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SURVEY

Artificial Intelligence and Biosensors in Healthcare and Its Clinical Relevance: A Review

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ABSTRACT Data generated from sources such as wearable sensors, medical imaging, personal health records, and public health organizations have resulted in a massive information increase in the medical sciences over the last decade. Advances in computational hardware, such as cloud computing, graphical processing units (GPUs), Field-programmable gate arrays (FPGAs) and tensor processing units (TPUs), provide the means to utilize these data. Consequently, an array of sophisticated Artificial Intelligence (AI) techniques have been devised to extract valuable insights from the extensive datasets in the healthcare industry. Here, we present an overview of recent progress in AI and biosensors in medical and life sciences. We discuss the role of machine learning in medical imaging, precision medicine, and biosensors for the Internet of Things (IoT). We review the latest advancements in wearable biosensing technologies. These innovative solutions employ AI to assist in monitoring of bodily electro-physiological and electro-chemical signals, as well as in disease diagnosis. These advancements exemplify the trend towards personalized medicine, delivering highly effective, cost-efficient, and precise point-of-care treatment.Furthermore, an overview of the advances in computing technologies, such as accelerated AI, edge computing, and federated learning for medical data, are also documented. Finally, we investigate challenges in data-driven AI approaches, the potential issues generated by biosensors and IoT-based healthcare, and the distribution shifts that occur among different data modalities, concluding with an overview of future prospects.

INDEX TERMS Artificial intelligence, explainable AI, medical imaging, domain adaptation, biosensors, federated learning, big data analytics, large language models.

I. INTRODUCTION

About 10% of global gross domestic product (GDP) (10 trillion USD) is spent on healthcare annually [1]. The recent advancements in technology, especially data-driven methods and computational processing power can benefit,

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both the patients and the medical industry, as well as reduce the huge expenditures. Moreover, massive healthcare data is available from sources such as; electronic health records (EHRs), genomics profiles, medical imaging, chemical, and drug databases. Analytical methods, especially deep learning-based Artificial Intelligence (AI) methods, can provide the tools to design useful clinical and medical applications to process these large datasets. Data-driven methods could offer benefits in medical record digitization, clinical trials, diagnosis assistance, prognosis evaluation, and the design of optimal prevention and treatment strategies, as well as precision medicine, drug discovery, and health policy.

Advances in computational infrastructure have provided the capacity to generate, store, analyze and visualize large, complex, and dynamic datasets typical of modern biomedical studies [2]. New treatment options are being developed and tested in clinical trials [3]. In the last decade, artificial intelligence has moved from theoretical studies to real-time applications thanks to the rise in the computational capacity of GPUs and TPUs. Methods like AutoML [4] and explainable artificial intelligence (XAI) [5] are advancing, which have the potential to transform the current medical practice. However, there are still many bottlenecks to realizing the full potential of analytical methods in the healthcare industry. Important challenges for data science in medicine include data collection, standardization of data formats, missing data values, developing large and efficient computational infrastructure, data privacy and security, and others.

For example, to deal with the small sample size issue in medical images, generative models can be used to generate synthetic medical images of high quality. Generative Adversarial Network (GAN), a type of neural network that can generate synthetic data, can be used to generate synthetic magnetic resonance imaging (MRI) scans or positron emission tomography (PET)-scan images using computed tomography (CT) scans. A subset of images, regardless of size, is a subset of the universal set. Using that small subset, generative models learn the probability distribution of the universal training set. After extracting the representative features, the model can generate high-quality synthetic images by sampling from the probability distribution. These synthetic images can be used to build generalized medical image analysis models for various clinical applications.

The interrelated nature of biomedical data is one of its most important properties. Such data can be represented in the form of graphs. Graph machine learning allows for the modeling of unstructured multimodal datasets. Graph machine learning can model more complex relationships between disease and patients, understand tumor micro-environment, predict drug response, and re-purposing. Additionally, graph machine learning coupled with attention mechanism may provide more interpretable machine learning models than typical traditional black-box models.

The recent breakthrough of the artificial intelligence (AI) system Alphafold2 [6] in predicting the three-dimensional structure of proteins solely from the amino acid sequence is a huge success. AlphaFold2 won the Critical Assessment of Structure Prediction (CASP) [7], the worldwide event for protein structure prediction, since 1994. Meta AI also joined the race and developed an AI system to predict structures of about 600 million proteins [8]. However, how to translate this into the in vivo situation is still an open question. AlphaFold2 can predict unbound protein structures; however, most practical applications require protein-drug complex predictions.

There have also been significant advancements in processing power and biosensor technologies. For example, with the help of parallel processing methods and powerful GPU clusters, such as NVIDIA-DGX, we can now process massive complex multi-dimensional biomedical datasets [9]. Moreover, wearable electronics, such as electronic tattoos (E-tattoos), epidermal electronics systems (EES), and flexible electrochemical bioelectronics, coupled with machine learning algorithms can be used to monitor various biomarkers in real time [10].

As the use of AI in healthcare has been a very active research area, several surveys were found covering this topic [11], [12], [13]. In [11], a discussion about the use of medical sensors with artificial intelligence is presented. In this respect, various sensing systems and the use of AI in medical decision-making are studied. The study in [12] provides coverage of the different wearable sensors for healthcare delivery, primarily from a hardware perspective, and briefly highlights the benefits and challenges of AI. More recent work [13] covers the use of AI in the internet of medical things and its different applications concerning various algorithms. AI methods for combating various medical diseases were also discussed. A survey about AutoML was presented in [14].

Given the enormous progress in recent years for AI in healthcare, an updated review will benefit the community. In this article, we present an updated survey of the recent progress in data-driven methods for healthcare. We specifically discuss practical applications of artificial intelligence, biosensors, and computational infrastructure, concerning clinical relevance. The recent methods which have the potential to become a part of the healthcare industry, such as AutoML [15], explainableAI [16], and Federated learning [17] are evaluated. Moreover, existing clinical tools and emerging AI-based start-up companies are presented. We also highlight the existing challenges for AI in healthcare and present some potential solutions. The use of AI for drug discovery, nano-medicine, and medical robotics is out of the scope of this review. The survey is organized as follows; Section II highlights applications of machine learning in various healthcare sectors. AI-based clinical tools and start-up companies are presented in Section III. Sections IV and V discuss applications of big data analytics and biosensors, respectively. Computational advances, federated learning, and edge computing are discussed in Section VI. The recent challenges in AI for healthcare with potential solutions are explored in Section VII, and Section VIII concludes this review.

II. MACHINE LEARNING IN HEALTHCARE

Data science and machine learning have been successful in many areas related to computer vision, such as self-driving cars, recognizing actions, image classification, and intelligent robots. These are well-posed tasks where the problem is known, and the solution is verifiable. However, healthcare-related tasks involve safety and security risks, leading to privacy concerns. These problems are neither well-posed nor well-defined, and their solutions can be hard to verify. Assessing the risk of life-threatening disease in people infected with the SARS-CoV-2 virus is a recent broad, complex, and urgent problem where data science has been used to suggest prognostic indicators from a wide variety of genetic and physiological markers and the presentation of symptoms [18]. Figure 1 shows an ecosystem for machine learning in healthcare tasks. Machine learning can produce actionable insights for clinical practice, provide recommendations to governments for optimal health policy, and help accelerate and optimize drug discovery and design processes. More established use cases of different machine learning applications in healthcare are presented in Table 1.

A. EXPLAINABLE ARTIFICIAL INTELLIGENCE

While machine learning models applied to biomedical data, have the potential to produce clinically useful judgments, the models, particularly deep learning, are frequently regarded as black boxes that are difficult for humans to understand [5]. This lack of transparency leads to a bottleneck in the clinical implementation of machine learning-based findings, as any decision will directly affect a patient's health. One way to increase the transparency in machine learning predictions is to highlight the feature importance or to visualize features at different layers. This way, we can analyze each feature's importance in the prediction model and better understand the predictions. One such method is known as Grad-CAM visualization [19], based on the target concept's gradients, which flow into the final convolutional layer to build a coarse localization map highlighting significant locations or heat maps in the image for concept prediction. Explainable models, or explainable artificial intelligence, are needed to build the trust of healthcare professionals.

