Advancements, Applications, and Future Directions of Artificial Intelligence in Healthcare

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Abstract

Background: The integration of artificial intelligence (AI) into healthcare represents a transformative shift in medical procedures, offering substantial benefits across various domains. With advancements in AI technologies such as machine learning (ML), deep learning (DL), and natural language processing (NLP), healthcare systems are witnessing improvements in early detection, patient treatment, and overall administration. This article traces the evolution of AI, from foundational contributions by Alan Turing during World War II to contemporary applications like ChatGPT, and examines the impact of AI in enhancing diagnostic accuracy and treatment outcomes. Methods: This comprehensive review analyzes the existing literature on AI applications in healthcare, focusing on various AI methodologies and their integration into clinical settings. It evaluates the effectiveness of AI in processing large datasets, improving diagnostic precision, and facilitating data-driven decision-making. The study also explores the ethical, legal, and technical challenges associated with AI deployment in medical environments. Results: AI technologies have demonstrated significant improvements in healthcare, particularly in early disease detection, personalized treatment plans, and resource management. The use of AI in analyzing vast medical datasets has enhanced diagnostic accuracy, reduced costs, and optimized patient care. However, challenges related to ethical considerations, patient privacy, and system reliability remain critical barriers to full-scale AI adoption. Conclusion: Despite the challenges, AI is positioned as an indispensable tool in modern medicine, capable of enhancing preventive care, personalizing treatments, and improving healthcare delivery. This review proposes a framework for evaluating the benefits, challenges, and strategies of AI integration in healthcare. Further research is essential to maximize AI's potential while addressing ethical and practical concerns, ensuring safe and effective implementation in clinical settings.

Keywords: Artificial Intelligence, Medical System, Smart Healthcare, Diagnosis, Machine Learning

Significance | This review discusses the AI's transformative role in healthcare, focusing on patient care, diagnostics, early detection, and cost reduction.

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Introduction

Since the advent of the industrial revolution, there has been significant advancement and focus on technology in the fields of manufacturing and economic expansion (Li et al., 2017; Ali et al., 2022). Technological developments in machines have replaced labor-intensive duties, promoting human growth (Kaplan and Haenlein, 2020). In addition to physical efforts, artificial

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intelligence (AI) signifies a significant technical advancement that enables individuals to replace manual tasks with enhanced cognitive abilities in several industries (Chien et al. 2020; Kumar et al., 2023). AI is a discipline that combines technology and science to enable computers and apps to carry out tasks that often need human intellect (Aiken and Epstein, 2000). One of the key advantages of AI is its ability to do many human-like tasks, learn from experiences, and adjust to new information and surroundings. In order to achieve optimal performance in certain activities, AI leverages relevant data sources such as Big Data (Kaplan and Haenlein, 2020).

AI has made significant advancements in several domains, particularly in healthcare, providing numerous advantages (Minz and Mahobiya, 2017; Ribbens et al., 2014; Strachna and Asan, 2020). AI has automated several areas of healthcare machinery, reducing the need for humans to perform basic activities related to patient care and medical resources (Comito et al., 2020; Yu and Zhou, 2021; Bernardini et al., 2021). AI additives are being used more frequently to handle complex approaches. Artificial intelligence (AI) healthcare systems are rapidly advancing, particularly in the areas of early detection and diagnostics (Chen, 2018; Dhieb et al., 2020; Yu and Zhou, 2021; Merhi, 2022). These technological improvements enable AI to perform activities quickly, easily, dependably, and attentively, often at a reduced expense compared to humans (Sqalli and Al-Thani, 2019; Zhou et al., 2020). AI systems that are well-designed have the ability to effectively handle the more challenging scenarios that arise from the digitization of healthcare (Tobore et al., 2019). AI has the potential to significantly improve patient care while also reducing healthcare costs (Wahl et al., 2018; Dhieb et al., 2020; Kaur et al., 2021). With the increasing human population, there will be a greater need for fast healthcare services. This will need the use of innovative AI solutions to enhance efficiency and effectiveness without increasing expenses (Pee et al., 2019). AI plays a crucial role in delivering novel solutions and helping the management of the healthcare industry's expansion (Maduri et al., 2020; Comito et al., 2020).

Current advancements in artificial intelligence (AI), such as the utilization of big data, machine learning applications, and robots, are employed for the purpose of monitoring, identifying, and assessing health hazards and advantages (Hossen and Armoker, 2020; Dharani & Krishnan, 2021; Duan et al, 2022). The healthcare business primarily depends on medical data and research to enhance operations and oversee medical services. The volume and intricacy of medical data have grown tremendously, leading to the development of electronic health records (EHRs), medical imaging, and data from diverse monitoring devices by practitioners, researchers, and patients (Antoniou et al., 2018; Liu, etc., 2020). AI technology has the capability to acquire, process, evaluate, and create outcomes from this data, which may be efficiently utilized for medical purposes (Comito et al., 2020). These applications are commonly executed by employing machine learning methods, which are aided by data storage and processing capabilities (Charan et al., 2018; Woo et al., 2021). Technologically sophisticated hospitals are progressively using AI technologies to enhance service accuracy and decrease operational expenses (Zhou et al., 2020; Mary et al., 2020). Artificial Intelligence (AI) offers extensive and detailed information on various treatment options, therefore assisting doctors and patients in making well-informed decisions regarding their treatment plans (Deng et al., 2019).

