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Healthcare; state of the art and what lies ahead of us

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Abstract

The healthcare landscape is undergoing a radical transformation driven by Information and Communication Technology (ICT), leading to the emergence of Digital Transformation in Healthcare (DT in HC). This paradigm shift encompasses innovative technologies, including Artificial Intelligence (AI), big data analytics, telemedicine, and the Internet of Things (IoT), which are reshaping healthcare practices and patient interactions. This article presents a comprehensive review of these transformative trends and their implications.

The integration of AI and IoT has empowered predictive healthcare models capable of early disease detection and personalized care strategies. While promising, these advancements also raise technical and ethical challenges. Telemedicine has transcended geographical barriers, improving healthcare accessibility and redefining patient-doctor interactions.

Furthermore, the convergence of Digital Transformation in Healthcare with big data analytics has led to data-driven insights, paving the way for population-level healthcare strategies and personalized treatments. In addition to these technological advancements, the article envisions the future of healthcare in 2030, anticipating significant transformations in medical facilities, the role of robots and AI in healthcare, and the revolutionization of pharmaceuticals through 3D printing.

In summary, the future of healthcare promises a landscape characterized by remote care delivery, individualized medical data, disease prevention, and the integration of advanced technologies. As healthcare evolves, it presents opportunities and challenges that require careful consideration and strategic planning.

Keywords: *Healthcare, AI, Digital Transformation, Telemedicine, Big Data, IoT, Future of Healthcare.*

Introduction

The healthcare landscape has experienced a revolutionary shift due to the integration of Information and Communication Technology (ICT), leading to the emergence of Digital Transformation in Healthcare (DT in HC). This technological revolution has brought forth a reimagining of healthcare practices and patient interactions, facilitating improved research methodologies and enhanced care delivery (Bajwa et al, 2021) The introduction of the Internet in the mid-1990s marked a pivotal juncture, altering communication dynamics among healthcare stakeholders and setting the stage for a paradigm shift in the sector (Foster et al, 2014).

Digital Transformation in Healthcare encompasses the adoption of innovative technologies that enable secure and high-quality care delivery, extending beyond traditional boundaries (Ghosh et al, 2023). As stakeholders across the healthcare ecosystem navigate this transformation, connotations of DT in HC overlap with the broader realm of digital health, emphasizing the utilization of information and communications technologies to enhance healthcare services and individual wellness. This integration has paved the way for novel research avenues that explore the impact of technology on healthcare practices and patient outcomes (Jiang et al, 2017).

Furthermore, the convergence of Digital Transformation in Healthcare with big data analytics has reshaped the healthcare landscape through comprehensive data-driven insights (Dash et al, 2019). The adoption of big data analytics in healthcare leverages clinical research results, Electronic Health Records (EHR), and personal data from wearable devices, contributing to an extensive repository of healthcare information (Pashazadeh & Navimipour, 2018). This reservoir of data has not only paved the way for personalized care strategies but also enabled the development of predictive models for population-level healthcare strategies (Raj & Chatterjee, 2018).

In tandem with the transformative potential of big data, the concept of telemedicine has emerged as a cornerstone of Digital Transformation in Healthcare (Wootton et al, 2017; World Health Organization, 2010). Telemedicine leverages ICT to provide remote healthcare services, ranging from teleconsultation to telemonitoring, transcending geographical barriers and enhancing healthcare accessibility (Athena et al, 2020). The utilization of these technologies necessitates an understanding of integrated information management, medical imaging, electronic medical records, and privacy concerns related to medical data (Timmermans & Berg, 2003).

Also, Artificial Intelligence (AI) has rapidly found extensive applications in the field of healthcare. In healthcare 4.0, AI plays a crucial role in predicting diseases early and accurately, ultimately aiding doctors in making timely decisions to save patients' lives. (Bodenstedt et al, 2020) The integration of the Internet of Things (IoT) has further empowered AI applications in healthcare by capturing patient data through IoT sensors and employing machine learning techniques for analysis. These technologies have led to the development of machine learning-based healthcare models capable of predicting various diseases. Utilizing algorithms like decision trees, support vector machines, artificial neural networks, and others, these models have achieved impressive accuracy rates for diagnosing conditions such as heart disease, diabetes, breast cancer, and more. (Hamet & Tremblay, 2017) These advancements, while promising, also bring forth technical and ethical challenges like data scarcity and the potential for bias. However, as these challenges are addressed, AI holds the potential to revolutionize healthcare, making it more precise, efficient, and accessible to patients worldwide. AI's proficiency extends across diverse clinical domains, with techniques such as artificial neural networks and fuzzy expert systems being applied to various clinical settings. Yet, it is essential to conduct well-designed clinical trials to effectively integrate these emerging techniques into real-world healthcare settings. (Kakhi et al, 2022)