Explainable AI methods are classified based on the complexity and scope of their interpretability [20] and the level of dependencies in the AI model. Explainability has different levels of understanding, including interpretability, stability, robustness, and confidence. A user can not only see but also learn how inputs are mathematically transferred to outputs in an interpretable system, whereas a stable system is not misled by small perturbations or noise in the input data. The possibility of an event occurring is measured by confidence. The purpose is to quantify the level of confidence in the decision [21].

Complex deep learning models are generally less interpretable, and there can be a trade-off between accuracy and interpretability. Easy-to-interpret models could be designed, but they may compromise accuracy. Highly complex, uninterpretable models with high accuracy that require a separate set of algorithms for interpretation are more commonly used in XAI. Another way to explainability is to check whether the model is agnostic or model-specific. Agnostic methods are used for any machine learning algorithm, such as neural networks and support vector machines, while model-specific methods are limited to interpreting the specific model [22].

It is also important to consider human factors when enhancing the model interpretability, such as a medical expert, to guarantee the interpretability and explanations of the model. It is expected that Explainable AI will further advance research in machine learning for healthcare as it solves the critical challenges of healthcare, such as fairness, transparency, safety, security, privacy, and trust.

1) HUMAN AND MACHINE INTERPRETABLE VISUALIZATIONS

One important aspect of Explainable AI is the use of human interpretable visualizations that allow humans to understand the reasoning behind AI models easily. For example, decision trees, rule lists, and other interpretable models can be visualized in a way that is easy for humans to understand. In addition to human-interpretable visualization techniques, machine-interpretable visualization techniques are also important in Explainable AI. These techniques enable AI models to explain their predictions or decisions in a way that is easily understandable by other AI systems. For example, SHAP (SHapley Additive exPlanations) [23] is a machine-interpretable visualization technique that can be used to explain the output of complex machine learning models, such as deep neural networks.

However, deep learning models work differently than humans, and it is difficult to interpret a model with billions of parameters. For example, if we visualize the grad-cam heatmap for a dog, we can see that most of the heat is concentrated around the dog's ears. Humans recognize dogs by the uniqueness of their shape.

2) CAUSAL INFERENCE

Health science-related tasks demand more explanation than mere predictions. With the abundance of data, many deep learning algorithms just only look for correlations among variables and make predictions or classifications without explaining the actual cause. To be practical and utilized in daily clinics, machine learning models must have strong causal evidence. Several methods are developed to convert the deep learning black box to a white box, for example, feature visualization [24], gradcam visualization [25], regularization via causal graph discovery [26], causal-aware imputation via learning missing data mechanisms [27], domain adaptation [28], tools such as Shared Interest [29] and learning generalized policies [30].

The causality can be defined in three stages. First is the association, for example, between the training image and

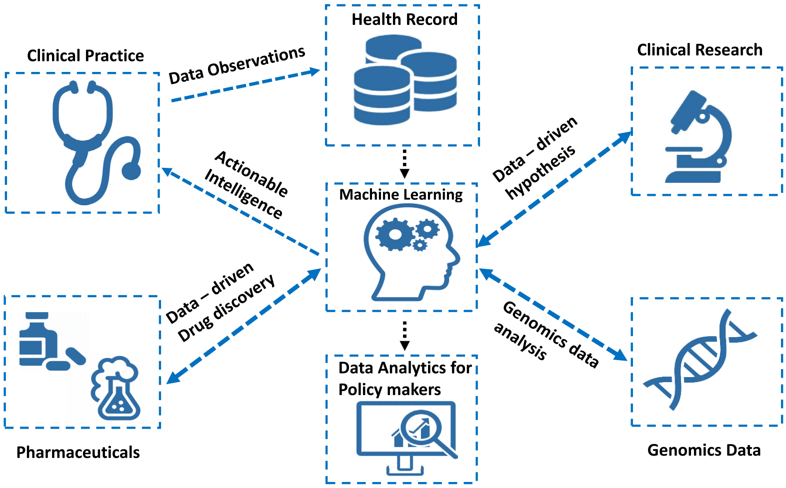

FIGURE 1. An ecosystem for machine learning in the healthcare industry. Clinical decision support systems, policy-makers, and pharmaceutical companies can benefit from machine learning methods.

its label. The second is intervention, which aims to predict the outcome based on altering the system (treatment plan or patients). The last one is counterfactual, which predicts the output in a different condition and environment. Causal machine learning models can guide us to make informative and timely interventions and rethink different treatment regimens and outcomes.

B. MACHINE LEARNING FOR PRECISION MEDICINE

Traditional medical models have treated an average patient with a 'one size fits all approach'. Precision medicine, which takes treatment approaches based on an individual patient's unique clinical, genetic, epigenetic, and environmental information, is a growing field of healthcare, and it is becoming a viable alternative due to the increase in the amount of medical data [31]. In Figure 2, we show a conceptual diagram for precision medicine by utilizing different data modalities.

Data, such as a patient's age, weight, blood pressure, medical history, and genomic sequences, can be used by analysis algorithms to identify hidden patterns and identify correlations between patient profiles and disease phenotypes. A personalized drug response model developed for non-small cell lung cancer patients [32] used the binding free energy of a drug-mutant complex and personal features of the patient (age, sex, smoking history, medical history) to build a personalized drug prediction model. Extreme learning machines were used to predict the drug response into two classes with an overall accuracy of 95%, driven by the addition of personal features. Personalized medicine is used for complex diseases such as cancer, heart disease, and diabetes [33]. If it is used carefully, this technology could improve performance in healthcare and potentially reduce inequities https://www.csail.mit.edu/news/seeing-future-personalized-cancer-screening-ai(MIT-CSAIL).

C. AI IN REMOTE PATIENT MONITORING

The combination of edge artificial intelligence (machine learning on edge devices) and the IoTs has facilitated the deployment of remote healthcare systems. Such systems can monitor a patient's vitals and other physiological parameters in real-time while the patient remains at home and push it to the cloud [34]. AI embedded in smart devices democratizes healthcare by putting AI-enabled health services (for example, AI-based clinical decision support) into patients' homes or remote healthcare [35]. The centralized data gathered for the patients can be used for knowledge discovery to improve disease prognosis or by doctors to monitor the patient and make/update prescriptions.

Several commercial wearable devices offer services measuring physiological parameters such as heart rate, ECG, and other variables through smartwatches and biosensors. There have been considerable targeted systems proposed as well for a variety of ailments, including but not limited to diabetes [36], where devices can also be used for the management of insulin as well [37], cardiac disease through ECG [38], sleep apnea monitoring [39] or as generic monitoring platforms such as smart-monitor [40] to provide 'a la carte' system based on the patient health circumstances. Machine learning methods can then be applied to these physiological signals for predictive health management.

III. CLINICAL AI TOOLS AND EMERGING AI HEALTHCARE COMPANIES

The primary question is when AI tools will be used in ordinary clinical practice to support real-time health challenges, such as improved diagnostic and clinical decision support systems [41]. Despite the promise of AI in solving key healthcare challenges, several issues about the usage of AI must be addressed. In this Section, we discuss some of the practical AI tools in the clinics, as well as AI-based emerging healthcare companies.

A. AutoML

Machine learning models have aided the healthcare industry by lowering costs and improving outcomes, but only a small

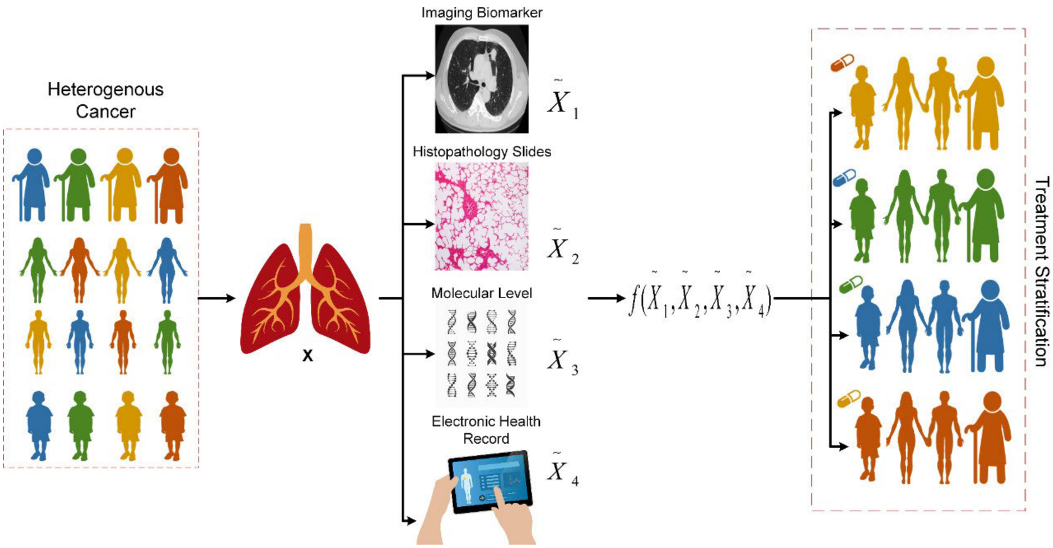

FIGURE 2. A conceptual diagram for precision medicine, where different data modalities are used to find patient-specific features and treatment plans.

number of hospitals are currently using them [4]. Healthcare professionals likely lack the expertise to build, deploy and integrate these models in clinical workflows. To assist the deployment of machine learning models in daily work with reduced input required from a data scientist or machine learning engineer, AutoML [42], which automates machine learning processes, has been developed. AutoML automates fundamental steps like feature selection, model selection, and hyper-parameter optimization, making it easier for health professionals to develop machine learning models for clinical data.

