therefore, stroke prevention and treatment research are critical. In the upcoming decades, artificial intelligence techniques are associated with an increasing number of stroke-related investigations. In the three main regions of healthcare, prematurely cancer observation and recognition, therapy, results, and prognosis evaluation, above we summarised some of the most significant AI techniques [23].

4.1. Premature Detection and Diagnosis

Blood clotting in the vessel, known as cerebral infarction, causes a heart attack 85% of the time. Only a few individuals were able to receive prompt treatment due to a lack of recognition of early stroke symptoms. Villar *et al*. created a device that detects movement and predicts strokes early [24]. The two types of Machine Learning algorithms — in an attempt to provide such a methodology developed, the device was equipped with a biological blurry finite state machine and Patient-controlled Analgesia (PCA) [25]. The detection method included a phase of human detection and the phase of stroke onset detection. A stroke alert is initiated when the patient's behaviour differs from the regular pattern [26]. The sufferer is assessed as soon as possible for therapy. Mannini *et al*. proposed a smartwatch to estimate stroke that gathers information on physiologic and pathologic gait [26]. Hidden Markov models and Support Vector Machine (SVM) would be used to extract and model the data, and the method could accurately categorize 90.5% of the participants to the correct category [27].

Neuroimaging tools, such as MRI and CT scans are useful for stroke diagnosis and illness evaluation. Certain learnings have tried to use ML approaches for neuroimaging information to assist in stroke diagnosis. In nonactive functional MRI data, SVM was used to identify and classify endophenotypes of motor dysfunction following stroke by Rehme *et al.* [28]. With an accuracy of 87.6%, SVM can properly diagnose stroke patients. Griffis *et al*. used nave Bayes classification in T1-weighted MRI to identify stroke lesions [29]. The outcome is comparable to manual lesion delineation by a human specialist. In a multimodal brain MRI, Kamnitsas *et al.* used 3D CNN to separate tumours [30]. They have used a fully connected conditional random matrix framework for the last compositing of CNN's delicate segmented. When Rondina *et al*. employed Gaussian mixture analysis to evaluate stroke structural medical images, they found that cluster arrangements significantly improved predictive characteristics over damage amount on the region [31].

CT scans from stroke patients have also been analysed using machine learning algorithms. After a stroke, a free-floating intraluminal thrombus can become a tumour that is difficult to identify from the clogging of blood vessels that deliver blood to the brain in CT imaging. Jiang *et al*. colleagues employed two ML algorithms to categorize these two categories using quantitative shape analysis. The method's accuracy varies between 65.2% and 76.4% [32].

5. IMAGE-BASED DIAGNOSIS

Presently, mechanized medical image identification is perhaps a promising sector of healthcare AI technology. Various surgical subspecialties include radiography, ophthalmologist, dermatitis, and pathologists, who use image-based diagnosis. In the following section, we will review recent advancements in using artificial intelligence in all health specialties (Fig. **5**) [33].

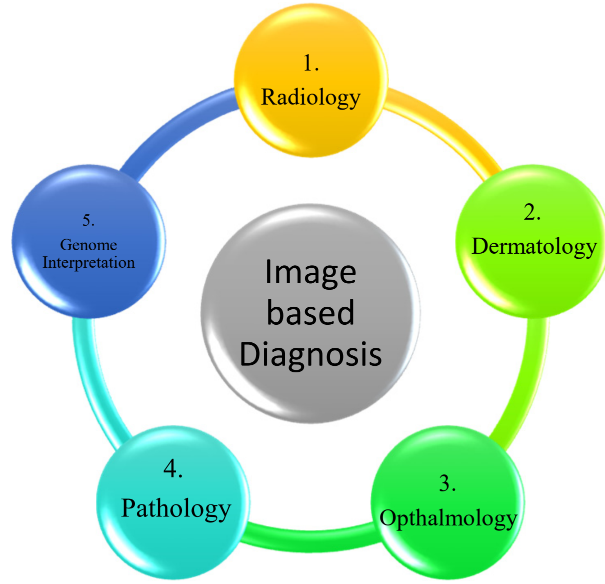

Fig. (5). Image based diagnosis. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

5.1. Radiology

Diagnostic radiology implements a variety of imaging modalities to diagnose illnesses, the most popular of which are X-ray radiation, computerized tomography, MRI, and positron emission tomography. Radiologists employ a collection of images to search for diseases, diagnose them, pinpoint the origin of sickness and analyse the person's improvement over time in these operations [34].