Technology and medical advances

Advances in AI have propelled the field farther and faster than expected, enabling complex tasks like image classification, speech recognition, and medical diagnosis. (Nwoye et al, 2022) Robotics is emerging as a transformative force in surgery, enhancing outcomes and reducing hospitalization times. 3D printing holds promise in making healthcare more accessible and personalized through the production of medical equipment and even human body parts. (Osouli-Bostanabad et al, 2022) Telemedicine facilitates remote access to medical expertise, particularly post-operation visits, and is gaining traction. E-healthcare leverages modern technology to bridge the gap between remote areas and healthcare providers. Nanotechnology, enabled by smart devices and body-centric nanonetworks, is revolutionizing patient monitoring and diagnosis by providing real-time health information. (Chen et al, 2023) These innovations collectively mark a profound shift in healthcare, offering new possibilities for both patients and practitioners. These technological advances will be discussed in more detail in the following sections.

Internet of medical things

The emergence of advanced communication technologies has propelled our world towards the status of a global village. The continuous evolution of these technologies has given rise to the concept of the Internet of Things (IoT), a loosely defined network comprising interconnected devices. (Ahmad et al, 2022) The principles underpinning IoT have already found practical use in diverse fields such as intelligent residences (Dai, 2020), wearables (Qureshi et al, 2018), overseeing traffic patterns, agricultural practices, and more. (Asghari et al, 2019 ; Bandyopadhyay & Sen, 2011) Even within critical safety applications such as healthcare, IoT is gaining traction through m-health, a system that delivers medical services via mobile devices (Jara et al, 2013). M-health facilitates the retrieval of pertinent medical data within dynamic and dispersed healthcare systems, leading to more efficient and cost-effective healthcare provisions. The Internet of Medical Things (IoMT) represents a subset of IoT encompassing an assortment of interconnected medical devices and sensors. The interconnected communication between medical professionals and patients can also be perceived as an element of IoMT (Vishnu et al, 2020). Patient health data is captured by sensors affixed to their bodies, and subsequently, this amassed data is transmitted to medical experts for purposes of diagnosis, supervision, and treatment.

The realm of the Internet of Medical Things (IoMT) encompasses various subdivisions or components, including wearable devices designed for monitoring health, medical implants, mobile applications for health (mHealth), systems for telemedicine and telehealth, the utilization of big data analysis, the integration of artificial intelligence in healthcare, and the practice of remote patient monitoring (RPM), as detailed in numerous review articles (Xu et al, 2020; Taloba et al, 2023; Malasinghe et al 2019). Illustrative instances of wearable health monitoring technology presently in operation encompass smartwatches, activity trackers, and medical sensors. A learning framework based on ontologies is employed, utilizing established ontologies and logs of activity data to recognize novel activities, identify triggers for development, and acquire knowledge of patterns, thereby enhancing personalized assistance within adaptive smart home environments. (keyo et al, 2011) These sensors and frameworks contribute to the monitoring of critical patient metrics such as heart rate, blood pressure, and respiratory rate (Pereira et al, 2019).

An IoT-based smart thermometer developed by Kinsa, a health technology company from the United States, is effective in detecting individuals with high body temperatures. This service can be used on a large scale to identify potential hotspots of COVID-19. (Winn, 2020) Various advanced methods are being used around the world for COVID-19 surveillance. For example, an IoT-based occupancy system has been developed that can detect the level of occupancy in areas such as buildings, public spaces, classrooms, office rooms, and transportation. (Ferna´ndez-Carame´s et al, 2020) This system is secured with blockchain and maintains decentralized traceability while not recording any unauthorized personal data.

Abdulrazaq et al. developed an IoT-based smart helmet that can detect potential COVID-19 cases using thermal imaging from a camera mounted on the helmet. (Abdulrazaq et al, 2020) This device shows promise in detecting suspected cases in public or hospital settings. It detects individuals with higher body temperatures and sends a notification to a paired mobile device or database with the captured face image and GPS location. Healthcare professionals or other concerned parties can then take necessary actions based on the received information. Similarly, IoT-based smart glasses have been developed for the same purpose. (Abdulrazaq & Istiqomah, 2020)

In the realm of lung cancer prediction, significant strides have been made through the fusion of sophisticated technologies, such as Deep Learning (DL) and Artificial Intelligence (AI). The synergy between AI and IoT is driving advancements in healthcare. The ability to process large data sets and meet user demand for better analytics has contributed to the expansion of AI-based systems (Jeffree et al, 2020). These technologies have enabled the creation of predictive models that offer early detection and accurate classification of lung cancer. Approaches such as the DL Mask R-CNN model employ image segmentation techniques to identify and categorize pulmonary nodules, while neural network models trained on comprehensive datasets enhance the accuracy of disease classification (Rustam et al, 2020)The adoption of IoT further amplifies the capabilities of these models, allowing for the real-time monitoring of patient's health statuses through the Internet of Medical Things (IoMT) devices. The ability to process large volumes of medical imaging data offers the potential to revolutionize lung cancer diagnostics. (Chiu et al, 2022)