Generally speaking, about 80% of a data scientist's time is spent on data preparation and feature engineering, which also often requires domain knowledge experts [43]. The task is to find the most discriminative features to provide insights into the problem and to consider learning situations that will be difficult for the classifiers. Several machine learning frameworks have been developed to select, rank, and optimize feature engineering processes [44].

A popular approach is expand-reduce, which applies transformation functions to obtain optimal features, and has been implemented in [45]. Genetic programming, based on the concept of natural evolution and a survival function, has been used for feature construction and selection.

Hyperparameters can also affect model performance, and optimizing them is an art that requires practical experience. Sometimes a brute force search is needed by a grid search with a manual specification of a subset of the hyper-parameter space. However, the dimensionality of the search space may make this impractical. Random searches, which sample hyper-parameter configurations from a user-defined subset, can be limited to a specific computational budget. Another approach is a guided search that iteratively generates new configurations of the hyper-parameters based on the prior performance. AutoML automates this feature engineering and hyper-parameter optimization and model selection process. Hence, non-technical professionals can use machine learning models to solve healthcare problems.

Auto-weka [45], another machine learning platform based on Bayesian optimization methods, can be used to optimize hyper-parameters and model selection [46]. Other practical products used are Google's cloud AutoML system, Amazon's Comprehend, and Microsoft's Azure AutoML. The performance of AutoML models largely depends on the quality of the datasets. Adopting AutoML models in the healthcare environment will also require overcoming their operation as a black box.

B. AI TOOLS AND COMPANIES FOR CLINICS

The development and use of computer aided diagnosis or AI tools in clinical practice confront several hurdles despite the huge advancement in this new age of machine learning. For example, medical imaging [47] is an essential diagnostic tool for various disorders. A variety of imaging modalities have been developed, with X-ray imaging, whole slide imaging, computed tomography (CT), ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET) being some of the most widely utilized techniques. Moreover, several publicly available imaging and biological databases also offer excellent opportunities to build AI systems.

For example, PathAI [48] uses AI methods to assist pathologists in clinical diagnostics, clinical trials, and clinical translational research. Similarly, Viz.ai [49] is an AI-powered computer application to accelerate care coordination by reducing the time delays in clinical workflows. It uses AI to generate alerts and send them to clinicians for timely intervention. Similarly, Freenome [50] uses AI for cancer screening, diagnostics, prevention, and better management of cancer. Table 2 lists the companies that are completely based on AI tools to equip medical professionals to save lives.

TABLE 1. Broad categories and applications of AI in healthcare industry.

Category	Specific Applications
Patient care	Diagnosis and Prognosis Real-time case prioritization Personalized medication Electronic health records, Smart health
Medical Imaging	Tumor segmentation and Detection Early diagnosis and Imaging Biomark-ers Treatment effect monitoring
Management	Public Health Policy Market research Forecasting (Pandemics)
Biosensors	Remote health care Real-time health monitoring Soft computing
Computational Biology	Drug Discovery and efficacy analysis Single-cell analysis Multi-omics data analysis

1) SaMD: SOFTWARE AS A MEDICAL DEVICE

SaMD [51] is meant to be used for one or more medical purposes and is not part of physical medical equipment. Since 1995, more than 500 software packages/applications have been approved by the FDA to assist doctors in various healthcare problems [52]. Most of these software packages are related to analyzing radiology images. In many medical imaging tasks, AI algorithms have outperformed humans, and innovative companies have built AI-based systems to analyze radiology images and digital pathology slides. For example, Chan et al. [53] created a computer-aided diagnosis system to identify micro-calcification on mammograms and carried out the first observer performance research that showed how well the developed tool improved breast radiologists' ability to detect micro-calcifications. Also see Table 1.

AI researchers and developers must comprehend how clinicians desire to be assisted with different clinical works, construct efficient AI solutions, and produce interpretable results by considering the practical concerns in clinical settings. If properly created, verified, and applied, effective data analytics from AI technologies complement or support doctors' intelligence to increase accuracy, workflow, and, ultimately, patient care.

IV. APPLICATIONS OF BIG DATA ANALYTICS IN HEALTHCARE

The healthcare system consists of multiple stakeholders; patients, doctors, hospitals, industry, and policymakers, which are regulated by strict compliance. Healthcare systems generate a huge amount of data at a very high speed, which makes it a perfect avenue for big data analytics. Using big data analytics in healthcare may enable personalized medicine, timely interventions, better health policy management, and planning [65].

Big data analysis systems aim to collect, clean, extract, visualize, and analyze very large datasets and are associated with three key concepts. These are volume (large datasets), variety (highly dimensional/many attributes), and velocity (the speed at which the data is generated, made accessible, and analyzed). Healthcare datasets, usually large, complex, and arising from various sources, offer valuable opportunities for big data platforms [66]. For example, on average, a cancer patient generates 2GB of data annually in the form of images and medical records. New experimental techniques, such as immunotherapy, targeted therapy, omics research, high throughput screening, and parallel synthesis [67] may generate even larger amounts of data that require advanced data analytic methods.

In Figure 3, we show how complex high dimensional data from wearable sensors (ECG, Electromyograms (EMG), Electroencephalograms (EEG)), imaging data (X-rays, CT-Scans, MRI), electronic health records, and multi-omics (genome, proteome, and microbiome) data are generally collected and stored at a central repository, where pre-processing and data cleaning are performed. Missing values imputation methods may be used for further processing using statistical and machine learning methods. Centralized and mobile applications for patients, clinicians, hospitals, government agencies, and global health organizations can be developed. For example, the FDA has approved Ziopatch [68], which measures the heart rate and the ECG signal.

Multi-variate statistical methods, such as principal component analysis and other clustering methods, can be used to find patterns in a big dataset that may identify different disease states, mortality rates, susceptible age groups, forecast future pandemics, and economic costs [69].

A. MULTI-MODAL DATA FUSION: A TRASH OR A GOLDMINE

Many quantities in the universe vary co-currently. Biological data is usually diverse, and a complete understanding of a complex biological system may require an ensemble of related data sets to extract hidden data dependencies [70]. However, combining these multi-modal data may result in a goldmine or trash. It requires domain knowledge and strong data engineering skills for efficient feature representation and any downstream analysis. For example, in [71] showed fusing histopathological, radiological, and clinicogenomics information improves risk stratification for cancer patients.

1) HETEROGENOUS DATA

The vast amounts of healthcare data generated daily, such as medical images, sensor data, medical histories, and genomic data, are heterogeneous. Machine learning is well suited to analyze multi-modal data and extract valuable insights.

Three major areas where multi-modal data fusion can be useful:

- **Diagnosis**: Machine learning applied to health records and medical images can assist in the diagnosis of disease states.
- **Prognosis**: Applying machine learning algorithms to the heterogenous data available on a patient can predict the expected development of a disease from its early stages.
- **Treatment**: Optimal treatment plans can be generated by machine learning algorithms, especially

TABLE 2. AI-based Tools and companies in the field of Medical Sciences.

