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Pervasive Nature of AI in the Health Care Industry: High-Performance Medicine

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ABSTRACT

In recent years, there has been a rapid development in artificial intelligence (AI) in terms of hardware implementation, software algorithms, and applications across a wide range of fields. AI has the potential to completely change healthcare delivery and medical practice. This paper discusses the potential future path of AI-augmented healthcare systems, outlines current advancements in the field, and outlines a road map for developing efficient, dependable, and safe AI systems. The utilisation of labelled large data, together with significantly increased processing power and cloud storage, has made artificial intelligence and the deep-learning subtype in particular, possible in all fields. This is starting to affect medicine on three fronts: first, by allowing physicians to interpret images quickly and accurately; second, by enhancing workflow and potentially lowering medical errors in health systems; and third, by empowering patients to handle their own data to improve their own health. This research work will address the applications present limitations—such as prejudice, privacy and security concerns, and a lack of transparency—as well as their potential future paths. It is expected that significant gains in accuracy, productivity, and workflow will be realised over time; however, it is unclear if these gains will strengthen or worsen the patient-doctor bond.

KEYWORDS:

Artificial intelligence, Machine learning, Deep learning, Neural network, Biomedical research, Healthcare applications.

1. Introduction:

The definition of artificial intelligence (AI) is the intelligence possessed by machines as opposed to that of humans or other living things [1]. The study of "intelligent agents," or any agent or device that can sense and comprehend its environment and then react appropriately to maximise the likelihood that it will achieve its goals, is another definition of artificial intelligence (AI) [2]. Artificial intelligence (AI) also describes scenarios in which machines are able to learn and analyse like human minds and, as a result, solve problems. Machine learning (ML) is another term for this type of intelligence [3]. Artificial Intelligence usually comprises a system that is composed of hardware and software. From an algorithmic standpoint, artificial intelligence is especially focused on software. A conceptual framework for implementing AI algorithms is called an artificial neural network (ANN) [4]. It is a simulation of the human brain, which consists of a network of connected neurons with weighted communication channels between them. A single neuron can respond to several inputs from nearby neurons, and the network as a whole can alter its state in response to various environmental stimuli [5]. Because of this, a neural network (NN) can produce outputs in reaction to external stimuli, much like the human brain does in response to various environmental alterations. Usually, NNs are multi-layered structures with different topologies. The most intriguing development is that scientists working in the biomedical domains have been actively attempting to use AI to enhance analysis and treatment results, hence raising the effectiveness of the healthcare system as a whole [6].

The number of publications in this field over the last 20 years, from 1999 to 2018, is displayed in Fig. 1. It is clear that interest has grown, particularly in the previous five years, and future growth is predicted. A few decades ago, it was anticipated that AI might assist biomedicine [7]. Indeed, reviews of AI's application in biomedical engineering have been published [8]. Recent years have seen new developments in AI and its uses in biology.