5.2. Dermatology

Regarding detecting a variety of skin lesions, visual inspection is crucial. Typical skin melanoma, for example, includes visual characteristics that distinguish it from benign moles [35]. The most well-known ABCDE rule was created by a dermatologist as a rule of thumb for detecting skin carcinoma through observation. Criterion A refers to the tumour's geometric irregularity, Criterion B to irregular borders, Criterion C to pigment variegation, Criterion D to a dimension of 6mm or higher and Criterion E to the lesion's surface extension or developing tumour [36].

5.3. Ophthalmology

Retina cinematography can be defined as a technique that does not involve the introduction of instruments in the body that uses retinal cameras to take pictures of the retina, optic disc, and macula. It can identify and evaluate diabetic retinopathy, glaucoma, retina neoplasms, and age-related vision problems and determine the reasons for avoidable blindness. The American Diabetes Association's clinical guidelines recommend screening yearly for diabetes patients with mild or no damage to the retina and more regular examinations for people with progressive retinopathy [37]. Ophthalmologists typically inspect and interpret fundus (part of the eyeball opposite to the pupil images), which is difficult to scale to the millions of diabetes individuals at risk of sight-threatening [38].

5.4. Pathology

After turning a biopsy or surgery sample into defining as the extraction and dyeing the slides with dye, professional pathologists analysed the slides underneath the microscope based on the visual evaluation. However, there have been observed differences among pathologists, and the approach is not easily scalable [39, 40].

5.5. Genome Interpretation

Because human DNA information is always evolving, compared to an individual's genes, knowledge and control only through human filtering are difficult. In identifying deleterious gene mutations, deep learning models outperform standard methods like regression analysis and support vector machines [41], as well as identifying DNA activities that are not coded [42].

6. PATIENT MONITORING

The popularity of smartphones and fitness bands and the acceptance of electronic health records have provided an unmatched allowance for electronic information and the potential to employ AI to monitor individuals [43]. As a result, we now have unprecedented access to information about individuals' sleep habits, blood pressure, the status of the cardiovascular system, and various vital signs. In addition to these developments, we have seen increases in various other areas. Waveform pattern learning, for example, could assist hospitals in improving electrocardiograms, electroencephalographs, electromyographs, and Delta ultrasonography monitoring and interpretation [44]. In intensive care units, AI-enabled software can monitor cardiovascular and respiratory health by interpreting vital signals. Following a visit to the hospital, health practitioners can utilize automated systems using natural language processing (NLP) to send patients important data and rearrange appointments (Fig. **6**) [45].

6.1. Different Types of Wearable Devices

Wearable gadgets are categorized in this section:

6.1.1. Smart Phones

Many sensors are built-in smartphones that collect data about the user's movements. People frequently keep their smartphones in their pockets, which meets data collection requirements. Data can be collected for various applications, including movement tracking, fall detection, monitoring older adults and patient recovery training [46].

6.1.2. Smart Watches and Wristbands

Smartwatches and wristbands are now popular, with various built-in sensors that track the user's daily activities, calorie consumption, heart rate, and sleep quality, allowing them to exercise more healthily and sleep better [47].

6.1.3. Smart Glasses

Smart glasses' recording and shooting capabilities may infringe on other people's privacy. Smart glasses, on the other hand, will not become a threat to privacy if the purpose is clear and the monitor system is great, but rather a useful life aid and medical tool if the purpose is clear and the monitor system is flawless. Google, for example, is developing contact lenses with built-in sensors that can detect a user's blood sugar levels [48].

6.1.4. Smart Clothes and Socks

Smart garments use textiles, sensors, and collection devices to collect body data from wearers, tracking exercise and heat consumption. Smart baby garments are also available for infants to check their physical status [49].