Artificial Intelligence The primary hazards and difficulties encompass potential harm to patients resulting from system faults (Aljaaf et al., 2015; Srivastava and Rossi, 2019; Madanan et al., 2021; Dwivedi et al., 2021), issues regarding patient confidentiality, as well as ethical and legal considerations, and the use of AI for decision-making in medical contexts. Medical concerns associated with its usage have been documented in studies conducted by Liu et al. (2020) and Shaban-Nejad et al. (2021). One of the primary advantages of AI is its ability to enhance preventative care and enhance overall health and well-being. Apps may empower patients by providing them with greater autonomy in managing their health. This allows people to make informed choices on preventative health matters, such as type 2 diabetes and hypertension, based on scientific data (Antoniou et al., 2018; Jaiman and Urovi, 2020). To achieve prompt identification and assessment, a diverse array of artificial intelligence (AI) applications must be employed. This is necessary to ensure the precision, swiftness, and dependability of illness diagnosis (Ribbens et al., 2019; Sasubilli et al., 2020; Jahan and Tripathi, 2021). Artificial intelligence (AI) utilizes enormous datasets, known as Big Data, to do comparative analysis. It compares patient profiles with the data from these datasets to uncover patterns. This analysis helps physicians in the diagnosis and management procedures. (Charan et al., 2018; Woo et al., 2021). AI technology can enhance the efficiency of medical services, supporting complicated medical operations (Deng et al., 2019; Daltayanni et al., 2012).

This systematic study examines the advantages, difficulties, tactics, and advantages of artificial intelligence in the field of healthcare (Murphy et al., 2021). Additional investigation into the practical and theoretical dimensions of AI is necessary in order to gain a more comprehensive understanding of these notions (Chen et al., 2020; Johnson et al., 2022). Current areas of research include on the impact of AI on physicians' rights and obligations (Yang, 2018; McGregor, 2020), challenges related to privacy protection (Wang et al., 2020; Zhou et al., 2021), and an ethical examination of data-driven AI (Liu et al., 2020; Shaban-Nejad et al., 2021). Authorities have the ability to implement legislative regulations in order to safeguard health information (Gomoi and Stoiku-Tiwadar, 2010; Bhaduri et al., 2011). When gathering data for machine learning and expert systems, it is crucial to take into account ethical issues (Liu et al., 2020; Shaban-Nejad et al., 2021). In order to effectively implement AI in the field of medicine, it is crucial to develop clear and precise standards for technology and healthcare applications. This paper provides an overview of the current status of artificial intelligence (AI) in the healthcare industry and suggests a framework for evaluating the advantages, difficulties, approaches, and initiatives related to AI in healthcare.

The article discusses the current uses of artificial intelligence (AI) in the healthcare industry. It provides information on how AI is applied in healthcare, a systematic approach for mapping the process of systematic review (SR), and the results of evaluating different categorization algorithms.

AI, short for artificial intelligence, is a field of computer science that specifically deals with programming machines to do tasks that typically require human intellect. The study conducted by Tsang et al. (2020) focuses on the background and intellect of individuals. Through the use of specifically designed algorithms, computers and machines are capable of comprehending, investigating, and acquiring knowledge from data (Sasubilli et al., 2020) authored in 2020. Contemporary AI applications encompass several tasks such as facial recognition using cameras, voice translation using computers, product searches in e-commerce, and decision assistance for clinicians (Sasubilli et al., 2020). The origins of AI may be traced back to the 1930s when Alan Turing pioneered the development of the first Turing machines for advanced mathematical calculation, which served as the groundwork for AI technology. Since its establishment as an academic field in the 1950s, research has thrived in several domains including natural language processing, learning, reasoning, and knowledge representation. In recent times, AI research has broadened its scope to encompass disciplines such as psychology, linguistics, philosophy, and education. AI is now being used in various fields such as commerce, robotics, transportation, healthcare, agriculture, military, marketing, and gaming. Some popular AI applications today include search engines like Google, recommendation systems like Netflix, self-driving cars like Tesla, and voice assistants like Siri and Alexa.

AI techniques may be categorized as machine learning, robotics, natural language processing, computer vision, and data analysis (Bernardini et al., 2021; Patii and Iyer, 2017; Murray et al., 2019; Jahan and Tripathi, 2021; Hossein and Armoker, 2020). The primary methodologies employed in AI machine learning are classification and clustering, which utilize many types of data, including numbers, text, pictures, and video. (Jahan and Tripathi, 2021) Classification methods, such as neural networks, decision trees, and Bayesian networks, are commonly used for training with large datasets. These algorithms may be applied in both supervised and unsupervised learning scenarios. Supervised learning relies on the utilization of labeled data for training, whereas unsupervised learning does not include the usage of labeled data. Clustering methods are utilized in unsupervised learning and do not necessitate labeled data. This forecasting system is comprised of prediction algorithms that have been trained using historical data. Decision trees, naïve Bayes classification, random forests, neural networks, deep learning, support vector machines, k-means, mean shifts, expectation maximization, Gaussian mixture models, linear regression, vector quantization, logistic regression, and K-nearest neighbors are commonly used algorithms in classification, clustering, and prediction (Elbasi et al., 2021).

There exists a clear differentiation between "hard AI", which strives to attain human-level intelligence for robots, and "soft AI", which has restricted uses. The authors of the publication are Gomoi and Stoicu-Tivadar, and the publication was released in 2010. Basic implementations of artificial intelligence (AI) encompass e-commerce recommendation systems, medical assistants, and voice-based personal assistants similar to Siri. Strong AI encompasses robots capable of independent decision-making without human involvement, encompassing areas such as cybersecurity, emotional well-being, behavior analysis, and predictive applications. Deep learning, a subtype of machine learning, employs multilayer artificial neural networks to tackle intricate issues in several domains like self-driving vehicles, fraud detection, healthcare, entertainment, machine translation, and virtual assistants. Additionally, they are extensively utilized for resolving problems.