Tool/Company	Services
Viz.ai [49]	It aims to reduce delays and make the healthcare team react faster with AI solutions regarding decision-making, treatment plans, and prescription providers.
PathAI [48]	It develops machine learning for pathologists to assist in diagnostics by reducing errors, specifically for cancer patients and personal treatment.
Buoy Health [54]	A chatbot attends to a patient and records the history, symptoms, and other health concerns; then guide the patient to the appropriate health facility. It is developed by a team at Harvard Medical School to speed up and optimize the treatment cycle.
Enlitic [55]	Enlitic creates deep learning radiology technologies. The company's deep learning engine analyses unstructured medical data to provide clinicians with improved insight into a patient's real-time demands.
Freenome [50]	It employs AI algorithms for cancer screenings, diagnostics, and blood work to identify cancer early and suggest innovative treatments.
Beth Israel Deaconess Medical Center [56]	It employs AI to diagnose blood disorders early. The robots were taught to detect germs using 25,000 blood sample photos. Machines learned to predict hazardous blood bacteria with 95% accuracy.
Iterative Scopes [57]	It uses AI for gastrointestinal diagnosis and therapy. They have submitted the first clinical study of their AI-powered SKOUT tool to the FDA for assessment.
VirtuSense [58]	It employs AI sensors to monitor patients' activities and alert them about accidents. VSTAlert can anticipate when a patient plans to get up and inform hospital services.
Caption Health [59]	It integrates AI and ultrasonography for illness detection. AI assists physicians through the scanning procedure in real time to collect early diagnosis results.
BioXcel Therapeutics [60]	It applies AI to develop immuno-oncology and neurological drugs. The company's medication initiative uses AI to uncover new uses for old pharmaceuticals.
BERG [61]	BERG is a clinical-stage, AI-powered biotechnology company taking a bold 'Back to Biology™' approach to healthcare.
Atomwise [62]	Atomwise utilizes AI to accelerate small molecule drug discovery and explores new undruggable targets to make them druggable.
XtalPi [63]	XtalPi's ID4 platform combines AI, the cloud, and quantum physics to anticipate small-molecule medicinal characteristics.
Deep Genomics [64]	Its AI platform finds neuromuscular and neurodegenerative medication possibilities. "Project Saturn" examines 69 billion cell molecules.

reinforcement learning strategies, given the medical histories of patients and the number of treatment options available.

Medical data often consists of different data modalities such as images, signals, text, and molecular structures that are likely to be related. New machine learning or deep learning models enable us to integrate these diverse data sources, in a data-harmonization attituede [72] to produce multi-modal insights [73]. The extracted multi-modal features can also be used to form a knowledge graph to provide support for clinical decisions or understanding the mechanism of a specific disease [74] or visualisation for orthopaedic surgery [75]. In Figure 3, we show how multi-modal data can be used for different healthcare applications for patients, clinics, government and global healthcare organisation.

The integration of multiple data types may also increase the trust of clinicians. Since different data-modalities provide complementary information in describing a treatment plan or a disease process. In Figure 2, we show how different data-modalities can be used for precision medicine. The main goal of methods used to combine multimodal data is to combine the data with values from various scales and distributions into a global feature space, where the data may be represented more consistently [76].

It is also pertinent to mention that in many real-world cases, fusing data from different data modalities may decrease the performance. The healthcare data are produced by extremely complex systems and instruments, including biological, environmental, social, and psychological ones, among others [77]. These systems are driven by a variety of underlying processes that are dependent on a wide range of variables, that may be not accessible in many cases [78]. In addition, the diversity among different data types; a number of samples, scales, and research questions further complicate the learning process. In small clinical cohorts, it may also suffer from the curse of dimensionality [79].

B. GENOMICS DATA ANALYSIS

Genomic datasets, facilitated by next-generation sequencing, often contain vast amounts of raw data [80] and require big

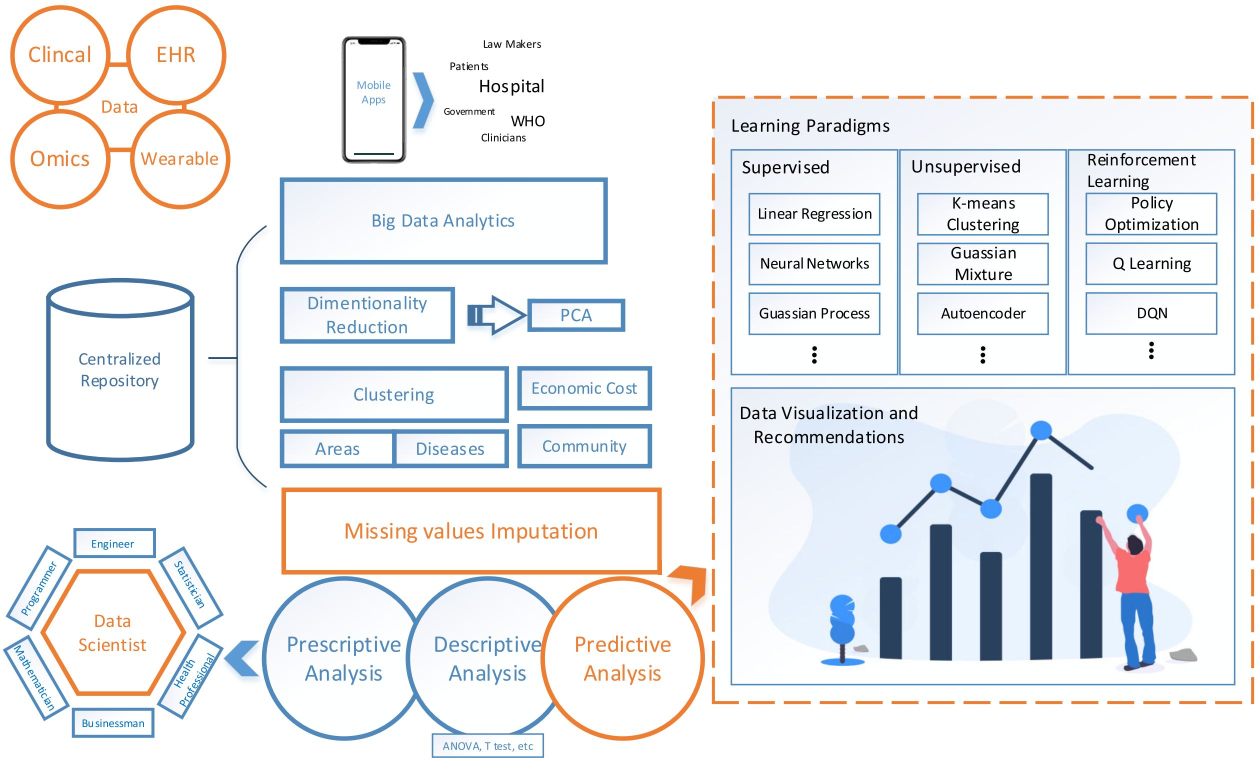

FIGURE 3. Big data analytics in healthcare. Learning from various data modalities in the big data environment may aid patients, clinicians, hospitals, governments, and global health organizations. Different machine learning paradigms can be applied to analyze and visualize biomedical data.

data analysis and computational methods. Examples are the encyclopedia of DNA elements (ENCODE) [81] gene annotation and expression data, the Cancer Therapeutics Response Portal (CTRP) [82], which can provide insights into the action of small molecules leading to personalized drug discovery based on predictive biomarkers. The Cancer Cell Line Encyclopedia (CCLE) [83], and the Genomics of Drug Sensitivity in Cancer (GDSC) [84] database of large scale molecular screens on panels of hundreds of characterized cancer cell lines demonstrates the potential of modern machine learning algorithms to develop drug response predictors from molecular profiles.

However, current data resources are inadequate for reliable prediction of drug resistance or response [85]. Analyses of independent cohorts may reach different conclusions, and inconsistency between datasets and missing clinical information can hinder predictions. Data imputation techniques may address missing values, and the high dimensionality of the data could be dealt with by feature filtering techniques or sparse principal component analysis [86].

C. MEDICAL IMAGING

Deep learning can rapidly construct magnetic resonance (MRI) images directly from sensor data of partially observed measurements. Task-oriented reconstruction allows the reconstruction of a specific part of the image with high quality and a confidence score. Super-resolution images (high-quality images or sequences built from low-resolution images) can be constructed by deep learning, such as single (no reference information) brain MR images built using convolutional neural networks (CNNs) or super-resolution using GANs [87]. In Figure 4, we show various applications of deep learning in medical imaging.