6.1.5. Smart Shoes

Smart shoes typically gather user activity data to assist individuals' betterment of their workout routines. Furthermore, certain smart footwear, such as Nike's Fuel Band SE, includes additional motion-sensing elements that urge users to stand up and walk around more frequently [50].

6.1.6. Smart Earphones

Smart headphones offer innovative application methods for, *e.g.*, intelligent voice analysis and processing, which make it easier for users to manage the equipment with voice commands. In the future, sensors that measure heart rate, body temperature, and activity could be integrated directly into in-ear headphones [51].

7. DIFFERENT APPLICATIONS

This section will cover a few artificial intelligence and wearable device applications (Fig. **7**).

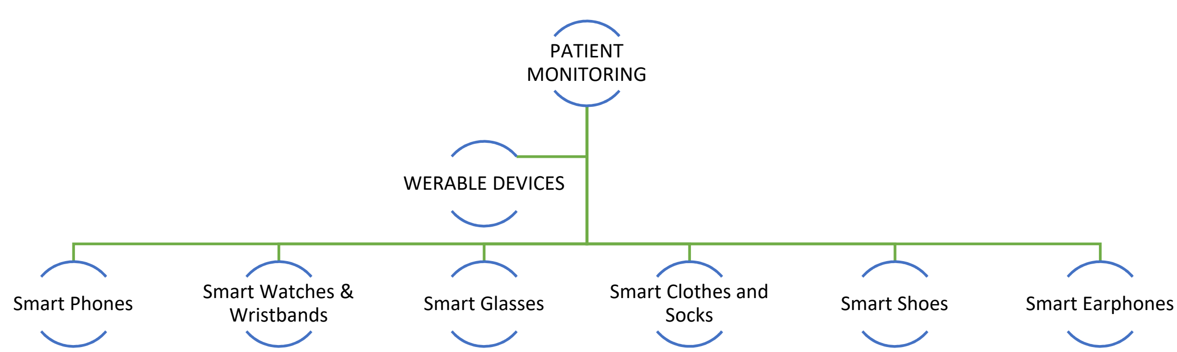

Fig. (6). Patient monitoring. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

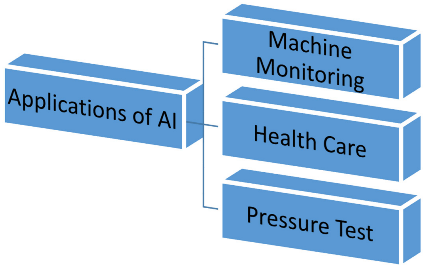

Fig. (7). Application of artificial intellegence. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

7.1. Machine Monitoring

Smartwatches collect information from body parts to monitor falls, warn of special cases, and monitor the elderly to ensure that they receive the required treatment after falling, improving their quality of life and promoting healthy aging.

7.2. Health Care

The records could also be used to decide physical state, health management, chronic disease management, and prevention of disease for the elderly, monitor abnormal conditions in patients with heart disease, and detect ear diseases after physiological data of the human body is collected from integrated embedded intelligent electronic devices or which directly contact the body, such as heart rate, blood pressure, and ear infections. Smartwatches and smartphones, for example, are utilized to collect physiological data connected to Parkinson's disease for scientific treatment and monitoring [52].

7.3. Pressure Test

Smartphones and wristbands record information such as emotion, sleep patterns, fatigue, overall wellness, and liquor intake or adrenaline. This even gathers information about the individual's interactions, such as calls and messages, push notifications, and digital device usage. The emotional trauma levels of users are assessed using a range of data sources [53].

8. ARTIFICIAL INTELLIGENCE IN MEDICAL ROBOTS

Assistive medical robots and devices are among the applications of medical AI technology. Telerobots, *e.g.*, can help patients connect to healthcare personnel; assistant moving devices can aid in navigation and mimic the action of animals, such as robots that can communicate and keep an occupied individual. They are utilized to aid surgeons in surgery. The da Vinci Surgical System is a widely used system of robotic surgery, with more than 3400 units in use as of 2015 (Fig. **8**) [53].