Artificial Intelligence (AI) and its related areas, such as robotics, the Internet of Things (IoT), and machine learning, have a significant influence on society. They enhance people's lives by simplifying tasks, increasing comfort, and improving efficiency (Malik et al., 2021; Grover et al., 2020). AI applications have various benefits, including facial recognition for security, automation in industries, natural language processing for translation, robotics for home services, and machine learning and vision for healthcare (Herath et al., 2022). The Industry 4.0 revolution is propelled by the integration of artificial intelligence with Internet of Things (IoT), cloud computing, robotics, and cyber-physical systems. This change is primarily driven by the interconnectedness of devices and networks, as highlighted by Votto et al and colleagues in 2021. The effective integration of intelligent automation and interconnectedness has the potential to reduce time consumption, strengthen organizational control, and promote adaptability and cooperation (Kar et al., 2021; Ahsan et al.). This is an ongoing field of study in several sectors, such as healthcare. The objective of this study is to examine the utilization of artificial intelligence (AI) in the healthcare sector.

2. Methodology

Extensive searches were conducted in databases such as the National Library of Medicine, Scopus indexed journals, and EMBASE for a substantial duration. Only papers published in English were included. This study aims to comprehensively examine the issue by consolidating and evaluating many sources, while also identifying significant discoveries, patterns, and areas that require more investigation. To enhance search efficiency, utilize keyword combinations such as Artificial Intelligence Overview, Artificial Intelligence Applications, Artificial Intelligence in Healthcare, Artificial Intelligence in Medicine, Artificial Intelligence Diagnosis, Role of Artificial Intelligence in Medical Sector, Machine Learning in healthcare, Deep Learning in Healthcare, Large language Models in Healthcare, Artificial Intelligence for patient monitoring, AI ethics in healthcare, Healthcare Prediction, Neural Network for medical diagnosis, and so on. The collected papers underwent a comprehensive screening process to extract significant material and details. Prior to this initiative, a thorough evaluation was conducted on the title and abstract of the publications to confirm their suitability. Subsequently, several perspectives were employed to examine a specific set of publications. In several instances, incomplete matches and relevant literature references were utilized.

3. All About AI

Prior to delving into the practical uses of artificial intelligence, it is crucial to possess a comprehensive understanding of the subject matter at hand. Put simply, an autonomous entity, such as a machine or system, possesses the ability to independently make judgments and predictions, hence exhibiting intelligence. In essence, it is a collection of algorithms that rely on mathematical and statistical equations, collaborating to tackle intricate real-world issues, given adequate computer capacity. In order to properly acquire decision-making capabilities, algorithms depend on data presented in many formats such as numerical, textual, auditory, visual, and video. The algorithms acquire distinct parameters from the dataset, and this process of acquiring knowledge is referred to as training. The recent surge in artificial intelligence may be attributed to the extended development of algorithms, which have become more effective due to the availability of a substantial quantity of data. Nevertheless, the proliferation of the internet has led to increased accessibility of datasets, hence creating favorable conditions for the flourishing of artificial intelligence.

3.1 Evolution of the AI algorithms

In World War II, the Germans implemented the Enigma machine as a means of encrypting messages. In 1942, Alan Turing and his colleagues at Bletchley Park in the UK pioneered the application of Artificial Intelligence to decipher the codes of Enigma. This was the first instance of employing machine intelligence to tackle intricate problems (Rakus-Andersson, 2003). In 1950, Turing proposed the Turing Test as a means to evaluate the capacity of a computer to exhibit human-like intellect, thereby paving the way for the advancement of Artificial intellect (Moor, 2003). John McArthy, renowned as the progenitor of AI, organized the Dartmouth Conference in 1956, during which he coined the phrase "Artificial Intelligence." This event is widely regarded as the inception of the contemporary AI period. John McCarthy developed the LISP programming language in 1958, introduced the idea of time-sharing in the late 1950s and early 1960s, and has been dedicated to enforcing program adherence to specifications since the early 1960s (Andresen, 2002). In 1964, the first machine-human interaction occurred with the creation of the first chatbot. This chatbot utilized pattern matching and substitution methodology, which demonstrated the potential of Natural Language Processing (NLP). In 1995, ALICE (Artificial Linguistic Internet Computer Entity) was developed based on this idea, showcasing the progress made in the field (Shum et al., 2018). In 1997, a significant advancement occurred when the former grandmaster Garry Kasparov was defeated by the machine intelligence Deep Blue on the chessboard, showcasing the exceptional prowess of AI (Campbell et al., 2002). As the area progressed, human-robot interaction became more intricate with the introduction of the emotionally endowed robot 'Kismet' in 1998 (Breazeal, 2003). AI acquired its speech recognition capability in 2008, hence enhancing the ability of humans to interact with robots. In 2011, IBM Watson was unveiled as a question-and-answer computer system, taking human-machine interaction to a higher level (Chen et al., 2016). In 2020, OpenAI created ChatGPT, an impressive conversational AI powered by the LLM (Large Language Model). This development showcases the potential of intelligent machines and tools, as highlighted by Roumeliotis and Tselikas in 2023. The creation of AI algorithms started long ago, but their efficiency and widespread usage have only been achieved in recent years. This is mostly due to the requirement of a substantial amount of data for AI models to attain robust accuracy, which was not adequately available during the initial stages of algorithm development. Since its inception in 1969, the Internet has facilitated the collection and accessibility of data, which continues to increase every year. Through the accumulation of substantial data over time, we are already witnessing the remarkable potential of Artificial Intelligence in several sectors, including Healthcare. Figure 1 illustrates the progression of Artificial Intelligence through a continual development process.