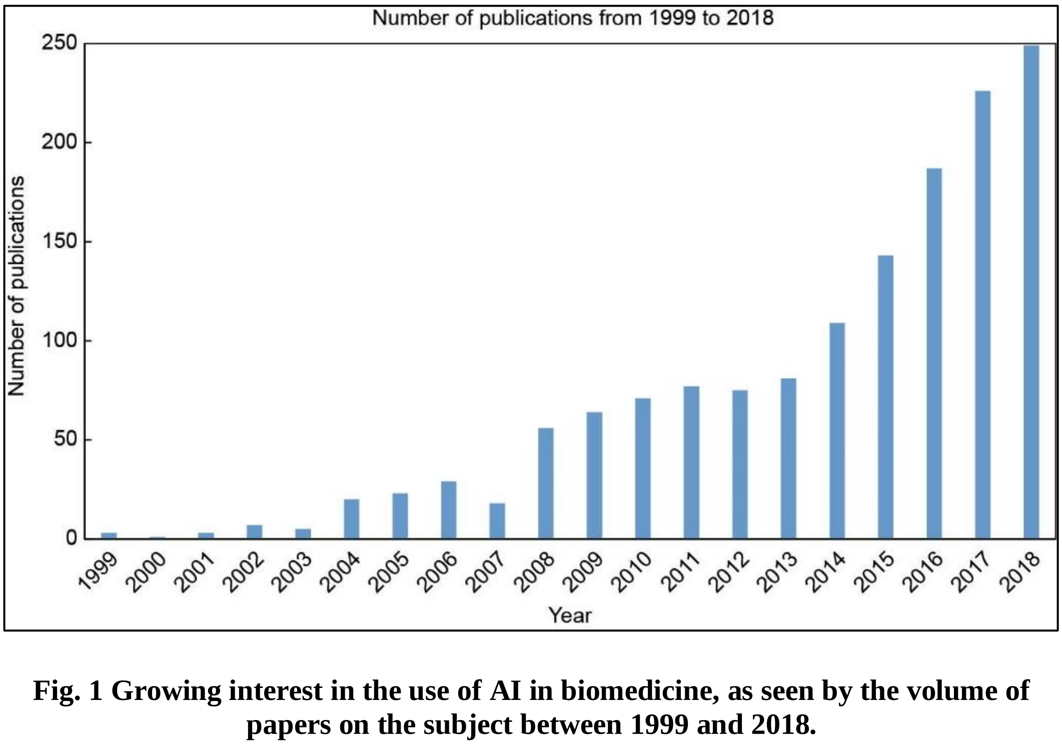

Fig. 1 Growing interest in the use of AI in biomedicine, as seen by the volume of papers on the subject between 1999 and 2018.

In medicine, two significant trends are intersecting. The first is a failing business model that has led to rising healthcare costs and employment, but has also resulted in declining major outcomes, such as lower life expectancy and high rates of infant, child, and maternal death in the United States [9]. This is a prime example of a contradiction that is not unique to American medicine: greater human capital invested yields worse health results for people.

The second is the vast production of data from sources including genome sequencing, computerised medical records, biosensors that continuously produce physiological measurements, and high-resolution medical imaging. It is obvious that human examination of such data is no longer sufficient, and a greater dependence on robots is required [10]. Algorithms are therefore badly needed to assist at a time when healthcare is more dependent than ever on humans. However, the use of AI and human intelligence (HII) to medicine is still in its early stages. If we dig a little more, we find that the healthcare system has long-standing, significant flaws that contribute to its declining returns.

These comprise a high frequency of severe diagnostic errors, treatment errors, massive resource waste, inefficiencies in workflow, disparities, and insufficient time between patients and providers [11]. Leaders in computer science and healthcare have expressed a desire for change and said that artificial intelligence (AI) might play a part in solving all of these issues. That may prove to be true in the end, but scientists are only just beginning to use neural networks to improve the negative aspects of practicing medicine. We have compiled a large portion of the body of research supporting the application of AI in medicine in this review, outlining both the advantages and disadvantages [12]. More personal, predictive, preventative, and participatory healthcare is the aim, and AI can play a significant role in achieving these goals. Based on a summary of the achievements, we predict that artificial intelligence (AI) will keep growing and becoming an increasingly potent tool for biomedicine.

2. Artificial Intelligence for Medical Professionals:

In the future, almost all clinical specialties—from specialised physicians to paramedics—will use artificial intelligence (AI) technologies, particularly deep learning. Deep neural networks (DNNs), which can assist in the interpretation of medical scans, pathology slides, skin lesions, retinal pictures, electrocardiograms, endoscopy, faces, and vital signs, were primarily used for pattern recognition in this process. A receiver operating characteristic (ROC) plot of true-positive against false-positive rates is commonly used to compare the neural net interpretation with doctors' assessments. The accuracy level of this plot is expressed as the area under the curve (AUC).

2.1. Radiology:

Radiology is one area where AI applications have drawn a lot of interest. Around 2 billion chest X-rays are taken annually all around the world, making them the most used type of diagnostic imaging. In one study, four radiologists' and one algorithm's accuracy in identifying pneumonia in approximately 112,000 labelled frontal chest X-ray pictures was compared. The algorithm's performance was shown to be superior. The algorithm was built on a 121-layer convolutional neural network. The algorithm's AUC of 0.76 for chest X-ray interpretation is far from ideal, although being somewhat better than that of two previously tested DNN systems [4]. Furthermore, a radiologist's daily activities are not always equivalent to the test employed in this study, as they will diagnose much more than pneumonia in any one scan. It is recommended to compare the findings of this study with those of over four radiologists in order to further corroborate the findings. The same image collection as in the previously stated study was analysed by a Google team using an algorithm, and the results showed 14 distinct diagnoses with AUC scores ranging from 0.63