8.1. Requirements of Robotics in Healthcare

The use of robotics and automation in healthcare and related sectors is increasing now more than ever. Surgical robot demand is expected to increase in the upcoming era, according to the International Federation of Robots (IFR), with a business worth USD 9.1 Billion predicted by 2022. Robots not only support doctors and healthcare experts in executing specific and intricate tasks but also lower their workload, boosting the healthcare organization's efficiency [54].

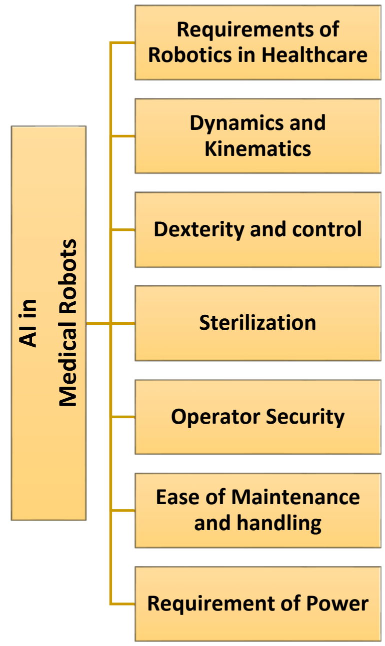

Fig. (8). Artificial intelligence in medical robots. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

8.2. Dynamics and Kinematics

The application determines the kinematics and dynamics of a medical robot. Serial and parallel robots are used in various activities by surgical and rehabilitative robots and service robots click [55]. Flex Picker (ABB, Zurich, Switzerland), often called the "Delta" robot, is a Parallel Kinematic Manipulator (PKM) that was developed for clinical uses but is now majorly applied in the field of the food processing industry [56]. Most medical robotics technologies are ambulatory machines with a significant loading capacity but limited Degrees of Freedom (DOF). Medical robots with many variables on either side are adaptable, precise, and trustworthy equipment that functions like a well-trained human surgeon, with a minimal error range of centimetres or less [57].

8.3. Dexterity and Control

The control of medical robotics is a dissimilar subject [58] since it needs excellent precision, reliability, and repeatability while limiting the effects of external disturbances. Furthermore, designers must give enough degrees of freedom (DOF) for the results to move in the logged axis by addressing the difficulty of control and dexterity. Cleaning, sterilizing, transport, nursing, rehabilitation, and surgery are all performed by medical robots, which utilize cutting-edge technology. Adaptive robust embedded controllers are often utilized to control and navigate such complex and nimble robots [59].

8.4. Sterilization

Robots used in wellness programs and medical must be free of viruses that convey easily transferable and contagious viruses to other victims; thus, they must be thoroughly cleaned [60]. The majority of surgeons and effectors are designed to be used once [61]. Service robots must be sterilized regularly to avoid becoming infective carriers. Because cooking robots may be washed after usage, they have their cleaning routine.

8.5. Operator Security

This is one of the most important needs in medical robotics because when working with a robot in a hospital, the operator's safety is critical [62]. The operator, medical staff, physician/surgeon, and patients should all be able to be near the robot within the hospital without being at risk. Surgical robots must adhere to the IEC 80601-2-77 standard's safety requirements. The IEC 80601-2-78 standard specifies the essential safety and performance requirements for rehabilitation robots [63].

8.6. Ease of Maintenance and Handling

Health personnel, surgeons, and other hospital employees with no mechanical skills are trained to operate robots. Therefore, for the brief use of such apparatus, designers must constantly ensure simple architecture, easy handling, and quick maintenance. Healthcare service automatons help individuals with simulators, prosthetics, ear monitors, and retinal prosthetics, all of which are low-maintenance devices [64].

8.7. Requirement of Power

Medical robots require continuous AC/DC electricity to operate. Several renewable energy sources are employed to provide reliable electricity to medical facilities ranging in size from majority numbers, middle situated metropolitan hospitals to small hospitals [65]. Wireless power transmission for mobile robots in hospitals is also being explored to decrease the need for frequent recharge.

9. CLASSIFICATION OF THE UTILIZATION OF ROBOTS USED FOR HEALTHCARE

Robots are differentiated mostly according to their use in medical and similar fields. The classification includes receptionist robot areas, hospital nurse robot areas, ambulance robot areas, telemedicine robot areas, hospital serving robot areas, cleaning robot areas, spraying/disinfestations robot areas, surgical robot areas, radiologist robot areas, rehabilitation robot areas, food robot areas, and outdoor delivery robot areas (Fig. **9**) [66].