3.2 Definition and Types

"Artificial Intelligence" is a comprehensive word that encompasses several subfields. Artificial intelligence, sometimes known as AI, is the ability of a computer to do tasks independently without relying on human intelligence or conventional programming methods (Shukla Shubhendu & Vijay, 2013). Machine Learning (ML) is a branch of Artificial Intelligence (AI) in which algorithms have the ability to autonomously learn and enhance their performance based on inputs. Within the field of machine learning (ML), there exists a specialized area called deep learning (DL) that focuses on the usage of neural networks. These networks are meant to mimic the functioning of the human brain and are particularly successful in applications like as computer vision (CV) and recognition (Janiesch et al., 2021). Another subfield of AI is Natural Language Processing (NLP), which specifically deals with the identification and creation of natural human text and speech (Cambria & White, 2014). Figure 2 illustrates the interconnection between the many domains of artificial intelligence.

In order to function, each AI model must undergo training using a substantial amount of data, a process referred to as 'learning'. There exist several categories of learning:

Supervised: The model is trained using a substantial dataset that has been labeled, meaning that for each feature, there is a corresponding output. Once the training process is over, the model has the ability to make predictions based on data that it has not encountered before. It is employed in tasks like as regression and classification.

Semi-Supervised: The model is trained using a combination of labeled and unlabeled data. The objective is to enhance the precision and resilience of the model in making predictions. It is appropriate for tasks like as text recognition and categorization.

Unsupervised: The model is trained without the usage of any labeled data. The objective is to identify the underlying patterns in the data, without having knowledge of the corresponding labels. This approach is commonly utilized for tasks including as clustering and dimensionality reduction.

Reinforcement: This approach utilizes a reward-based decision-making technique inside a specific setting to determine the optimal outcome. It is utilized in several domains including as gaming, robotics, and others.

Self-Supervised: It is a form of unsupervised learning in which the model autonomously predicts inputs based on certain parameters and creates output for the input data. Predictive text creation serves as a prime illustration of this concept.

Transfer learning: In this scenario, the model is first trained on a substantial labeled dataset to acquire the capacity for generalization and feature extraction. Subsequently, the pretrained weights of the model are adjusted to better suit the target dataset. This approach allows for the creation of a highly efficient model with reduced computing time and expense. It is extensively utilized in the domains of Computer Vision and Natural Language Processing.

3.3 The State of the Art

The healthcare industry has made considerable advancements in the application of artificial intelligence (AI) in recent years, particularly with the development of different machine learning (ML) and deep learning (DL) algorithms. By employing supervised learning, several models have acquired the capability to examine medical pictures, allowing the system to evaluate illnesses such as cancer through the detection of patterns in radiology and histology images (Litjens et al., 2017; Esteva et al., 2017). The field of genomics and personalized medicine has been enhanced by the advancement of unsupervised learning techniques, such as clustering algorithms. These algorithms enable the model to find previously unknown illness subgroups and locate biomarkers (Jiang et al., 2020). In the field of reinforcement learning, researchers have devised methods to deliver tailored healthcare to patients, optimizing it over time based on the patient's state (Yu et al., 2019). Scientists have developed excellent methods for diagnosing illnesses in situations when there is a lack of labeled data by using transfer learning techniques and fine-tuning pre-trained models (Raghu et al., 2019). Advanced natural language processing (NLP) techniques are currently facilitating effective communication between patients and doctors, while also transforming clinical documentation through the use of large language models (LLM) such as GPT (Brown et al., 2020). The aforementioned techniques are also being employed in several other domains within the healthcare sector, which will be further elaborated upon in this article, highlighting the cutting-edge advancements.

4. Contribution AI in the different systems of the Human Body

Because of to the accessibility of data and significant computational capacity, researchers may now create reliable models to assist in the healthcare system. Artificial intelligence is now exerting a substantial influence on several crucial systems of the human body, including the Nervous System, Circulatory System, Respiratory System, and others. Over time, scientists have created several intelligent systems to discover anomalies, diagnose illnesses, and estimate related hazards in these systems. Table-1 presents a concise overview of the latest progress and the significant impact that artificial intelligence has on our daily bodily functions.

5. Artificial intelligence in performing diagnostics

Artificial intelligence (AI) in diagnostics use advanced algorithms and machine learning approaches to evaluate medical data for the purpose of illness diagnosis. Artificial intelligence (AI) has the capability to analyze vast amounts of data from many sources such as genetic data, electronic health records, and medical imaging, with the purpose of identifying patterns and making predictions. AI systems in diagnostic imaging can accurately and rapidly detect abnormalities in X-rays, MRIs, and CT scans. This facilitates the rapid identification of issues by radiologists. In addition, AI-driven diagnostic technology can provide precise and evidence-based information to aid in the early diagnosis of diseases, develop personalized treatment plans, and improve overall patient outcomes.