Similarly, in the management of T1DM (Type 1 diabetes mellitus), IoT-based systems play a crucial role in monitoring and maintaining blood glucose levels. T1DM, characterized by the body's inability to regulate glucose levels due to the destruction of insulin-producing cells, demands continuous monitoring and insulin administration (Haller et al, 2005; Riddell et al, 2017). Intelligent Data Analysis (IDA) techniques, coupled with wearable devices and continuous glucose monitoring (CGM) systems, provide a comprehensive approach to tracking glucose fluctuations (Rodriguez-León et al, 2021). The integration of IoT platforms with patient monitoring tools such as wearable devices and continuous glucose monitoring systems has the potential to revolutionize T1DM management (Xie, 2021).

Advancements in cloud computing, biometric sensing, and wireless connectivity have further strengthened the role of IoT in healthcare. IoT platforms offer real-time data collection and analysis, allowing for the creation of accurate predictive models for disease management (Jeffree et al, 2018; Rustam et al 2020). The vast amount of data generated by IoT-enabled devices presents new opportunities for sophisticated data analysis, contributing to better understanding and management of chronic diseases. Cloud computing facilitates the execution of complex algorithms, enhancing the accuracy of disease prediction and glucose level modeling ((US Preventive Services Task Force, 2020).

Blockchain and its application in healthcare

The Blockchain concept was first published by a (fictional) person named Satoshi Nakamoto in 2009 in the form of a white paper about a peer-to-peer electronic cash system called Bitcoin (Kulkarni, 2019). It is a distributed P2P (Peer-to-peer) ledger technology to process transactions in immutable blocks of data using cryptography. The blockchain is deployed as a distributed and decentralized network that processes, verifies, and maintains (multiple copies of) its data; autonomously. The blockchain records transactions in the form of an immutable ledger. It is deployed via a distributed network of untrusting peers, each maintaining a copy of the ledger (Musa et al, 2020). Data is created in the blockchain in the form of a time-stamped ledger which cannot be changed, updated, or deleted in any way because the provisions to do so simply do not exist. This data is therefore termed immutable. Its time-stamped ledger also enables provenance, enabling us to trace the origin of the data and its evolution over time. Computable blockchains can execute pre-programmable code called smart contracts, which are preprogrammed codes that can be written and deployed into the blockchain with rules to self-execute and self-enforce themselves (Pandey et al, 2021). Smart contracts are transparent, run autonomously and once deployed cannot be changed or manipulated. The blockchain architecture then allows untrusting parties with common interests to co-create a permanent, unchangeable, and transparent record of exchange and processing without relying on a central authority (Pereira et al, 2010). UPLX or Unified Patient Ledger is built on Hyperledger Fabric and designed as a blockchain platform to securely record and store patient data. (Musa et al, 2020) Hyperledger Fabric is a modular and extensible open-source system for deploying permissioned blockchain networks (Seo & Cho, 2020).

UPLX is a blockchain-powered interoperable health data platform and can be integrated with any hospital information systems (HIS) through API (Application Programming Interface) technology. To provide real-time data, UPLX can also be integrated with health-tracking apps, wireless-enabled wearables, or IoT devices. Blockchain-based data architecture is the leading candidate to enhance interoperability whether for existing application systems, IoT platforms, or other smart devices because it can ensure security, privacy, and performance (14). UPLX is divided into two phases: a Write Phase and a Read Phase. In the Write Phase, each medical or health institution participating in the UPLX network is represented as an “Organization” object, with rights to create and endorse transactions. The Write Phase provides tools for organizations to record their patient data via integrating UPLX APIs into their information systems. Their data is encrypted and patient information is anonymized before being recorded into the blockchain. UPLX anonymizes patient identity by applying an SHA-256 cryptographic hash function; utilizing information such as patient name and identity number combined with the organization's private keys to create a unique representation of that data Since the private keys are unique to each organization, their patient information cannot be read by other organizations within UPLX network. (Musa et al, 2020; Tariq et al, 2020)

As blockchain technology continues to gain more exposure, the adoption of blockchain technology into industry applications is something that should be looked into to fully reap its benefits. Many blockchain projects are kicking into high gear as researchers and practitioners continue to experiment with its capabilities and limits. The blockchain at its core, generates a set of secure, immutable, and trusted data. Data is the foundation of research and analysis in many areas of industry and academia. The validity, accuracy, and reliability of any research stem from the trustworthiness of its data source. (Esposito et al, 2018)