for pneumonia to 0.87 for heart enlargement or collapsed lung [13]. More recently, in another related work, it was demonstrated that a DNN, which is being used in Indian hospitals, was at least as accurate as four radiologists in interpreting the important findings of four separate chest X-rays. In the more specific task of identifying malignant pulmonary lesions on a chest X-ray, a DNN that evaluated scans from more than 34,000 patients in the past was able to surpass the accuracy of 17 out of 18 radiologists [14]. While diagnosing wrist fractures can be challenging for ER physicians, the use of a DNN significantly improved the diagnostic process, lowering misunderstanding by 47% and raising sensitivity from 81% to 92% [15].

2.2. Pathology:

Compared to radiologists, pathologists have adopted scan digitization significantly more slowly; they still do not often scan glass slides to digital pictures or utilise whole-slide imaging (WSI), which allows one to observe a tissue sample in its entirety on a slide [16]. There has been a great deal of research on the marked variability and inconsistent interpretation of slides by pathologists. One example of this is the lack of agreement in the diagnosis of common kinds of lung cancer (K=0.41–0.46) [17]. A few retrospective studies have evaluated the potential benefits of deep learning on digitised pathology slides, including increased speed and accuracy of interpretation. The duration that the pathologists had to analyse the slides had an impact on the findings of a study of WSI of breast cancer, with or without lymph node metastases, which compared the performance of 11 pathologists with that of different algorithmic interpretations [18]. The results varied. A subset of the five algorithms outperformed the team of pathologists with differing levels of experience. Less than one minute was allotted to each of the 129 test slides that the pathologists had to review, which probably does not reflect typical workflow. On the other hand, the findings were comparable with the algorithm for detecting non-invasive ductal carcinoma when one expert pathologist reviewed the identical slide set over the course of 30 hours with no time constraints [19].

2.3 Dermatology:

Deep learning networks have been comparable to dermatologists in terms of diagnosis accuracy for algorithms that classify skin cancer using picture analysis. An algorithm with an AUC of 0.96 for carcinoma and 0.94 for melanoma particularly outperformed 21 US board-certified dermatologists in a study that used a sizable training dataset of over 130,000 digitised photographs from photography and dermascopic work [20]. A convolutional neural network was then used to assess the accuracy of diagnosing melanoma skin cancer among 58 worldwide dermatologists. The mean ROCs were 0.79 versus 0.86, respectively, indicating that the algorithm performed better than the majority of the doctors [21]. In a third investigation, 12 skin conditions, including melanoma, squamous cell carcinoma, and basal cell carcinoma, were assessed algorithmically and compared to the opinions of 16 dermatologists. For melanoma, the algorithm achieved an AUC of 0.96 [22]. These investigations were not carried out in a clinical environment, where a physician would conduct a physical examination and be accountable for providing a precise diagnosis. Despite these reservations, primary care physicians identify the majority of skin lesions, and accuracy issues have been noted. It would be a major advancement if AI could be consistently demonstrated to mimic skilled dermatologists.

2.4 Ophthalmology:

Numerous studies have compared the accuracy of algorithms and ophthalmologists in the diagnosis of various eye disorders. A neural network was trained with over 128,000 retinal fundus photos labelled by 54 ophthalmologists. The neural network was then trained with over 10,000 retinal fundus photos from over 5,000 patients to assess for diabetic retinopathy [23]. The neural network's grading for all-cause referable diagnoses (moderate or worse retinopathy or macular edoema; scale: none, mild, moderate, severe, or proliferative) was compared with the scores of seven or eight ophthalmologists. The AUC was 0.99 in two different validation sets [24]. The accuracy of DNN algorithms varied from 88% to 92% in a research where retinal fundus pictures were used to diagnose age-related macular degeneration (AMD), almost matching the accuracy of skilled ophthalmologists [25]. The ability of a deep learning algorithm to analyse retinal optical coherence tomography (OCT) and diagnose either of the two most prevalent causes of vision loss—diabetic retinopathy or AMD—was compared to that of ophthalmologists. Following training on a dataset containing more than 100,000 OCT pictures, the algorithm's performance was assessed using six ophthalmologists and 1,000 of these images for validation. For OCT-based urgent referral, the algorithm's AUC was 0.999 [26].