5.1 ***Diagnosis Accuracy***

The application of artificial intelligence (AI) in non-axial imaging research reveals that the domain of patient selection had the most unknown potential for bias, while the domain of the index test had the highest potential for bias among the 89 publications included in the five systematic reviews. The majority of studies included in all five evaluations had modest concerns regarding their applicability. Specifically, in the areas of patient selection, index test, and reference standard, these problems were identified in 79.1%, 79.1%, and 90.7% of the studies, respectively (Jayakumar et al., 2021). Among the 231 research studies included in 11 systematic reviews, the patient selection domain in artificial intelligence (AI) for photographic pictures had the highest risk of bias. On the other hand, the flow and timing sector had the most uncertain risk of bias. More than half of the studies conducted by Jayakumar et al. (2021) raised concerns about the high or questionable applicability issues in the patient selection field. The index test and reference standard domains had a lower level of applicability worries, with 67.5% of studies showing low concerns and 53.8% expressing low concerns in the former Jayakumar et al. (2021). AI in pathology: Two evaluations utilized QUADAS to do quality evaluation. Mahmood et al. employed a tailored QUADAS-2 instrument. Out of all the reviews, only one provided a tabular representation of the QUADAS assessment in the suggested format. This review also mentioned that the majority of the studies included in all areas had a low risk of bias and low concerns about applicability. Specifically, for patient selection, 64% of the studies were deemed low risk, for the index test, 80% were low risk, for the reference standard, 92% were low risk, and for flow and timing, 84% were low risk. The application of artificial intelligence in cancer diagnosis A total of 86 individuals, with a range of 1 to 15 positive cores per patient, were diagnosed with prostatic adeno-carcinoma out of the 118 patients included in the research. These diagnoses were based on the analysis of 1876 core biopsies. Additionally, 32 patients were confirmed to be clear of cancer. Paige Prostate's study found that out of the 32 patients without carcinoma or glandular atypia, 26 of them did not have any cores labeled as suspicious. However, out of the 86 patients with adenocarcinoma, 84 of them had at least one core classed as alarming. Perincheri et al. (2021) found that among the 1876 core biopsies, 489 cores showed a clear diagnosis of either adenocarcinoma, PIN-ATYP, ASAP, or FGA. The remaining cores were classified as benign or as lacking prostatic glandular tissue. The accuracy of AI-assisted CT imaging in diagnosing COVID-19 disease, The diagnostic odds ratio (DOR) was 88.98 (95% confidence interval [CI], 56.38–140.44) in the 37 studies that employed image-based analysis. The combined sensitivity and specificity were both 0.90 (95% confidence interval [CI], 0.90–0.91), 0.96 (95% CI, 0.91–0.98), and 0.96 (95% CI, 0.91–0.98), respectively (Moezzi et al., 2021). Artificial intelligence's precise medical diagnostics A total of 200 diagnoses were accurately made, accounting for 56.8% of the cases. The 95% confidence interval for this percentage is 51.5% to 62.0%. The diagnostic accuracy of the intervention group (101/176, 57.4%) and the control group (99/176, 56.3%) did not differ significantly (absolute difference 1.1%; 95%CI, −9.8% to 12.1%; p = 0.91). Harada et al. (2021) conducted the study. During the analysis of chest x-rays for pulmonary tuberculosis using computer systems based on artificial intelligence, a total of 4712 different citations were examined. Out of these, 2821 studies were rejected based on their title and abstract. Following a thorough analysis of the full text, 338 out of the remaining 391 studies were eliminated. Out of the 53 papers that were included, 13 publications were categorized as clinical, while 40 were classified as development studies. The software developers financed the research or were the authors in all 40 out of 40 Developments investigations (100%) and in 9 out of 13 Clinical studies (69%), according to Harris et al. (2019).

5.2 ***Medical Imaging***

In recent years, there has been substantial progress in the utilization of artificial intelligence (AI) in several therapeutic fields and imaging techniques. A recent study shown that artificial intelligence (AI) has the ability to identify and distinguish between four specific illnesses on chest radiographs: pneumothorax, active pulmonary TB, pneumonia, and pulmonary malignant neoplasms, which encompass primary lung malignancies and their metastases. Alexander et al. (2019) conducted the study. Considering the high prevalence of these diseases and the capacity of AI to aid radiologists in detecting and ranking patients with the most critical or intricate conditions, this is a noteworthy advancement. The study also demonstrated the ability of AI to serve as a supplementary reader alongside a radiologist, enhancing the identification of lesion site. This was exemplified by Hwang et al. (2019). As per a separate study conducted by Mayo et al. (2019). AI-based computer-aided design software shown a higher level of accuracy in detecting false positives in digital mammograms compared to FDA-approved software, while maintaining the same level of sensitivity. Significant progress in AI has also been achieved in several domains, such as the development of brain tumor treatment strategies and the detection of tubes and catheters in pediatric x-ray images. The studies conducted by Yi et al. (2019) and Kickingereder et al. (2019) are relevant to the topic.

6. AI technologies for medical treatment

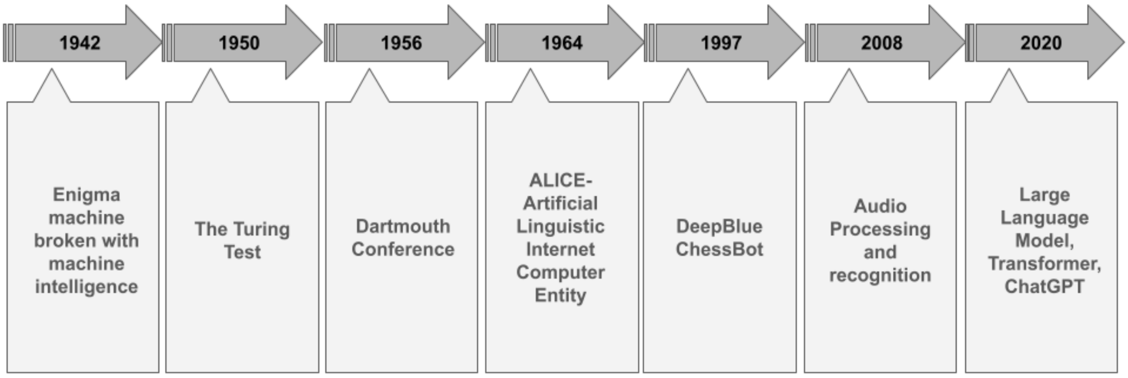

Figure 1. Evolution of Artificial Intelligence

Table 1. Summary of the advances in artificial intelligence dedicated to the different systems of the Human Body