3D printing

The introduction of 3D printing in healthcare has been transformative due to its ability to generate physical objects from digital files. This technology has been instrumental in the production of patient-specific medical models, assisting surgeons in planning complex surgeries with precision (Hurst, 2016). It has also revolutionized the creation of custom-fitted replacement organs, offering hope to patients in need of immediate intervention (Trenfield et al, 2019). The technology's applications extend to the production of medical equipment such as prosthetics, wheelchairs, surgical tools, implants, and even respiratory masks. Also, one of the most fascinating developments is 3D bioprinting, which uses living cells and biomaterials to create tissues and organs. Bioprinting holds promise for reconstructive surgery, creating synthetic organs, and personalized drug printing (Gungor-Ozkerim, 2018). This approach has enabled researchers to explore the possibilities of creating functional human tissue and could potentially revolutionize drug testing and clinical trials (Fu, 2022).

3D printing has not only impacted the production of medical devices but also supply chain management. It offers a cost-effective solution for low-volume manufacturing, reducing the need for costly molds and allowing for greater flexibility (Andreadis et al, 2022). However, it is crucial to note that 3D-printed medical devices must meet regulatory standards similar to traditionally manufactured products (Prasad, 2016). In addition, 3D printing has opened new horizons in pharmaceuticals by enabling the creation of custom medication regimens (Awad et al, 2018). It allows for the production of personalized drug dosages and the development of complex drug delivery systems tailored to individual patients. This technology enhances medication adherence, reduces the likelihood of adverse effects, and simplifies drug intake for patients with specific needs. (Dodziuk, 2016) As 3D printing technology continues to advance and become more accessible, its impact on healthcare is expected to grow. Innovations like 4D printing and the integration of 3D printers into clinics and pharmacies hold the potential to revolutionize drug manufacturing and distribution, making healthcare more patient-centered and efficient (Sheikh et al, 2022).

Artificial intelligence (AI) in healthcare

Artificial Intelligence (AI) is making swift advancements within the healthcare sector, primarily driven by its capacity to harness extensive data for informed clinical decision-making and the pursuit of value-driven healthcare. Healthcare professionals must grasp the current landscape of AI technologies and their potential applications in enhancing the effectiveness, safety, and accessibility of healthcare services, thereby facilitating the digital transformation of the healthcare industry. Thus, AI has several applications that can help medical professionals to make the healthcare system more efficient and effective.

Li et al proposed. (2020) argues that there should be three principles based on which AI is used in healthcare, (1) a significant portion operates within complex adaptive systems, necessitating that AI can seamlessly adapt to this intricacy. (2) Instead of being an end product, AI should be perceived as a facilitating element within larger solutions. (3) Solutions empowered by AI frequently encompass intricate constellations of individuals, processes, and technologies. (Li et al, 2020)

Significant strides have been achieved in the realm of natural language processing for biomedical applications. In the sphere of biomedical question answering (BioQA), the objective lies in swiftly and accurately responding to user-generated inquiries from a pool of documents and datasets. Here, the role of natural language processing techniques becomes pivotal in the quest for informative solutions. The initial step involves categorizing biomedical questions into distinct segments to extract pertinent information from the responses. Machine learning enters the scene, proficiently sorting biomedical questions into four fundamental categories, boasting an accuracy rate of almost 90%. Following this, an astute biomedical document retrieval system adeptly pinpoints document sections that are most likely to harbor answers for the posed biomedical queries. A fresh approach emerges in the form of a scheme tailored for processing one of BioQA's basic types—the generator for yes-or-no answers, drawing inspiration from word sentiment analysis, effectively contributing to information extraction from binary responses.

In the context of gathering biomedical data from varied sources across an extended timeframe, several pivotal tasks come to the fore: amalgamation, comparison, and resolution of clinical information, each of which has long been characterized as time-intensive, labor-demanding, and less than satisfactory when performed manually. In pursuit of heightened efficiency and precision, AI has showcased its capacity to execute these tasks with outcomes that align with the accuracy achieved by seasoned evaluators. Furthermore, the processing of medical narrative data through natural language techniques emerges as a necessity to unburden humans from the intricate responsibility of chronologically tracking events while simultaneously upholding structures and rationales. Machine learning emerges as a tool to grapple with complex clinical information, embracing multifaceted data forms including text and a diverse array of interconnected biomedical data. It infuses logical reasoning into the dataset, leveraging acquired knowledge for an array of purposes. (Rong et al, 2020 ; Wu et al, 2022)

The demand for AI in biomedicine, particularly disease diagnosis, is evident (Sajda, 2006). AI advancements lead to faster and more precise diagnoses, benefiting patient care. AI aids in gene expression analysis, such as microarray data interpretation, enhancing disease identification (Molla, 2004; Pham et al, 2006). In cancer diagnosis, AI categorizes microarray data for improved understanding and classification (W Shi et al, 2017). AI integrated with biosensors and point-of-care testing detects cardiovascular diseases early (Vashistha et al, 2015). AI also predicts survival rates for cancer patients, including colon cancer (Ahmed et al, 2005). Despite progress, AI's role in diagnosis has limitations that researchers aim to address (Foster et al, 2014).