2.5 Cardiology:

Cardiologists primarily utilise two types of pictures in their practice: echocardiograms and electrocardiograms (ECGs), both of which have been evaluated using DNNs. Rules-based algorithms have been used to read ECGs by machines for almost 40 years, yet their accuracy has been noticeably poor. A sensitivity of 93% and specificity of 90% were observed when deep learning was used to identify heart attack in a small retrospective dataset of 549 ECGs, which was similar with cardiologists [27]. A DNN and six cardiologists evaluated nearly 64,000 one-lead ECGs (from over 29,000 patients) for arrhythmia, and their accuracy was equivalent across 14 distinct electrical conduction disturbances [28]. A DNN and cardiologists categorised a small sample of 267 patient studies (with approximately 830,000 still pictures) for echocardiography into 15 conventional perspectives (such subcostal or apical 4-chamber). Although the algorithm's overall accuracy for a single still image was 92% and the four board-certified echocardiographers' accuracy was 79%, the real-world reading of studies—which are in-motion video loops—does not correspond to this [29].

High accuracy for the classification of cardiac amyloid (AUC, 0.87), pulmonary artery hypertension (AUC, 0.85) and hypertrophic cardiomyopathy (AUC, 0.93) was found in even bigger retrospective research using over 8,000 echocardiograms [30].

2.6 Gastroenterology:

It can be quite challenging for gastroenterologists to find tiny (<5mm) sessile or adenomatous polyps during a colonoscopy. In a real-time, routine colonoscopy, 325 patients with a total of 466 small polyps underwent the first prospective clinical validation of AI, which found 94% accuracy and 96% negative predictive value [6]. With no need for dye injections, the AI optical diagnosis algorithm performed well for both inexperienced and seasoned gastroenterologists, taking only 35 seconds to complete. Another independent study confirmed the findings of increased speed and accuracy [8].

These findings are thematic: machine vision can rapidly and accurately evaluate some medical images at high magnification, matching or surpassing human performance.

2.7 Mental Health:

The massive burden of mental health—350 million people worldwide suffer from depression, for example—is particularly notable since AI may be able to help both the patients and the glaring shortage of clinicians. Digital techniques for measuring depression and mood are being developed. These include audio, voice, facial recognition, keyboard input, sensors, and interactive chatbots. Research indicates that Facebook posts can accurately predict the diagnosis of depression that is later recorded in electronic medical records [31]. It has been investigated if machine learning can predict antidepressant medication success, characterise depression, predict suicide and predict psychotic episodes in schizophrenia [32].

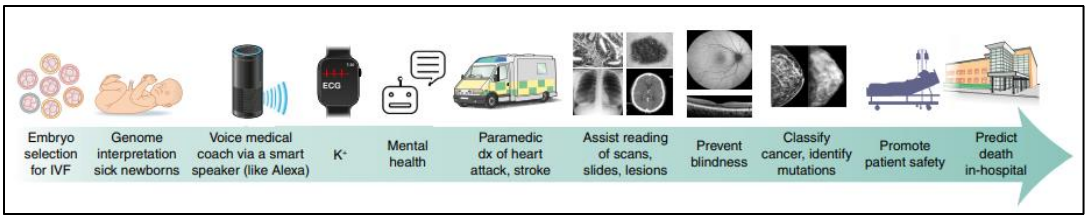

Fig. 2 Examples of applications of AI for people of all ages.

3. AI in Health Systems and Biological Information Processing:

In natural language processing, advances have been achieved for biomedical applications. The goal of biological question answering (BioQA) is to quickly and precisely retrieve responses from a database of documents and datasets in response to inquiries posed by users. As a result, it is reasonable to anticipate that natural language processing algorithms will look for instructive responses [22]. In order to obtain relevant information from the answers, the biological questions must first be divided into various categories. With an accuracy of about 90%, machine learning can classify biological issues into four fundamental categories [23]. Subsequently, areas of the documents that are most likely to contain the answers to the biomedical queries can be effectively retrieved using an intelligent biomedical document retrieval system [24]. Information extraction from binary responses can be successfully accomplished using a novel approach for processing one of the four fundamental forms of BioQA: the yes-or-no answer generator, which comes from word sentiment analysis [25].