9.1. Robots as Receptionist

This type of robot works best in a hospital's welcome area, where it may disseminate information about the hospital's various units/sections and direct patients and visitors. They can take care of a large group of people without growing weary and refer them to the doctor of their choice. They are especially enticing to hospitalized children since they astound them by providing exciting experiences. As a result, their symptoms of malaise will be reduced [65].

9.2. Robots as Nurses in Hospitals

This type of robot is designed to assist doctors like human nurses in the hospital. Robots as nurses are widely utilized in hospitals in Japan, as the country has the greatest proportion of old people (over 75 years) among Organisation for Economic Co-operation and Development (OCED) countries. Medical facilities in the country are facing an increasing problem because of this. More Japanese residents are socially compelled to look after aged family members at home instead of working due to inadequate recruitment for senior care [67]. Furthermore, nurses and healthcare workers are stressed and exhausted due to the heavy patient load. As a result, the Japanese government is considering technology alternatives to care for the country's elderly patients [68].

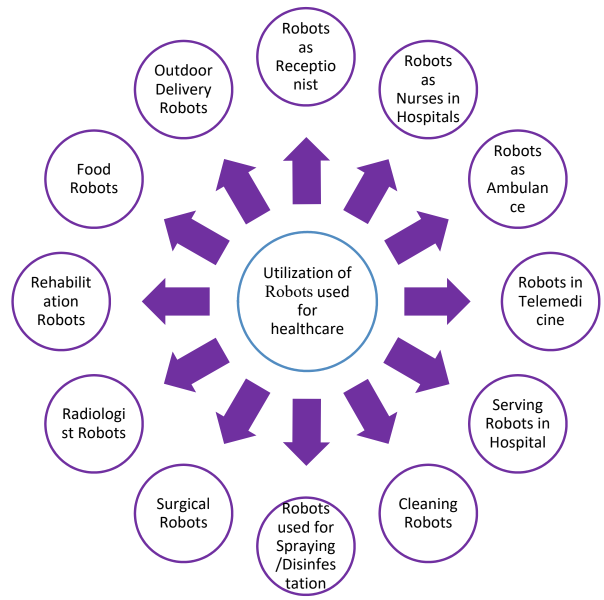

Fig. (9). Utilization of robots used for healthcare. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

9.3. Robots as Ambulance

Immediate medical attention is necessary following an accident to prevent the trauma from worsening. Because of the faster recovery, more lives can be spared. This is especially true in drowning, heart failure, shocks, and breathing issues. Emergency medications, cardiopulmonary resuscitation (CPR), and Automated External Defibrillator (AED) equipment are made to be small and can convey to an emergency site by a flying drone [69]. These robots can provide emergency treatment to a mobile or remote patient with a short response time.

9.4. Robots in Telemedicine

These robotics are utilized in telemedicine services, in which a nearby doctor collects all physical data and treatment of virus *via* audio-visual help [70]. These devices are especially beneficial for diseases in rural parts with few healthcare practitioners.

9.5. Serving Robots in Hospital

Transfer of products is essential for numerous tasks in hospitals. Using serving robots, these heavy-duty chores may be completed quickly. Robots are also used to deliver food to a variety of hospital patients. They are used to distribute edibles, dispense drugs and discard material to be washed, bring beddings, and transfer waste, among other things, within the hospital [71].

9.6. Cleaning Robots

Vacuuming and/or mopping robots are utilized in cleaning. They are also used for sanitizing hospital environments that appear capable of delivering the needed non-industrial robot system inventors predicted years ago. These robots sanitize hospitals and eliminate bacteria and pesticides [72].

9.7. Robots Used for Spraying/Disinfestations

They are commonly employed to spray antiseptic concoctions over vast outdoor areas, such as city residential neighbourhoods. Such robots are being controlled remotely to avoid dangerous interaction with the antibacterial mist. Hand sanitizer spraying robots with autonomous directions are being created to prevent diseases on individuals' hands and faces. Alcohol-based sanitizers prevent infection, parasites, and other microorganisms and minimize the transmission of infectious agents among many individuals [73].