Systems	**Algorithms**	**Key Findings**	**Publisher**
Nervous system	CNN	An ischemic stroke detection system is developed with an accuracy of 90% (Chin et al., 2017)	IEEE
	PCA with DNN	At 84.03% accuracy, the system predicts medical history and behavior of stroke patients (Cheon, Kim, & Lim, 2019)	MDPI
	DNN	Development of a classifier for Alzheimer disease and mild cognitive impairments with 99% accuracy (Basaia et al., 2019)	Elsevier
	CNN	The model detects Parkinson disease studying EEG signals with 91.77% accuracy (Oh et al., 2018)	Springer
	Deep CNN	Classification of multi-grade brain tumor at 90.67% accuracy (Sajjad et al., 2019)	Elsevier
Circulatory system	Deep CNN	An Arrhythmia detection system with an accuracy of 98.03% (Zhou, Jin, & Dong, 2017)	Elsevier
	CNN	With a precision of 0.80, the model predicts cardiological levels of Arrhythmia (Hannun et al., 2019)	Nature
	CNN	Detection of intracranial hypertension with 92% accuracy. (Quachtran, Hamilton, & Scalzo, 2016)	IEEE
	Knowledge-based system	AI-based treatment recommendation systems, MYCIN (Buchanan and Shortliffe, 1984)	Addison-Wesley
	CNN	Prediction of hypertension event risk at 92.55% accuracy (Liang et al., 2018)	Biosensors
Respiratory System	MLP	Detection of early stage of Asthma with an accuracy of 80% (Edo-Osagie et al., 2019)	ICPRAM
	FFNN	Classification of Chronic Obstructive Pulmonary patients with acute deterioration at 92.86% accuracy (Nunavath et al., 2018)	Springer
	DL	Abnormality diagnosis from chest CT images of COVID-19 patients with 95% accuracy. (Ni et al., 2020)	Springer
	DNN	Observing the area of improvement of Acute Bronchitis patients at 90% accuracy (Saust et al., 2018)	Taylor & Francis
	CheXNeXt	Analyzing chest radiography for detecting Lung Cancer with 95% accuracy. (Rajpurkar et al., 2017)	PLoS
Digestive System	DenseUNet	Segmentation of Esophageal Gross Tumor Volume from CT images with a precision of 0.94 (Yousefi et al., 2018)	Springer
	CAD-DL	Detection of early oesophageal adenocarcinoma from MICCAI images at a sensitivity and specificity of 92% and 100%, respectively (Ebigbo et al., 2018)	BMJ
	CNN+SVM	Gastrointestinal Polyp detection from endoscopy images with 98.65% accuracy (Billah, Waheed, & Rahman, 2017)	Wiley
	CNN	Classification Gastric precancerous diseases using GPDNet at 88.90% accuracy (Zhang et al., 2017)	PLoS
	Faster R-CNN + Inception Resnet	Detection of Colon Polyp from augmented colonoscopy images with 91.4% precision (Shin et al., 2018)	IEEE Access
Urinary System	SVM	Urinary Proteomics Pilot Study for diagnosis of Heart Failure from 103 potential HFrEF peptide biomarkers with 92.9% specificity (Rossing et al., 2016)	PLoS
	SVM	Urinary Peptidomic Classification for Heart Failure prediction (Zhang et al., 2017)	JAHA
	SVM	Detection of deep vein thrombosis and pulmonary embolism from Urine proteome with 83% specificity (von Zur Mühlen et al., 2016)	Wiley
	Decision Tree	Detection of Bladder Cancer from urine samples with 76.60% accuracy (Shao et al., 2017)	Oncotarget
	ANN	Urinary tract infection prediction in women with 76.4% accuracy (Heckerling et al., 2007)	Elsevier

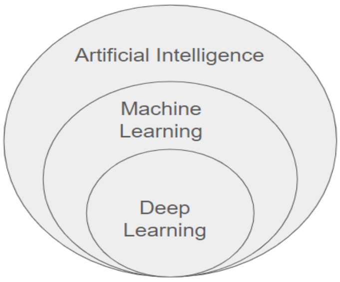

Figure 2. Relationship among the fields.