Theoretically, accurate and efficient utilisation of hospital palliative care resources could result from the ability to forecast important outcomes. For instance, actions may be taken to prevent discharge and direct resources towards the underlying problems if an algorithm could be developed to assess the likelihood of a patient's hospital readmission that would not otherwise be detectable given the standard clinical criteria for discharge. An extremely high chance of short-term survival for a severely ill patient could be helpful to the patient, their family, and the physician when deciding whether to do invasive procedures such endotracheal tube insertion for artificial ventilation or resuscitation.

In a similar vein, AI prediction algorithms may help determine which patients would benefit from palliative care and who is most likely to suffer sepsis or septic shock. Machine- and deep-learning algorithms have been able to predict a wide range of critical clinical indicators, from Alzheimer's illness to death, using data from electronic health records in Table1 [33,47]. For instance, reinforcement learning was applied retrospectively on two sizable datasets in a recent study to suggest the dose of the chosen treatment and the use of vasopressors, IV fluids, and/or medications for sepsis patients. The treatment chosen by the "AI Clinician" was, on average, consistently more effective than the one chosen by humans [71].

Table 1: Selected reports of machine- and deep-learning algorithms to predict clinical outcomes and related parameters

Prediction	*n*	AUC	Publication
In-hospital mortality, unplanned readmission prolonged LOS, final discharge diagnosis	216,221	0.93*0.75^{+}0.85$^{\#}$	Rajkomar et al.
All-cause 3–12 months mortality	221,284	0.93$^{\wedge}$	Avati et al.
Readmission	1,068	0.78	Shameer et al.
Sepsis	230,936	0.67	Horng et al.
Septic shock	16,234	0.83	Henry et al.
Severe sepsis	203,000	0.85@	Culliton et al.
Clostridium difficile infection	256,732	0.82^{++}	Oh et al.
Developing diseases	704,587	Range	Miotto et al.
Diagnosis	18,590	0.96	Yang et al.
Dementia	76,367	0.91	Cleret et al.
Alzheimer’s Disease (+ amyloid imaging)	273	0.91	Mathotaarachchi et al.
Mortality after cancer chemotherapy	26,946	0.94	Elfiky et al.
Disease onset for 133 conditions	298,000	Range	Razavian et al.
Suicide	5,543	0.84	Walsh et al.
Delirium	18,223	0.68	Wong et al.

The findings of AUC accuracy range and cohort size exhibit significant heterogeneity. Furthermore, the data are retrospective in nature and have not been validated in an actual clinical environment. However, a number of businesses have already begun to commercialise these algorithms. One such business is Careskore, which gives health systems an estimated risk of readmission and mortality based on EHR data [48]. Beyond this problem, there are the distinctions between an individual prediction metre and the prediction metric for a cohort. A model's ability to predict an event, like death, for the entire cohort is indicated if its AUC is 0.95, which most would consider to be quite accurate. However, as most models are essentially classifiers rather than being able to make exact individual predictions, there is still a significant amount of uncertainty.

To improve predictive accuracy, imaging has been combined along with data from electronic health records [41]. Many research has tried to estimate biological age, and it has been found that DNA methylation-based biomarkers are the most effective way to do this [49]. Since a large portion of unstructured data—the free text in clinician notes that cannot be ingested from the medical record—and many other modalities, like socioeconomic, behavioural, biologic "-omics," or physiologic sensor data, have not been incorporated, the incompleteness of data input is noteworthy in terms of the accuracy of algorithms for predicting biological age.

Furthermore, because small sample sizes can often result in overfitting of the data, concerns have been expressed concerning this possibility. Additionally, it has been noted that the majority of these articles lack κ-fold cross-validation, which is crucial for validating a model using successive, mutually exclusive validation datasets. The use of AUC as the primary performance indicator is also hotly debated because it disregards actual probability values and can be especially deceptive when it comes to the sensitivity and specificity values that are important for clinical purposes [50]. In essence, until there is strong validation in prospective, real-world clinical settings, with rigorous statistical technique and analysis, it is unknown how well AI can predict important outcomes in the healthcare sector.