9.8. Surgical Robots

Compared to human surgeons, surgical robots provide precise and accurate minimally invasive surgery (MIS). For remote surgery, many teleoperators have been developed [74]. Fourth-generation Da Vinci surgical systems (Intuitive Surgical, California, USA) continue to advance MIS across many surgical methods. For surgeons utilizing Da Vinci systems, this provides an upgradeable design with variable setups and a trustworthy interface. Instrument and component standardization aids hospital inventory management and efficiency [75].

9.9. Radiologist Robots

Radiography is indeed one of the advanced components wherein robotics is employed with a greater reliance due to high levels of radiation and safety concerns for system interaction. The Siemens Twin Robotic X-ray [76]. Siemens Healthineers, Henkestr, Germany, is a radiology device that can perform imaging techniques, angioplasty, and 3D photography [77]. It can do a variety of X-rays in the same room, and the surgeon can watch 3D visual information as the motor is running rather than just the patient. A computed tomography (CT) 3D scan is essential to confirm the diagnosis because typical 2D X-rays frequently overlook small cosmetic cracks inside the marrow. The MultitomRax Twin Robotic X-ray system can collect a 3D image on the same system, eliminating the need for a CT system [78].

9.10. Rehabilitation Robots

The machines can be beneficial for the recovery of individuals who have had an accident or have had a stroke [79]. It can be useful in helping and caring for persons who are paralyzed, old, or in awkward situations. The machines encourage serviceable reorganization, recompense, and nervous system rejuvenation, which successfully reduces muscle wither. Hence, helpers are relieved of arduous work, allowing healthcare resources to be better utilized.

9.11. Food Robots

These machines are essential to a clinic's cafeteria and storage, ensuring that elevated food is delivered by hygiene requirements. Robots have devised a variety of mechanization and autonomous systems, ranging from dining to service. In Mandarin hospitals, a robotic cook is in use. In the hospital cafeteria, waiting robots will bring the food. Cookie (Sereneti Kitchen, Atlanta, Georgia, United States) and Moley (Moley Robotics, London, United Kingdom) are two different types of culinary robots having one and two robotic hands, respectively [80].

9.12. Outdoor Delivery Robots

The delivery robots are used in transporting/delivering drugs and blood samples to/from the hospital. These fully autonomous robots can operate on the ground or in the air autonomously or with the man-in-the-loop operation, whereas an operator at a distance can remotely control them [81].

Starship robots (San Francisco, USA) are another example of surface delivery robots that can transport things weighing below 100 pounds within a 4-mile (6-kilometer) radius. Pharmaceuticals, packages, foodstuffs, and meals are among the places of interest, shipped from clinics and retailers by orders placed by customers using a smartphone app. The robot's whole travel and whereabouts are tracked on a cell phone when the order has been placed.

Additionally, an electronic barrier is employed to lock the cargo compartment across the journey to assure secure delivery. The mobile phone app is used to open it at the user's end [82].

10. ARTIFICIAL INTELLIGENCE IN COVID-19 PANDEMIC

Artificial intelligence (AI) is another such thing that could help monitor the virus spread, identify and prioritize individuals, and control infections in real-time [83]. Thoroughly assessing the patient's historical data may also forecast mortality risk. By offering public screening, medical aid, notification, and infection management advice, AI can help us tackle this virus [84].

10.1. Important Applications of AI in the COVID-19 Pandemic

10.1.1. Early Detection and Diagnosis of the Infection

A computer program can easily detect abnormal symptoms and other 'risk factors, warning patients and medical workers [85]. It facilitates premium decision-making by allowing for speedier decision-making. It aids in the construction of fresh COVID 19 diagnostics and government policymakers employing relevant algorithms (Fig. **10**). Medical imaging technologies such as computed tomography (CT) and magnetic resonance imaging (MRI) scans of human body sections can help AI aid in the diagnosis of infected individuals [65, 86].