Table 2. AI technologies for medical treatment

S No	Technologies	Description	References
1	Machine Learning (ML)	• They can evaluate medical results automatically and present them with a probabilistic degree of accuracy. • Machine learning systems are programs that are self-improving and learning without experience or after being trained over time. • ML algorithms can make decisions using the following algorithms and methods: supervised learning, unsupervised learning, semi-supervised learning, and reinforced learning. • This technique is utilized in the medical field to determine the likelihood of a disease • Machine learning is useful in preserving patient records for improved care.	Kinnings et al. (2011), Varnek and Baskin (2012), Ain et al. (2015), Erickson et al. (2017), Zeng and Luo (2017), Li et al. (2018).
2	Artificial Neural Networks (ANN)	• Artificial Neural Networks (ANNs) function similarly to neurons because each ANN neuron has weight and is connected in a way that is inspired by the neural structure of the human brain. • ANNs operate on the concepts of back propagation and layers (Input layers, Hidden Layer, and Output layers). • The best weight corresponding to bond strength in a human brain neuron ensures that the optimal path is obtained by ANN training using vast amounts of data. • Beneficial in decision-making and in predicting the incidence of disease	Wesolowski and Suchacz (2012), Saravanan and Sasithra (2014), Pastur-Romay et al. (2016), Li et al. (2017), Abiodun et al. (2018).
3	Natural Language Processing (NLP)	• NLP is the study of speech recognition and language assessment using various methods. • Clinical decision trials can benefit from the application of this technology, which also supports and analyzes unstructured data in the medical field. • There are numerous independent NLP algorithms, such as those for parsing, POS, and tagging utilizing the Hidden Markov Model (HMM). • It also keeps track of the patient's clinical documentation and is utilized for automatic coding.	Shahid et al. (2019), Dutta et al. (2013), Heintzelman et al. (2013), Cai et al. (2016), Savova et al. (2017).
4	Support Vector Machines (SVM)	• Given the input data, Support Vector Machines identify the class groups of data. • It resolves the major base data classification issue. • After an SVM classifier is trained, they are utilized in email spam filters so that it may use and see fresh and unseen data points for future correlations. • Applied to the gathering and handling of medical data • Handle patients with appropriate care and assist in reaching an evidence-based choice.	Verma and Melcher (2012), Zhu et al. (2014), Gu et al. (2014), Retico et al. (2015), Wang et al. (2017),
5	Heuristics Analysis (HA)	• This method seeks to identify and discover solutions through a process of trial and error. • The fundamental algorithm underlying heuristic work is to use a workable solution that, while not producing the best result, still accomplishes the objective to the fullest extent possible. • The best method for ensuring patient safety and effectively identifying various issues is heuristic analysis.	Davies et al. (2015), Davies et al. (2016), Mohan et al. (2016), Davies et al. (2018)

Table 3. Overview of recent studies on the application of artificial intelligence (AI) in drug development. It emphasizes the potential benefits as well as the existing limits of AI technologies in this particular domain.

System	Algorithm	Key findings	publisher
Drug discovery	ANNs, SVM and RF	Clinical trial design and analysis based on various aspects of drug discovery, designing and optimizing potential drug candidates and accuracy more than 90% (Vamathevan, 2019)	Nature
	SVM	Identifying promising drug candidates with the desired biological activity and no dataset is used (Maltarollo, 2018)	Elsevier
Drug target interactions	GCNNs	Accuracy 91%, Predicting interactions between drug and targets (Altman, 2019)	American chemical society
	Multi-view-self attention model	Aiding in the development of new drugs, used benchmark dataset for drug target interaction and high accuracy compared to traditional models (Brighter Agyemang, 2020)	Elsevier
	ML (SVM and RF) and DL (CNNS and RNNS)	It highlights the machine learning method that can achieve good performance on benchmark datasets for DTI prediction. (Sofia D'Souza, 2020)	Elsevier
Target identification	ML (SVM and RF) and DL (CNNS and RNNS) and NLP	Identifying promising target faster than traditional methods and find therapeutic target for developing new drugs (Frank W. Pun, 2023)	Elsevier
	GENTRL	Hit rate of 35% for generated compounds, Identifying DDR1 kinase inhibitors for cancer treatment (Zhavoronkov,, 2019)	Nature
Drug toxicity prediction	SVM, RF, Naïve Bayes and deep learning Architecture	Effectiveness of machine learning in predicting drug toxicity based on the compound structure and accuracy can range from 80% to over 90%. For certain tasks. (Zhang, et al., 2018)	Bentham Science Publishers
Drug-drug interactions (DDIs)	CNN	Required a large amount of labeled data set for training. (Zhang C. L., 2022)	

Table 4. A concise overview of current publications on using artificial intelligence as a virtual patient assistant. These studies focus on utilizing remote patient monitoring, medical information management, and appointment scheduling.

System	Algorithm	Key findings	Publisher
Remote patient Monitoring	RF, SVM and LR CNNs, RNNs	Remote patient monitoring based on diabetes, heart failure etc. various conditions and also mental health monitoring and support (Ranjbar, 2024)	Kindle
	Machine learning and Data mining	Providing continuous health monitoring and real time feedback to the patients and healthcare providers (El-Rashidy, El-Sappagh, Islam, M. El-Bakry, & Abdelrazek, 2021)	MDPI
	AI, ML and Multi-hop networking algorithm	Integration of biosensor with multi-hop IOT system and cloud connectivity significantly enhances the efficiency and reliability of real time remote patient monitoring, managing chronic disease and health monitoring. (Raihan Uddin, 2023)	MDPI
Medical Information	ML, DL and NLP	Medical Chatbots and virtual assistants can significantly enhance patient engagement and providing reliable medical information (Huiying Zhang, 2021)	Francis Academic Press
Appointment Scheduling	ML	Predicting patient behavior and scheduling rules for optimization (Sharan Srinivas, 2018)	Elsevier
	NLP, Decision Tree, SVM, Speech recognition systems	Patient query handling, Appointment Scheduling, providing medical information and reminders (Priyanshu Shukla, 2021)	IRJMETS

Artificial intelligence has a significant impact with the assistance of several state-of-the-art technologies. Technologies are valuable for acquiring supplementary information that clinicians may have missed and accurately forecasting the outcome for the patient. These are employed in extensive medical institutions to oversee the retrieval of costs, healthcare expenses, and treatment outcomes to effectively administer the healthcare system. Table 2 displays the various AI technologies employed in the medical sector.