Disease diagnosis through medical imaging (2D) and signal processing (1D) is vital, aiding diagnosis, management, and prognosis (Krishnan et al, 2018). AI's impact is evident in extracting biomedical signal features (Krishnan et al, 2018), including EEG (Hamada et al, 2018), EMG (Kehri et al, 2016), and ECG (Rai, 2018). AI predicts epileptic seizures using EEG, crucial for patient well-being (Cook, 2013). Deep learning enhances seizure prediction accuracy (Assi et al, 2017; Fergus et al, 2015), integrated into mobile platforms (Stacey et al, 2018; Kiral-Kornek et al, 2018}. In biomedical image processing, AI enhances image quality and analysis efficiency (Stoitsis et al, 2006; Fasihi et al, 2016; Jo et al, 2016), even in portable ultrasound devices, expanding diagnostics in underserved regions (Rong et al, 2020).

AI collaborates with decision support systems (DSSs) (Elkin et al, 2018; Safdar et al, 2018) transforming diagnostic precision and disease management, seen in cancer, tropical diseases, and cardiovascular ailments (Ibrahim et al, 2015; López-Fernández et al, 2016). AI's role in decision-making reinforces its significance (Elkin et al, 2018), showcasing its power in early diagnostics, disease management, and condition prediction.

Another pertinent area of exploration pertains to the realm of predictive medicine, encompassing the application of artificial intelligence in forecasting and diagnosing diseases, along with foreseeing treatment outcomes and assessing future prognoses (Curchoe et al, 2020). The intrinsic capability of AI to discern meaningful patterns within raw data lends robust support to diagnostic procedures, treatment strategies, and prognostic assessments across a spectrum of medical scenarios (Phillips et al, 2022). This, in turn, empowers healthcare professionals to proactively manage the onset of diseases. Moreover, the potential for predictions comes to the fore, facilitating the identification of individual patient risk factors and determinants, thereby enabling targeted and precise medical interventions that yield superior outcomes (Lella et al, 2019). The methodologies rooted in AI also find practical utility in the development of novel medications, vigilant patient monitoring, and the tailoring of personalized treatment strategies (Paul et al, 2021). In this landscape, physicians stand to benefit from the luxury of more time and distilled data, thereby fostering the capacity for improved, patient-centric decision-making. The dawn of AI-powered automated learning holds the promise of reshaping the landscape of medicine, potentially giving rise to predictive models encompassing medications and assessments that seamlessly accompany patients throughout the entirety of their lifetimes (Johnson et al, 2021). The table below provides a summary of research on applications of AI in medical care services around the world.

Authors	**Disease**	**Techniques**	**Classifiers**	**Performance**	**Summary**
Perveen et al. (106)	Diabetes	AdaBoost, Decision Tree	AdaBoost, Decision Tree	89.31% accuracy	Healthcare model for diabetes prediction using AdaBoost and Decision Tree classifiers, based on age groups. AdaBoost outperforms Decision Tree.

Wu et al. (154)	Liver Disease	Random Forest, Naive Bayes, ANN, Linear Regression	Random Forest	87.48% accuracy with RF	A model predicting liver disease using multiple algorithms. RF achieves 87.48% accuracy.
Shankar et al. (125)	Thyroid	Feature Selection	-	97.49% accuracy, 99.05% sensitivity, 94.5% specificity	Model for thyroid data classification using feature selection, achieving high accuracy and sensitivity.
Sisodia and Sisodia (129)	Diabetes	Naive Bayes, SVM, Decision Tree	Naive Bayes, SVM, Decision Tree	76.30% accuracy with NB	Machine learning-based model predicts diabetes using Naive Bayes, SVM, and Decision Tree classifiers.
Kumar and Vigneswari (144)	Hepatitis	Multilayer Perceptron, RF, Decision Tree, C4.5, Logistic Regression	Random Forest	90.32% accuracy with RF	Model for hepatitis prediction using multiple classifiers, achieving 90.32% accuracy with RF.
Parisi et al. (102)	Hepatitis	SVM, MLP	Lagrangian SVM, MLP	Perfect accuracy and AUC	The hybrid model predicts hepatitis using SVM and MLP, achieving perfect accuracy and AUC.
Hameed et al. (46)	E-Healthcare	Cloud Computing	-	-	E-Healthcare model based on cloud computing and service-oriented architecture.
Vijayarani and Dhayanand (146)	Kidney Disease	SVM, Naive Bayes	SVM, Naive Bayes	SVM > Naive Bayes	The model predicts kidney disease using SVM and Naive Bayes classifiers. SVM outperforms Naive Bayes.
Harimoorthy and Thangavelu (50)	Heart Disease, Diabetes,	SVM-linear, SVM-Radial, RF	-	89.9% accuracy (Heart), 98.7% accuracy (Diabetes),	The model predicts multiple diseases with high accuracy using