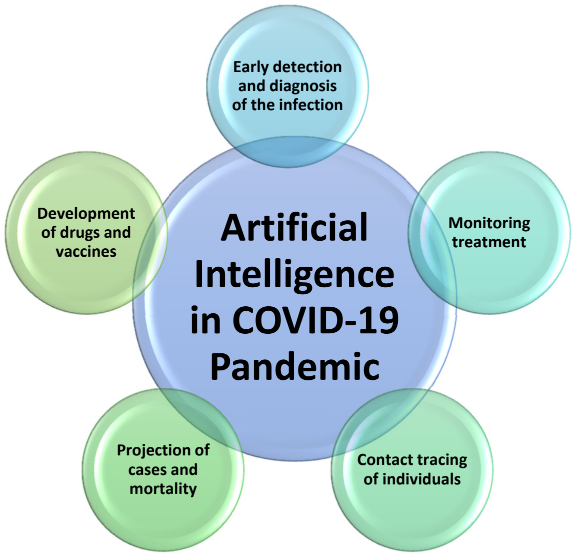

Fig. (10). Artificial intelligence in COVID-19 pandemic. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

10.1.2. Monitoring Treatment

AI could create a firm foundation for identity and epidemic prediction. The visual aspects of this sickness could be extracted using a neural network, leading to greater evaluation and treatment of those impacted [87].

10.1.3. Contact Tracing of Individuals

Intelligence can help determine the bacteria's contamination rate, detect groups & 'hot spots, and successfully surveil individual contacts. It can predict how the sickness will progress later and whether or not it will return [88].

10.1.4. Projection of Cases and Mortality

This system can track and anticipate the virus characteristics, the risks of infection and its expected propagation using existing data, social media, and media outlets. This can forecast the number of positive cases and deaths in a particular area. AI can assist in identifying its most susceptible regions, individuals, and nations to take appropriate action [89].

10.1.5. Development of Drugs and Vaccines

AI can help in drug research by analysing beforehand data on COVID-19. It could be used to generate fresh medicine delivery methods. When traditional testing takes a long time, this technology is utilized to speed up drug screening in real-time, which helps to greatly speed up a procedure that would be impossible for a human to accomplish. It has the potential to aid in the establishment of better COVID-19 treatments. It has become an effective component in creating medical techniques and immunizations. C-S66 AI accelerates vaccine and treatment development and drug testing during vaccine development [90].

CONCLUSION

- AI has improved clinical diagnostic and decision-making performance in various medical task categories.
- AI is intended to aid in investigating considerably more complex but closer-to-real-life clinical concerns, resulting in better stroke care decision-making. Recently, researchers have begun work on this approach, with promising preliminary results.
- Artificial Intelligence-based algorithms can provide accurate early warning and assist specialists in developing and implementing effective illness diagnostic, control, and preventive measures.
- Rapid breakthroughs in AI research and the resources offered by governments and businesses make it highly likely that AI will be widely applied in healthcare delivery, with enormous cost-cutting and service quality enhancement possibilities.
- While inspiring and driving innovation in the field, AI is created and applied in a transparent and public-interest-friendly manner. Patients with COVID-19 can benefit from AI-assisted treatment and reliable health monitoring.
- It can track the COVID-19 outbreak on various dimensions, including medical, molecular, and epidemiological data. It is also advantageous to make viral research easier by analysing existing data.
- AI can help in the discovery of pharmaceuticals and vaccines, as well as the establishment of successful treatment regimens and prevention measures.

LIST OF ABBREVIATIONS

AED	=	Automated External Defibrillator
AI	=	Artificial Intelligence
CNN	=	Convolution Neural Network
CPR	=	Cardiopulmonary Resuscitation
CT	=	Computed Tomography
DI	=	Deep Learning
DL	=	Deep Learning
DOF	=	Degrees of Freedom
EMR	=	Electronic Medical Records
EP	=	Equivalence Partitioning
IFR	=	International Federation of Robots
MI	=	Machine Learning
MIS	=	Minimally Invasive Surgery
ML	=	Machine Learning
MRI	=	Magnetic Resonance Imaging
NLP	=	Natural Language Processing
PCA	=	Patient-Controlled Analgesia

PKM = Parallel Kinematic Manipulator

SVM = Support Vector Machine

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CONFLICT OF INTEREST

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