For MRI images, image synthesis is a method to generate new parametric images or tissue contrasts from a collection of images acquired in the same session. Generative adversarial networks [88] could serve as a data augmentation tool as medical datasets tend to have limited numbers of samples, and they have been used to generate synthetic abnormal MRI images for a brain tumor based on pix2pix [89], [90].

Image registration, transforming data from multiple photographs, different sensors, views, or depths to a single coordinate system is used, through deep learning, for medical image registration to improve accuracy and speed. Examples are deformable image registration, model-to-image registration, and unsupervised end-to-end for deformable registration of 2D CT/MR images [91].

V. WEARABLE BIOSENSORS

Wearable biosensors measure electro-physiological and electro-chemical signals from the body. Electrical activities emanating from various biological processes in the body, such as human heart activity (ECG), muscle activity (EMG), and sweat gland activity (Electro-Dermal Activity (EDA)) can be extracted from diagnostic machines or wearable sensors and provide vital information about one's health conditions. Analysis methods for these data, such as princi-

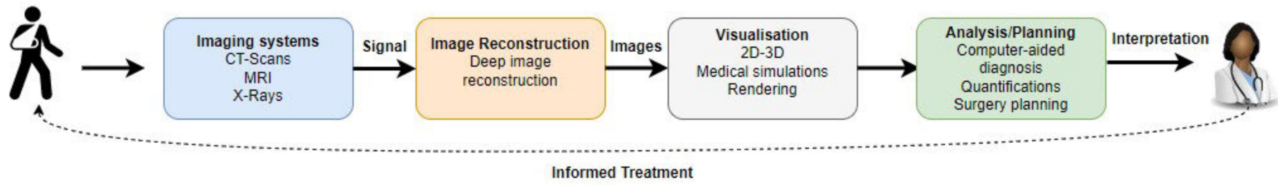

FIGURE 4. **Deep learning can be used to construct medical images at high speed, and facilitate the visualization and analysis of medical images.**

pal component analysis, discrete cosine transforms, autoregressive methods, and wavelet transforms, can extract time and frequency domain features from the physiological signals [92]. Examples are a bidirectional deep long short-term memory (LSTM) network based on wavelet transform to classify ECG signals [93], which achieved 99.39% accuracy on the MIT-BIH arrhythmia database [94] and a Fourier Transform and Wavelet-based feature model to classify patients with Alzheimer's Disease, Mild Cognitive Impairment and Healthy subjects from EEG signals [95].

A. AI-ASSISTED DESIGN OF BIOSENSORS

In the real world, medical signal data can also be passively gathered utilizing wearable sensors, such as smartphones or smartwatches [100]. The traditional way of acquiring signals has been through gel-electrodes that are placed on the body. In addition to the use of traditional wearables such as smartwatches and fitness trackers, recent advances in fabrication and electronics have led to the integration of bio-sensing electrodes in other devices such as eye-glasses [101], VR head-mounted displays [102], and textiles [97].

1) EPIDERMAL DEVICES

A new stream of computing devices termed *epidermal devices* allow for non-invasive capture of physiological signals through soft interactive tattoos [103], [104] (Figure 5). These epidermal devices can measure electro-physiological signals [97], [104] and electro-chemical signals in the body [105]. Another factor that has contributed to the widespread development of physiological sensing devices is the availability of open-source prototyping kits. Prototyping kits and platforms such as EMBody [106], Seeed,[1] OpenBCI,[2] Olimex,[3] BITalino[4] allow for rapid prototyping of custom physiological sensing systems. In addition to all these developments, computational tools and AI-assisted approaches are being actively explored to automate and customize the design of biosensing wearables. For instance, Nittala et al. [98] developed a computational design tool built with an integrated predictive model to optimize the design of multi-modal electro-physiological sensing devices.

Machine Learning and Optimization Techniques for processing Physiological Signals.

[1] https://www.seeedstudio.com/grove-emg-detector-p-1737.html
[2] https://openbci.com/
[3] https://www.olimex.com/Products/EEG/
[4] https://www.pluxbiosignals.com/

2) MACHINE LEARNING TECHNIQUES ON PHYSIOLOGICAL SIGNALS

Employing machine learning and deep learning techniques on physiological sensing is a commonly used approach. In the field of human-computer interaction, machine learning techniques have been commonly used for sensing gestures from EMG signals [107], identifying mood from EDA, Electrooculograms (EOG), EMG and ECG signals [102]. Deep learning approaches are also commonly applied on ECG data for denoising data [108], for simulating signals and detecting heart-related anomalies [109], [110], emotion recognition [111] or to assess mental health by analyzing the EEG signals or to detect psychiatric disorders [112]. Classen et al. [113] detected brain activity using machine learning on the EEG recordings of brain-injured individuals who were clinically non-responsive, which is a predictor of eventual recovery.

VI. COMPUTATIONAL ADVANCES

Advances in computer hardware, and architectures are required to process highly complex scientific problems. The growth in fast processors, multicore-chips, accelerators, memory designs, interconnections, field programmable gate array (FPGA) based processors, and GPUs with hundreds of cores have made computationally intensive applications, such as real-time image and video processing in healthcare, possible.

A. ACCELERATED ARTIFICIAL INTELLIGENCE

Deep learning systems are often trained on multiple core graphical processing units, which can optimize the highly parallel matrix operations that are essential components of deep neural networks. A recent example is the discovery of faster matrix multiplication using reinforcement learning [114]. Google introduced a tensor processing unit (TPU) as an accelerated artificial intelligence processor, especially for its TensorFlow software [115].

Training of a deep neural network can be expedited by either training more examples in parallel or training each example faster. Operations that cannot be accelerated by GPUs or TPUs, such as the earlier data processing stages or input-output between devices or disks, need to be improved in training. Data echoing [116], which reuses intermediate outputs from earlier pipeline stages to reclaim idle capacity, may be useful to ameliorate this.

As the quest to become a leader in AI continues, the model sizes are increasing from millions of parameters to billions

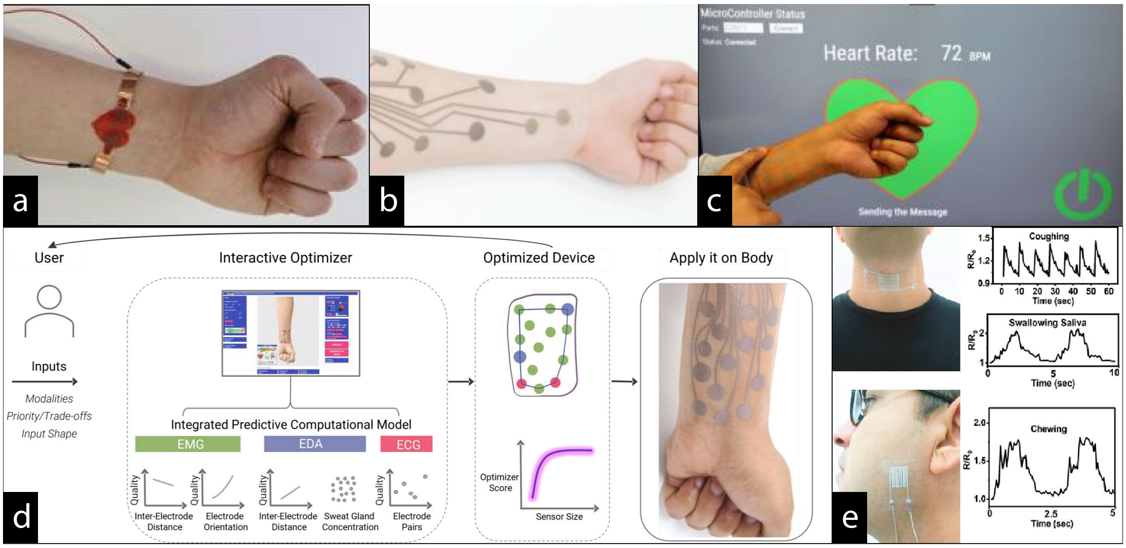

FIGURE 5. **Wearable Biosensors: (a) biosensors in a tattoo form factor that can sense electro-dermal activity (EDA) [96]. (b) multi-modal physiological sensing tattoo that can sense ECG, EDA, and EMG signals on the forearm [97]. (c) integration of user-interface controls e.g., touch buttons in bio-sensing tattos [97]. (d) AI-assisted fabrication and optimization of multi-modal electro-physiological sensing devices [98]. (e) Ultra-thin and skin-conformable strain sensors on a decal transfer substrate, employed to detect subtle human body movements [99].**

of parameters (Openai GPT models). Google reported the GLaM model with more than 1 trillion parameters (GPT-3 model had 175 billion parameters) [117]. The direct challenges associated with these models are the training cost and the porting out to small devices. One potential solution to enable small models to learn the behavior of bigger models is to use neural network compression techniques such as knowledge distillation [118] or structural sparsity [119]. An analogy for this is the teacher-student relationship, where the smaller model (student) learns from the bigger model (teacher). A survey in [120] presents efficient hardware architectures for accelerating deep convolutional neural networks.