	Kidney Disease			98.3% accuracy (Kidney)	various SVM and DT classifiers.
Jahangir et al. (56)	Diabetes	Auto MLP	Auto MLP	-	Framework predicts diabetes using Auto MLP and outlier detection.
Verma et al. (145)	Risk Factors	Particle Swarm, K-means	Multilayer Perceptron, Multilayer Logistic Regression, Fuzzy, C4.5	88.4% accuracy with MLR	CAD method for risk factor determination using Particle Swarm and K-means. 88.4% accuracy with MLR.
Haq et al. (49)	Heart Disease	Feature Selection	Logistic Regression, SVM	89% accuracy (Logistic Regression), 88% accuracy (SVM)	The hybrid model predicts heart disease using feature selection and achieves high accuracy with logistic regression and SVM.
Muhammad et al. (93)	Heart Disease	K-NN, AB, DT, RF, NB, LR, ANN, SVM	Multiple	94.41% accuracy	The model accurately predicts heart disease using various classifiers and feature selection techniques.
Alkeshuosh et al. (6)	Heart Disease	ML Techniques	-	87% accuracy	New diagnostics for heart disease prediction with an 87% accuracy rate.
Samuel et al. (120)	Heart Failure	K-NN, AB, DT, RF, NB, LR, ANN, SVM	-	91.10% accuracy	The model predicts heart failure with an accuracy of 91.10%.

Usually, decisions and predictions made by AI are subject to being criticized for not having transparency as to how AI systems achieve their outcomes. This lack of transparency may create confusion for medical professionals, making AI's recommendations less valuable. Thus, experts have tried to use Explainable Artificial Intelligence. Explainable Artificial Intelligence (XAI) refers to a transparent model that offers insights into the processes behind its predictions, aiming to establish reliability, causation, adaptability, assurance, equity, ease of use, and interaction. The table below gives a summary of what can be achieved using explainable AI.

Topic	**Summary**	**Details**

Explainable AI (xAI) in Drug Research(Minh et al, 2022)	xAI aids drug research, development, and clinical trials. Deep Learning (DL) integrates patient data, aiding ADR anticipation, and drug approval. Examples: INS018_055, Orphan Drug Designation. (Kimbal et al, 2022)	xAI facilitates new drug development, repurposing, and clinical trial design. - DL integrates patient data from sources like EHR, Genomic Libraries, and UK Biobank. - xAI helps in anticipating adverse drug reactions (ADR) and drug approval assessments. - Example: INS018_055 drug development with AI-discovered targets and AI-designed structure. - Use of tools like PandaOmics and Chemistry42 for target discovery and drug design enhancement. - FDA's recognition of xAI's potential in Orphan Drug Designation. (Moore & Bell, 2022)
Radiomics with Explainable DL (Chaddad et al, 2023)	Radiomics uses computational methods on medical images. xDL aids predictions from histopathology images, genetic inference, and treatment assessment. Examples: HE2RNA, TOAD, AD diagnosis.	Radiomics involves analyzing medical images (CT, MRI, PET scans) using computational methods. - xDL enhances predictions from routine histopathology images. - Applications: genetic alteration inference, patient survival prediction, and treatment response assessment. - Case studies: HE2RNA model predicts gene expression from whole slide images (WSIs) (Shimizu, 2020), TOAD aids in cancer origin diagnosis(Lu et al, 2021), and xDL aids in diagnosing Barrett's esophagus. - xDL's role in radiological applications: distinguishing patient groups, clinical diagnosis prediction, identifying brain regions related to Alzheimer's Disease (AD). (Liu et al, 2018). - CNNs' effectiveness in tasks like tumor diagnosis and cancer classification. (Desai & Shah, 2021)
Genomics and CDL	Genomics focuses on disease risk modeling. xDL captures non-linear relationships and addresses genetic interaction understanding. Examples: DeepCOMBI, DFIM, Informer.	Genomics focuses on the cumulative impacts of individual genetic variants in disease risk modeling. - HDL aids in capturing non-linear relationships in data and understanding genetic interactions. - Specific examples: DeepCOMBI classifies individuals based on SNPs (Mieth et al, 2021), DFIM estimates interactions between DNA sequence features(Lamy et al, 2019), and Enformer interprets DNA sequences for gene expression and chromatin states.(Karollus et al,2023) - xDL's involvement in transcriptomics: classifying tissue origins, exploring gene expression regulation by integrating chromatin and expression data. - Importance of feature attribution techniques for discovering cis-regulatory patterns.