4. AI and Patients:

Although there are a few deep-learning algorithms that have received FDA clearance or are in the last stages of clinical research, the work to build these algorithms so that the general population can manage their own healthcare has lagged behind that for clinicians and health systems. An FDA-approved smartwatch algorithm for the detection of atrial fibrillation was approved in late 2017 [51]. The FDA then approved Apple's algorithm for use with the Apple Watch Series 4 in 2018 [52]. The watch's accelerometer and photoplethysmography sensors pick up the user's algorithm. There are justifiable worries that the widespread application of this method may result in a significant number of false-positive atrial fibrillation diagnoses and needless medical evaluations, especially in the low-risk, young population that wears Apple watches [53]. On the other hand, individuals with renal problems may find the smartwatch's deep learning of the ECG pattern especially helpful since it can precisely identify if there is elevated potassium in the blood. The notion of a blood potassium level reading that is "bloodless" (Fig. 2) through an algorithm on a smartwatch represents the potential for an algorithm to offer information that was not previously available or perceptible without technology.

There is precedence for virtual medical coaching in the future with the use of AI and multimodal data to advise customised nutrition plans. Currently, glucose control in individuals with diabetes is achieved by the use of straightforward rules-based algorithms that depend on whether glucose readings are increasing or decreasing. Although they have been successful in preventing hypoglycaemic episodes, intelligent algorithms that take into account a person's whole set of data are probably going to be far more insightful and useful [54]. The majority of common chronic illnesses, including depression, asthma, and hypertension, may thus be better controlled with virtual coaching. Given the significant advancements in AI speech recognition accuracy and the concomitant surge in the popularity of smart speakers, it is not difficult to imagine this being done via a voice platform, either with or without an avatar.

An all-encompassing preventive strategy would eventually be achievable once all of a person's data and the body of medical literature are combined.

5. Identification and Prognosis of Diseases:

In biomedicine, disease diagnosis is where artificial intelligence is most urgently needed. In this field, several intriguing discoveries have been made. AI enables medical practitioners to diagnose many different types of diseases more quickly and accurately. Using biosensors or biochips for in vitro diagnostics is one of the main categories of diagnosis. For instance, machine learning (ML) can be used to analyse gene expression, a crucial diagnostic tool that involves classifying and identifying anomalies by interpreting microarray data. Classifying cancer microarray data for cancer detection is one new application [55]. Early detection of cardiovascular illnesses can be achieved using integrated AI in biosensors and associated point-of-care testing (POCT) systems [56]. AI can assist in the diagnosis as well as the prediction of cancer patients' survival rates, including those with colon cancer [57]. Additionally, certain limits of machine learning in biomedical diagnostics have been recognised by researchers, who have also proposed ways to mitigate these downsides. As a result, AI still has a lot of promise for prognostics and diagnostics.

Medical imaging, which uses two dimensions, and signal processing, which uses one dimension, constitute another significant class of illness diagnostics. These methods have been used for sickness prediction, management, and diagnosis. Artificial intelligence (AI) has been used for one-dimensional signal processing in biomedical signal feature extraction, including electrocardiography (ECG), electromyography (EMG), and electroencephalography [58]. Predicting epileptic seizures is a significant use of EEG. Predicting seizures is crucial to reducing their negative effects on patients. AI has gained recognition as one of the essential components of a trustworthy and accurate prediction system in recent years [59]. Deep learning has made predictions possible, and the prediction platform can be integrated into a mobile system [33]. AI has a significant impact on biomedical image processing-based diagnostics as well. In order to enhance image quality and analysis efficiency, artificial intelligence has been applied to image segmentation, multidimensional imaging, and thermal imaging [34]. Additionally, AI can be included into portable ultrasound devices, enabling even non-trained individuals to use ultrasound as a potent diagnostic tool for a wide range of diseases in developing nations [35]. Apart from the aforementioned uses, artificial intelligence (AI) can help conventional decision support systems (DSSs) to enhance diagnostic precision and ease illness management, hence lessening the workload on staff [36,37]. AI has been utilised, for instance, to assist the diagnosis and treatment of tropical diseases, cardiovascular diseases, and integrated cancer management, as well as to enhance the diagnostic decision-making process [38,39]. These uses highlight the potential of AI as a potent tool for early and precise diagnosis, treatment, and even illness and patient status prediction.

6. Data Analysis and AI:

AI advancement in life science has been noticeably faster than in clinical practice, despite being upstream. This is due to factors such as widespread peer-reviewed publication, a simpler validation process without regulatory monitoring, and a greater openness to use AI within the scientific community.