B. EDGE COMPUTING

Although most healthcare datasets are complex and large and require massive computational resources (often in remote computer clusters), processing data locally at the end nodes of a cluster in a real-time application is appropriate for privacy reasons or to reduce processing time and latency. The training of the model locally on end nodes is known as edge computing. In edge computing, edge (local) devices or servers can provide data storage and processing, potentially giving fast, secure, and real-time health analytics that may allow timely medical interventions. Thus, an edge computing-based AI model could provide better healthcare for patients far from major population centers with limited connectivity and access. The localized processing power of edge computing may facilitate access to medical interventions by rapidly analyzing data from smart medical sensors.

To make AI models portable and compatible with prototyping, the implementation of AI models on low-power devices is important. For example, Owais et al., [121] recently showed the implementation of the U-Net segmentation model on the Intel Neural Compute Stick. The work demonstrated that inference could be obtained on the NCS with proper tuning and suitable modifications of the U-Net model. However, the implementation was achieved with a trade-off for performance. Nevertheless, experimental results on brain MRI images and heart MRI images showed promising performance in terms of the dice scores for the segmentation tasks. Hence, such inference-enabled devices can aid in the clinical transformations of AI methods in real-time healthcare settings.

C. FEDERATED LEARNING

Data privacy and protection are general requirements for medical data, and new frameworks for training models are required that do not expose the underlying data. One such approach is Federated or Collaborative Learning [122], which is a machine learning technique that trains an algorithm across multiple edge devices or servers without exchanging local data samples. Multiple parties, for example, several hospitals/research centers, actively collaborate to train algorithms without centralizing their datasets. In developing AI models for medical data from multiple locations, federated learning has recently been shown to be effective. For example, with the rapid spread of COVID-19 globally, researchers needed to come up with quick responses and rapid developments of mechanisms for the assessment of COVID-19 patients. Multiple institutes around the globe collaborated to expedite AI model development for disease clinical support systems. However, sharing COVID-19 patient data from different locations had ethical and legal bottlenecks that complicated the process. Hence, the research community resorted to federated learning to make use of data from diverse sites without the need for data sharing. In [123], a federated learning model was developed to predict future oxygen requirements for COVID-19 patients making use of clinical and radiology

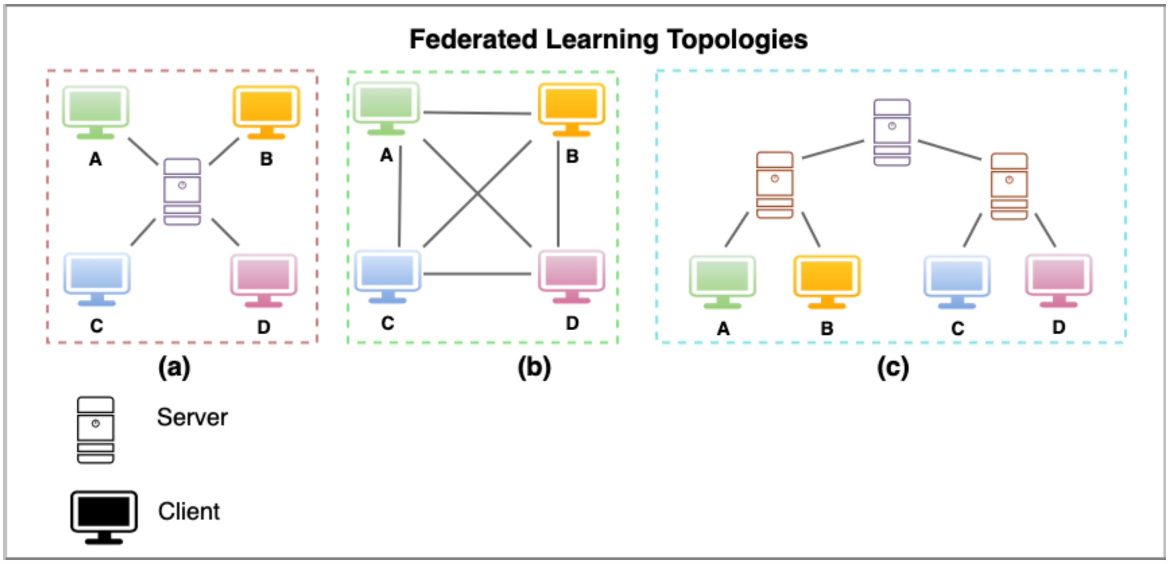

FIGURE 6. Common topologies of federated learning. (a) Client-Server. (b) Client-Client. (c) Federation of sub-federation (mix topology). In client server topology, all the client terminals are connected to a shared servers and the updates are routed via the server. In client-client topology, the clients can share training updates without depending on a centralised server. In mix topology, both the aforementioned phenomena are present.

(chest X-rays) data. The model referred to as the EXAM model facilitated the use of data from 20 different institutes from various countries.

Federated Learning frameworks are implemented with different topologies (also see Figure 6). To accomplish model training at multiple sites, the framework may execute model training at each site independently and then share the weights with other sites (a peer-peer topology), or the individual sites may share the weights with a centralized server node (client-server topology). According to the federated learning topology, the stochastic gradient descent (SGD) optimization of the model training is transformed into federated stochastic gradient descent (FedSGD) [124], [125].

VII. THE RECENT CHALLENGES IN AI FOR HEALTHCARE WITH POTENTIAL SOLUTIONS

AI has shown great promise to improve the healthcare industry, and it is expanding as technology advances. However, there are some limitations in this field that prevent AI from being integrated into current healthcare systems. In this section, we discuss some of the key challenges and provide suggestions to overcome these to improve healthcare.

A. DATA ISSUES

Data availability and access are two critical success factors for data science in healthcare. Moreover, the data quality, sample size, labels, disparity among labels, privacy, and ethical concerns, are the most prominent challenges that must be addressed to fully exploit the potential of AI in healthcare [126]. The first principle to build robust data-driven healthcare systems is to capture clean, accurate, and properly formatted data for use in multiple healthcare applications. A perspective about sharing biomedical data for strengthening the role of AI is presented in [127].

Machine learning methods can also assist in automated labeling, anomaly detection, missing value imputation, and other data cleaning processes [128]. For example, in [129], deep learning is used to identify bleeding events from electronic health records. Deep learning models are frequently used to improve the quality of radiology or pathology scans [130] or to identify anomalies in biosensors [131]. Some IT vendors also provide automated scrubbing tools that use logic rules to compare, contrast, and correct large datasets.

Another issue is the widespread perception in the community that larger datasets are required to make accurate predictions. The data quality, proper annotations, and hypothesis in consultation with healthcare experts are necessary to build robust machine learning models. The data generated by the push of technology, without appropriate hypothesis and domain knowledge, will remain difficult to analyze.

Data security is another top priority for healthcare organizations. Risks include high-profile data breaches, hacking, and ransomware incidents [132]. Machine learning can be used to make data and systems more secure. It allows security systems to analyze and learn from patterns to help prevent similar attacks and respond to changing behavior.

To deal with imbalanced, complex, unlabeled, and poorly understood data, the type of learning paradigms and evaluation metrics used is also important. To address these challenges and generate hypotheses for understanding complex diseases and signaling pathway patterns, unsupervised or semi-supervised learning can be used [133].

1) THE CHALLENGES IN DISTRIBUTION SHIFTS AND DIFFERENT DATA MODALITIES

Many real-world clinical AI systems suffer from the training and testing distribution shifts in the data. To deal with these distribution shifts, domain adaptation techniques are adopted in machine learning. In domain adaptation, we train a neural network on a source dataset X and achieve high accuracy on a target dataset Y, where X and Y have different data distributions.