The future and beyond

There are several different scenarios that we can't predict for the future. Nevertheless, what can be said is the fact that trends observed today will shape the future. Therefore, in this section, we try to use the current literature to better understand the future.

While the potential of blockchain in healthcare is immense, further research is necessary to optimize privacy, security, data access, and scalability. (Kumar et al, 2023) Implementation challenges persist, necessitating ongoing developments and clinical trials to manage blockchain limitations. Compliance with data regulations, including the General Data Protection Regulation (GDPR), is crucial to ensuring the ethical and legal use of blockchain in healthcare. (Taloba et al, 2023)

In recent years, 3D printing technology, also known as additive manufacturing, has witnessed significant advancements that are poised to revolutionize the healthcare industry. The adoption of 3D printing in healthcare holds immense promise, with its potential applications spanning various critical domains. One of the most notable prospects lies in the field of regenerative medicine, where 3D printing technology is making it possible to print biological materials, including stem cells, and construct organs and blood vessels at a cellular level. Pioneering organizations like Celprogen Inc. VR and ETH Zurich have already achieved groundbreaking feats in 3D bioprinting, such as the creation of a 3D printed human heart and pancreas from PLA (Polylactic acid) cultivated with human pancreatic stem cells. (Trenfield et al, 2019; Kumar Gupta et al, 2022) These advancements are not only poised to address the scarcity of organ donations but also open doors to alternative transplantation methods, particularly in the areas of aging and regenerative medicine. (Vijayavenkataraman et al, 2018) This emerging capability has the potential to transform healthcare by enabling the production of vital tissues, veins, and organs tailored to individual patient's needs, thereby ushering in a new era of personalized medicine. (Kantaros et al, 2022)

Furthermore, 3D printing's impact extends to clinical applications, with its ability to create tailored medical devices and surgical models that cater to the unique needs of patients. Shortly, we can expect 3D printing to play a crucial role in addressing the challenges associated with organ failure, birth defects, accidents, and aging. (Jin et al, 2021) 3D-printed surgical models will facilitate advanced procedural planning and surgeon training, particularly in fields like neurosurgery, orthopedics, and cardiovascular surgery. Beyond this, the technology is set to revolutionize the production of patient-specific implants, wearable medical devices, anatomical structures, and prosthetics. As 3D printing becomes more cost-effective and accessible, it is likely to reshape the landscape of anatomical and surgical sciences, benefiting not only healthcare professionals but also patients seeking more personalized and effective medical solutions. (Zandrini et al, 2022) In summary, the integration of 3D printing technology into healthcare promises to bring about innovative and personalized approaches to treatment and surgery, ultimately enhancing patient care and outcomes.

In the realm of medical diagnostics, artificial intelligence (AI) has demonstrated remarkable potential. Researchers from Stanford University have shown that machine learning algorithms can perform on par with board-certified dermatologists in diagnosing skin cancer. Leveraging an artificial neural network trained on a massive dataset of over 129,000 clinical images spanning 2,032 different diseases, this achievement underscores the capacity of AI to tackle highly variable tasks (Goyal et al, 2020).

Combining blockchain and AI holds the potential to address security, interoperability, and data management challenges (Tagde et al, 2021). Blockchain's secure and decentralized nature aligns with AI's capabilities, ensuring reliable and accountable outcomes (Phillips et al, 2022).

Expanding the scope of AI applications, machine learning is proving invaluable in the automated detection of lung nodules on CT scans and pneumonia on chest X-rays. (Palatnik de Sousa et al, 2021) Collaborative efforts between human specialists and AI agents, as evidenced by studies including one from MIT, yield more accurate predictions than either working in isolation. (Ozsahin et al, 2020) Furthermore, as researchers delve into the intricate relationship between gene expression and imaging features of tumors, AI aids in analyzing extensive imaging data to assess tumor genetics, behavior, and responses to treatment (Ahmed et al, 2005; Lu et al, 2021; Desai et al, 2021; Chiu et al, 2022).

Beyond cancer diagnostics, the potential of AI extends to various diseases related to genetics or imaging biomarkers. This suggests a promising future where AI systems could assist in diagnosing severe and degenerative conditions such as Alzheimer's and coronary heart disease. (Liu et al, 2018; Fabrizio et al, 2021) The versatility of AI in handling a wide spectrum of medical challenges showcases its potential to revolutionize healthcare and improve diagnostic accuracy. Potential uses of AI for different periods are shown in the table below. (Bajwa et al, 2021)

Timeline	**Connected/augmented care**	**Precision diagnostics**	**Precision therapeutics**	**Precision Medicine**	**Summary**