The microscope is the emblem of science, much as the stethoscope is the emblem of medicine. Christiansen et al. created in silico labelling using AI [60]. This machine-learning system anticipates the fluorescent labels, bringing in "image-free" microscopy in place of the conventional fluorescent staining of microscopic pictures, which can damage and kill cells and requires a laborious preparation procedure [60]. Subsequently, Nitta et al. duplicated and expanded this ability with image-activated AI cell sorting [61]. Shortly after, Ota et al. published another image-free flow AI analytical method they named "ghost cytometry" to reliably identify uncommon cells [62].

The difficult task of detecting and separating rare cells is addressed by a use of machine learning, which enables quick, accurate, high-throughput sorting based just on cell shape without the need for biomarkers. In addition to encouraging image-free cytometry and microscopy, deep learning AI has been applied to repair or correct out-of-focus images. Furthermore, high-throughput evaluation of 40-plex proteins and organelles within a single cell has been made feasible by computer vision [63].

Analytics of genomic and other -omics biology datasets have been a problem for machine learning and deep learning. For the purpose of categorising or examining whole-genome sequence pathogenic variants, somatic cancer mutations, gene–gene interactions, methylation, prediction of protein structure and protein–protein interactions, the microbiome, and single cells, open-source algorithms have been developed. Although these investigations have often used a single-omics method, multitopic techniques that combine the datasets are now being developed [64,65]. Algorithmic prediction of CRISPR guide RNA activity and off-target activities has also made genome editing more widely used [66].

AI has been used to recreate brain circuits from electron microscopy, enabling a better understanding of connect-omics. One of the most remarkable developments made possible by AI has been the comprehension of the grid cells in the human brain, which allow perception of the body's position in space as well as its speed and direction of movement [67]. Conversely, brain-machine interface development and brain circuitry understanding are facilitated by neuromorphic computing, or the reverse engineering of the brain to create computer chips [68].

Another illustration of the advancements being achieved is the machine vision tracking of animal and human behaviour using a transfer-learning algorithm. Artificial intelligence (AI) is revolutionising drug discovery in a number of ways, such as through sophisticated natural language processing searches of the biomedical literature, data mining of millions of molecular structures, designing and creating new molecules, forecasting toxicity and off-target effects, determining the ideal dose for experimental drugs, and creating large-scale cellular assays [69].

There is fresh hope that machine learning toxicity prediction will lessen the need for preclinical animal testing. Large proprietary pharmaceutical industry datasets have been combined using AI cryptography to find previously unknown drug interactions. Interest in using artificial intelligence (AI) to speed up the process has increased due to the story of the University of Cambridge and Manchester's robot "Eve," which autonomously discovered an antimalarial drug that is a component of toothpaste. As a result, numerous start-ups and partnerships with significant pharmaceutical firms have been formed [70, 72].

7. Conclusion:

In this study, we examined the most recent advancements in the use of AI in biomedicine, encompassing biomedical information processing, living aid, disease diagnosis and prediction, and biomedical research. There are numerous other fascinating uses for AI in the biomedical field. It is evident that artificial intelligence (AI) is becoming more and more relevant in the field of biomedicine. This is due to the complexity of biomedical problems and AI's ability to address them, in addition to AI's ongoing advancement. Innovative biomedical solutions are made possible by new AI capabilities, and biomedical advancements necessitate ever-higher AI skills. In the near future, both fields will be able to advance greatly thanks to this match between supply and demand and paired developments, which will ultimately improve the lives of those who are less fortunate. How well data security and privacy can be guaranteed will determine how much influence AI will have in medicine in the future. There won't be much interest in using algorithms that run the risk of disclosing patient medical history details, given the widespread issues of hacking and data breaches. Additionally, there is a chance that an algorithm will be purposefully hacked to cause widespread harm to humans, such giving diabetics too much insulin or making defibrillators trigger in the chests of heart attack victims. The ability to identify a person using face recognition or genomic sequences from large databases is becoming more and more common, which makes privacy protection even more difficult. Nevertheless, the potential for extreme health risks arises from the obfuscation of reality enabled by generative adversarial networks, which have an apparently boundless ability to alter content. The use of highly secure data platforms, new models of health data ownership with individual rights, and governmental legislation—as in Estonia—are required to combat impending security concerns that could otherwise impede or completely destroy the prospects for advancement in AI for medicine.

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