Domain adaptation can be sliced down into three categories: supervised, semi-supervised, and unsupervised learning, depending on the type of data from the training dataset. In supervised fast-expanding target dataset is substantially smaller than the source dataset since the target domain's data has been labeled. While unsupervised learning makes use of unlabelled data from the target domain, semi-supervised learning uses both labeled and unlabelled target domain data. As a result, deep domain adaptation was suggested to improve the model's performance and overcome the issue of insufficient labeled data by utilizing deep network features. Discrepancy-based, reconstruction-based, and adversarial-based adaptation are the three main deep-domain adaptation strategies that have been established.

In a discrepancy-based approach, the features that can be transferred come up with drawbacks due to its delicate co-adaptation and representation specificity. Reference [134] has illustrated that fine-tuning can improve generalization ability. When the fine-tuning is conducted on the deep model, a base network is trained using source data, and the first 'n' layers of the target network are then used directly. The target network's remaining layers are randomly initialized and trained using a loss function based on the discrepancy. Finally, considering the size of the target dataset and how closely it resembles the source dataset, the initial layers can be fine-tuned or frozen during the training procedure. Another deep domain adaptation [135] technique, reconstruction-based domain adaptation, uses an autoencoder to reduce reconstruction error and learn transferable and domain-invariant representations to align the discrepancy between domains.

Stacked Auto Encoders (SDAs) can be used to represent source and target domain data in a high-level representation manner [136]. However, because SDAs are computationally expensive, the marginalized SDA (mSDA), which does not require the use of stochastic gradient descent, was presented in [137] to overcome the computational cost. Transfer learning with deep autoencoders (TLDA) [138] used a softmax loss to encode the source domain's label information. In contrast, the embedding encoding layer uses the KL divergence to minimize the distance in distributions between domains.

Generative Adversarial Networks (GANs) obtain transferable and domain-invariant characteristics by minimizing the distribution discrepancy between domains. GANs are also used in the adversarial domain adaptation techniques [139]. CoGAN was suggested in [140], which generated synthetic target data and linked it with synthetic source data.

An approach for simulated-unsupervised learning was established in [141], in which adversarial and self-regularisation loss were minimized, using unlabelled real data to enhance the realism of synthetic images.

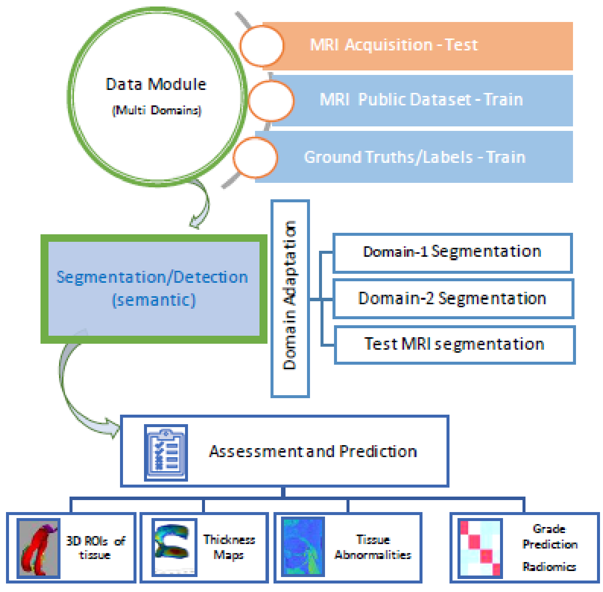

FIGURE 7. Domain adaptation in medical imaging.

2) CHALLENGES IN MEDICAL IMAGING

Perhaps, medical imaging is the most disruptive area where AI has made tremendous progress. However, there are various challenges in medical imaging as well [142]. Medical images are often three-dimensional, and the three-dimensional convolutional neural networks to process these 3D volumes require more memory and computational time. Generally, researchers treat 3D CNNs as stacks of 2D CNNs. However, adding a newer dimension adds additional constraints. Most deep learning models are built on anonymized public data, making privacy-related issues less relevant. However, this does not offer a permanent solution to handle privacy-related problems in medical imaging. One conclusion is that when these datasets are made public, there are always associated risks of leaking patient privacy [143].

High diversity of clinical scenarios is another challenge in medical imaging. This is because medical imaging can be used in various clinical situations, such as disease detection, including localization and classification and disease surveillance. On the other hand, deep learning is also being used for data quantification, such as pediatric bone age prediction [144]. As a result, there are many different clinical activities from the standpoint of medical imaging, and it is challenging for one individual or model to manage all of these operations using present methodologies. Developing task-aware deep learning solutions is the way forward.

Another significant challenge in medical imaging is the lack of transparency in algorithms and issues with validation and testing. AI-based applications differ in terms of data ingestion to output, and there is currently no established standard procedure. For example, algorithms with similar performance may use different strategies to solve the same problem, necessitating special pre-processing techniques before inference. As a result, scalability, which is critical in commercial AI-based products, becomes difficult because each application may require its own server or virtual environment. The transferability of the algorithm presents another challenge due to the stringent medical regulations in different nations. However, there is no statistical method available to evaluate an algorithm's transferability. One such initiative is the petabyte 'medical-imagenet' project of radiology and pathology images by Stanford University with genomics and electronic health record information for rapid creation of computer vision systems(Stanford-AIMI).

The challenge of a lack of large datasets can be addressed by image synthesis and data augmentation. Models may be hard to generalize as the distribution of the training data, usually high-quality images, may differ from real-world clinical data, which may cause a deep learning model to produce unexpected results. Transfer learning, fine-tuning, or pre-training can address this [145]. Transfer learning leverages the weights of a network already trained on a similar task. More emphasis might be placed on unsupervised machine learning models to overcome sample size issues. In Figure 7, we show the applications of domain adaptation for image segmentation tasks.

3) BIOSENSORS AND FLEXIBLE BIOELECTRONICS: A WAY FORWARD

Despite increasing advancements in the last few years, there are still numerous significant obstacles to overcome before AI biosensors for Internet of Things-based applications are commercially mature. For commercial applications, flexible bioelectronic materials are a key component. The human body and its internal organisms are naturally elastic and flexible. In this instance, integrating electronics into platforms made of flexible material is required. Current soft wearables on the skin are dominantly reliant on capturing physiological signals and transmitting those signals to an external computing infrastructure (e.g. mobile, laptop, etc.). Flexible bioelectronics is advantageous to match the human body and organs (such as skin, eyes, and muscles) with low mechanical damage to tissues and lessen adverse effects after long-term integration because of its exceptionally flexible mechanical qualities. Similarly, Medical AI biosensors will play a pivotal role in developing key technologies in the future with the help of nanotechnology. They will continue to advance in miniaturization, scalability, low power consumption, low cost, high sensitivity, multifunction, safety, non-toxicity, and degradation [146].

4) ADAPTABILITY

Another issue is that the majority of ML-enhanced biosensors currently lack adaptive learning capabilities. Biosensors can learn from their surroundings with adaptive learning rather than only depending on manually input training sets. An adaptable model continually improves and optimizes itself by learning from the environment, unlike a non-adaptive system. This might lessen the chance of disastrous mistakes and erroneous results, which a single fixed model can cause.

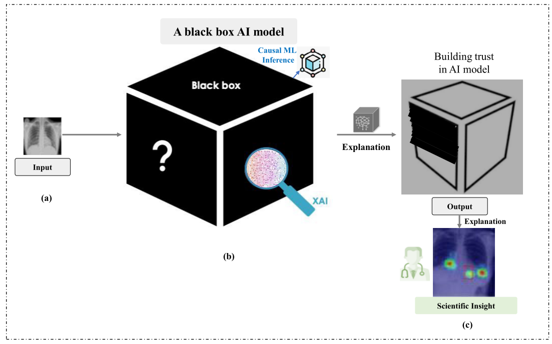

FIGURE 8. AI- black-box model. Algorithms like Explainable AI, feature visualization or causal inference can be used to interpret the predictions. Gradcams visualization can highlight important regions that can build the trust of healthcare professionals.

On the other hand, while non-adaptive ML models' excellent local performance may be sacrificed in the name of generalisability, particularly in clinical practice, adaptive learning provides a solution to resolve this conflict.