Short-term (0-5 years)	Internet of things in healthcare Virtual assistants Augmented telehealth Personalized mental health support	Precision imaging (e.g. diabetic retinopathy and radiotherapy planning)	CRISPR (increasing use)	Digital and AI-enabled research hospitals	AI automates time-consuming, high-volume repetitive tasks, especially within precision imaging
Medium-term (5-10 years)	Ambient intelligence in healthcare	Large-scale adoption and scale-up of precision imaging	Synthetic biology Immunomics	Customization of healthcare Robotic-assisted therapies	AI uses multi-modal datasets to drive precision therapeutics
Long-term (> 10 years)	Autonomous virtual health assistants, delivering predictive and anticipatory care Networked and connected care organizations (single digital infrastructure)	Holographic and hybrid imaging Holomics (integrated genomic/radiomic/proteomic/clinical/immunohistochemical data)	Genomics medicine AI-driven drug discovery	New curative treatments AI-empowered healthcare professionals (e.g. digital twins)	AI enables healthcare systems to achieve a state of precision medicine through AI-augmented healthcare and connected care

Also, AI-assisted robotic surgery has been available since 1985 and has found applications in various medical fields, including cardiac surgery, thoracic surgery, gastrointestinal surgery, gynecology, orthopedic surgery, spine surgery, transplant surgery, urology, and general surgery. (Jeffree et al, 2018) Traditional surgical limitations, where surgeons relied solely on visual observation, have been overcome by AI-powered robotic surgery, enabling precise procedures through small incisions. The technology aims to minimize postoperative complications and expedite patient recovery times. (Shein et al, 2023) Moreover, AI-assisted robotic surgery enables the collection of comprehensive data during procedures, which can be used for analysis and further improvements. (Kalis et al, 2018)

Clinical evaluations of AI-assisted robotic surgery have highlighted its advantages, such as shorter hospital stays (Bodenstedt et al, 2020), reduced blood loss (Nwoye et al, 2022), and fewer complications (Han & Tian, 2019). Notable studies have been conducted in areas like gynecological oncology, where AI-based systems have been explored for their potential to predict future conditions like acute kidney injury and circulatory failure. (Omiye et al, 2023) Although AI has demonstrated promise in predictive analytics and decision support systems, its integration into surgery-specific assistance systems remains relatively limited. To bridge this gap, researchers are exploring context-aware assistance systems that leverage AI and machine learning to optimize surgical workflows. These systems model surgical processes, recognize critical steps, and provide relevant information at the right time. (Kolbinger et al, 2023) Furthermore, the concept of cognitive surgical robotics is emerging, envisioning robots that understand surgical scenes and adapt to workflows. However, this level of sophistication requires extensive development and validation, aiming to create cognitive robots capable of performing complex surgical tasks through AI-driven understanding and learning. (Thai et al, 2020)

Conclusion:

Now, let's envision the appearance of forthcoming medical facilities. Considering the ongoing healthcare trends mentioned earlier and taking into account the anticipated medical and technological progress shortly, it's highly likely that healthcare institutions in 2030 will undergo significant transformations compared to their present counterparts. In these future healthcare establishments, space requirements will diminish significantly, rendering waiting areas unnecessary as a majority of healthcare services will be administered remotely, far removed from traditional hospital settings.

A remarkable development on the horizon involves the integration of individualized computer chips within each person's body, encompassing their comprehensive medical data. This data will be under the vigilant surveillance of artificial intelligence (AI), represented by a powerful computer system responsible for monitoring and regulating all aspects of human health.

Furthermore, with the advent of cutting-edge medical breakthroughs, many of the diseases currently afflicting humanity are poised to become virtually obsolete. This optimistic outlook is attributed to the increasing availability of vaccinations and pharmaceuticals that will effectively prevent a broad spectrum of human illnesses.

Looking ahead, a significant transformation awaits the landscape of hospital operations. Robots and artificial intelligence (AI) are poised to take center stage in the healthcare sector, gradually assuming control over a multitude of tasks, ranging from administrative duties like reception to intricate procedures such as radiology, scans, and even surgical interventions. Notably, due to the heightened reliability of robotic surgical procedures when compared to their human counterparts, it is anticipated that the majority of surgeries will be executed by robots. This shift will inevitably lead to a reconsideration of the architectural layout of operation departments and operating rooms to accommodate these technological advancements.

AI demonstrates exceptional speed and accuracy in the detection of diseases, rendering traditional laboratory or detection departments as we currently recognize them redundant in future healthcare facilities. A pivotal addition to these future hospitals will be dedicated spaces for activities like scanning and 3D printing. The versatility of 3D printers will empower them to manufacture an extensive array of items, encompassing medical equipment and even human body parts, such as artificial ears.

Furthermore, the influence of 3D printers may extend into the pharmaceutical industry, revolutionizing the way drugs are produced. Shortly, pharmaceuticals will be tailored to the specific requirements of each individual, enabling patients to conveniently order their prescribed medications online. These drugs will then be fabricated by 3D printers and subsequently delivered directly to the patients, introducing a groundbreaking dimension to the healthcare system.

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