5) BIGDATA IN SMART SENSORS

Establishing a smart sensor system that relies on enormous datasets and algorithms, is a significant barrier regarding the platform for data processing and storage. In recent years, cloud computing has been used to process sensor signals since it offers superior computational power and data storage. Cloud and biosensor integration is nothing new, especially for monitoring applications where the volume of data is continuously growing over time. The direct connection of many sensors to the cloud is sometimes too expensive and sluggish due to the exponential growth in the number of sensors. Edge computing has so been introduced in recent years. Instead of a single data centre, edge computing enables data processing at scattered edge devices. It benefits from great computational effectiveness, rapid network processing, low cost, and more. Therefore, biosensors will likely use this cutting-edge technology.

B. OPENING THE BLACK BOX OF DEEP LEARNING

A big hurdle in AI implementation is the black-box nature of the deep learning models; in critical healthcare scenarios, we can not fully rely on model predictions. We need interpretable and transparent models to make critical healthcare decisions. As the input data propagates through the layers of the neural network, it gets compressed and generates some predictors for the target label. Moreover, we do max-pooling at each layer and drop out certain neurons in the final layers to avoid over-fitting. Given these compressed representations, it is difficult to explain the predictions at each level; however, we can have a high-level idea about the inner-working of the model. Since complex deep learning models consist of hundreds of millions of parameters and, in our opinion, are nearly impossible to interpret at every point.

In Figure 8, we show various methods used to explain the working of the deep learning model. These methods can explain the predictions to a certain level without losing

TABLE 3. ChatGPT Applications in Healthcare.

Application	Description	Advantages	Disadvantages
Patient communication	ChatGPT can be used to communicate with patients and provide them with general medical advice. This can help reduce the workload on healthcare providers and improve patient satisfaction.	Provides immediate medical advice, available 24/7, can handle large volumes of inquiries simultaneously	May not be able to fully replace human interaction and empathy, may not be able to handle complex or critical cases, raises concerns about patient privacy and confidentiality.
Telemedicine	It can facilitate virtual consultations between patients and healthcare providers. By providing patients with access to medical advice and expertise, ChatGPT can help improve healthcare access and outcomes, particularly in rural or underserved areas.	Improves access to healthcare, reduces travel costs and wait times, increases patient engagement	May not be suitable for all types of medical consultations, may not be able to perform physical exams or provide hands-on care, raises concerns about patient privacy and security.
Medical education	Can be used as a tool for medical education, providing students and healthcare professionals with access to medical information and resources. By analyzing medical data and answering questions, It can improve medical knowledge and training.	Improves medical education accessibility, personalizes learning experience, can be used for quick reference and knowledge consolidation	May not be able to provide hands-on training, raises concerns about patient privacy and confidentiality, may perpetuate health disparities for students or institutions who do not have access to the technology or resources
Medical research	ChatGPT can be used in medical research to analyze large amounts of medical data and identify new patterns and trends.	Enables faster and more efficient analysis of large amounts of data, can identify previously unknown correlations and patterns	May require significant computing resources and expertise, may not be able to fully replace human researchers and medical experts.
Diagnosis support	It can assist healthcare providers in diagnosing diseases by analyzing patient symptoms, medical history, and other data.	Improves accuracy and consistency of diagnoses, saves time and reduces errors, can support rare and complex cases	May not be able to fully replace human diagnostic skills and expertise, and all clinical factors.

accuracy. There is a trade-off between accuracy and explainable AI, which depends on the problem at hand.

In a very intriguing study [147] proposed information bottleneck [148] to explain the working of deep neural networks. The information bound is the theoretical limit proposed by [148], at which the model can do the best given the set of features; no further compression is possible. The paper suggests that most of the training epochs are spent on learning the efficient representations of the input; the representation compression begins when training error starts to decrease. The model starts to converge, layer by layer, and the last layer keeps only the most relevant features to predict the output label.

1) MODEL FAIRNESS AND ACCOUNTABILITY

One of the challenges that the deployment of biosensors with AI will entail is the need to ensure no biases in the outcomes determined. Studies have shown [149], [150] that ML algorithms can sometimes provide unequal outcomes for different population groups, especially with populations already under-served in society. In this regard, several steps need to be taken and devised when working on ML applications using biosensors. These can include actions such as a conscious inclusion of diversity in the data collection process and developing robust policies governing post-application performance audits to quantify the impact on vulnerable communities. From a technical perspective, aspects to look for would be logging model performance to detect drift of performance in the model. Such processes included in deploying and monitoring biosensors utilizing AI applications would ensure healthcare professional and patient confidence in the services offered.

C. LARGE LANGUAGE MODELS FOR HEALTHCARE

While the development of Large Language Models (LLMs) has been the focus of researchers [151], [152], [153] for a while relating to application towards machine translation, text summarizing and paraphrasing and generation of text, the recent release of ChatGPT [154] from OpenAI has brought the potential use of chatbots into mainstream consumer use. LLMs are deep learning models trained on a large amount of textual data to cater to multiple tasks related to Natural Language Processing. LLMs make use of complex transformer architectures that enable it to capture longer dependencies than is possible with typical sequential models such as RNNs. LLMs also have the advantage of being able to be fine-tuned for specific tasks, thereby performing well in some desired niche or even work as the backbone for generic chatbots too with a fine tuned performance. Infact, Open AI's GPT-3 has been used as the back-end of several such offerings, including JasperChat (tailored for business use) and Poe by Quora, both of which are based on OpenAI's base models. The multifaceted use of LLMs for special domains has also been true for the case of healthcare, medical data, as part of the used training data corpus enables chatbots powered by LLMs to be useful in assisting healthcare practitioners. One such way this was performed was suggested by Wang et al. [155] who incorporate LLMs in to a CAD system for medical images called ChatCAD. They do this by generating prompts based on the output of different image based classifier/segmentor and report generator. These outputs are converted in to a prompt and are then passed on to the LLM so that its logical reasoning capabilities could be used to provide better and interactive care to patients. In order to provide a focused discussion on the potential use of LLM based chatbots for use in healthcare, we briefly discuss the current as well as potential uses of ChatGPT in this section.

1) ChatGPT FOR HEALTHCARE

The OpenAI's language chatbot ChatGPT [154] is an artificial intelligence language model that has been pre-trained on a large corpus of text data and is capable of generating human-like responses to natural language queries. Having passed successfully part of the US medical licensing exam, attesting to its capability to work with medical queries, ChatGPT has the potential to revolutionize clinical applications in many ways [156]. In Table 3, we enlist several applications of ChatGPT.

VIII. CONCLUSION AND FUTURE WORK

The use of AI and biosensors has been gaining increasing traction in the healthcare industry for different purposes. AI-based methods are being embraced in the healthcare industry, where low-cost, intelligent, and adaptable methods are influencing fields such as clinical decision support, diagnostics, prevention, remote healthcare, public health policy, and clinical recommendation. More user-friendly machine learning technologies, such as AutoML, ClinicalAI, patient-centricAI, and explainable AI, are required to boost the confidence of healthcare stakeholders and to make machine learning an integral part of daily clinical practice. Combining biosensors and imaging data, or other data modalities, may increase the model performance, as well as the confidence of clinicians.

In this regard, this review provides researchers and health practitioners with an overview of the state of technology in this area, both from a technical and clinical perspective. Various applications of AI towards diagnosis, prognosis, treatment as well as monitoring have been discussed, along with traits related to explainability and the tools useful in clinical practice. Moreover, technologies that enable the usage and development of biosensors for healthcare applications have been presented. Lastly, open research issues and challenges related to biosensor-based healthcare systems have been talked about, which require further work.

AI has great potential to transform the healthcare systems and improve the lives of patients and health professionals. However, clinical AI implementation is currently on a smaller scale due to trustworthiness, lack of coordination, data collection and privacy issues, and patient reluctance. We need to develop patient-centric AI systems and build the trust of health professionals in this exciting technology. AI can only assist health professionals and improve lives, and in no way can it replace them, of-course nobody would like to be treated with a robot. AI, in any sense, can not replace the human touch, which is the essence of every field. AI and clinicians should work in synergy to maximize the benefits for patients. In this regard, this article will guide further research and development in AI for healthcare. Given the enormous amount of data and processing power available today, we expect an increasing role of AI and biosensors in the clinics that will augment or help healthcare professionals and reduce their workload.

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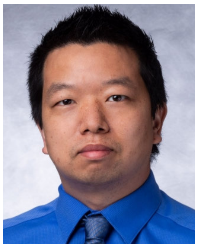

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