These technologies are employed in several health-related fields, such as neurology, cardiology, oncology, and orthopedics. It provides the patient with a more accurate and effective service. Physicians can now reduce their physical exertion while improving their clinical decision-making, planning, and treatment techniques (Wahl et al., 2018; Patel et al., 2009). It is now feasible to quickly determine the patient's medical history and inform the patient's relatives. Artificial intelligence can efficiently manage typical inquiries using data storage and backend processing. According to Bashiri et al. (2017) and Long et al. (2017), the patient will be notified when the lab test is overdue.

7. AI in the field of drug

Artificial intelligence (AI) has demonstrated its transformative impact in the field of drug research and development, significantly accelerating the advancement of medical innovation in the pharmaceutical business in recent years. Historically, the task of finding and producing novel medications without the assistance of artificial intelligence (AI) has been a time-consuming and costly endeavor. It mainly depends on trial and error approaches, frequently leading to significant failure rates and lost resources. Scientists have difficulties in manually processing huge quantities of biological data, resulting in delays in the identification of targets. However, thanks to the assistance of artificial intelligence (AI), several limitations in the conventional drug development process have been surmounted. This has facilitated progress and significantly diminished the time and resources required, which were before inconceivable (Blanco-González, A, 2023). The rapid and precise analysis of large datasets by AI has the potential to revolutionize the identification of therapeutic targets based on biological knowledge. This can greatly accelerate the process of drug development with a high level of precision (Veer, 2021). In addition, AI is utilized to identify precise target locations within the body where medication should be administered, aiding scientists in the development of new drugs that can effectively target those areas. AI is also employed to assess the potential adverse effects of new medications on the body, thereby enhancing the safety evaluation process. Furthermore, AI improves the efficiency of clinical trials by selecting the most suitable candidates for participation. Additionally, AI assists in discovering alternative applications for existing medications and supports healthcare professionals in prescribing the most appropriate treatment for individual patients. State-of-the-art machine learning and deep learning algorithms in the realm of artificial intelligence are used to select potential lead compounds for experimental verification (· Carlos Roca, 2021). Table-3 presents a concise overview of current studies on artificial intelligence (AI) in drug development. It includes information on the algorithms employed, the applications of AI in this sector, and the accuracy of the AI technologies utilized.

However, there are obstacles and factors to consider when using artificial intelligence in pharmaceutical research. The ethical implications of AI, such as bias, transparency, and accountability, present significant challenges that require careful consideration to maintain ethical standards and foster trust in AI-driven decision-making. Further research is necessary to fully comprehend the benefits and limitations of AI in this domain. Despite the obstacles, we anticipate that AI will significantly impact pharmaceutical research, revolutionizing the process of discovering, designing, and delivering novel medications to patients.

8. AI as a Virtual Patient Assistant

The utilization of artificial intelligence (AI) in the healthcare sector has brought about significant changes, especially in the creation of virtual patient assistants (VPAs). AI technologies like Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning are being developed to aid patients in managing their health. They provide assistance with chronic disease management (Barnett, 2012), remote patient monitoring, appointment scheduling, telemedicine support, health monitoring, and medical information. These technologies also enhance patient engagement and satisfaction. Natural Language Processing (NLP) aids in comprehending inquiries from patients and empowers Virtual Personal Assistants (VPAs) to provide responses using natural language (Asadi & Olafsson, 2018). Machine learning algorithms empower this system to acquire extensive quantities of health data and deliver individualized advice. (Topol, 2019). Furthermore, the potential applications of Virtual Personal Assistants (VPAs) in the healthcare sector are vast. Virtual Personal Assistants (VPAs) offer round-the-clock availability, guaranteeing patients may obtain medical guidance and assistance at any hour. This is particularly advantageous for the management of chronic illnesses and crises. Thomas Davenport, in the year 2019. Table 4 presents a summary of current publications on AI as a Virtual Patient Assistant. These papers focus on using remote patient monitoring, medical information, and appointment scheduling.

AI-driven virtual patient assistants are a substantial improvement in healthcare due to their numerous benefits in terms of effectiveness, availability, and involvement. Nevertheless, in order to achieve successful and fair implementation, it is imperative to tackle challenges such as data privacy, algorithm accuracy, and patient confidence.

9. Consideration of legal, ethical and other risk associated

The utilization of artificial intelligence in the healthcare sector gives rise to several legal, ethical, and other potential hazards that want meticulous consideration. Ensuring patient confidentiality and safeguarding data are very important. AI is used in the gathering and examination of delicate patient information, which gives rise to problems regarding data breaches and illegal entry (Alami et al., 2017). The creation and implementation of AI algorithms give rise to ethical concerns, namely around fairness, transparency, and accountability (Carter et al., 2020). Algorithms that are trained using biased or incomplete datasets have the potential to worsen existing disparities in healthcare, therefore contributing to the continued amplification of socioeconomic inequalities (Floridi, 2018). Utilizing AI without proper supervision from regulatory authorities might compromise faith in healthcare and the safety of patients (Hosny & Aerts, 2019). Establishing explicit ethical principles and regulatory norms is essential to effectively tackle the issues associated with the development, deployment, and appropriate utilization of AI technology in the field of healthcare.The standards should encompass principles of openness, fairness, and accountability, to guarantee that AI systems operate ethically and in the optimal interests of patients (Floridi, 2018). Engaging with legislators, healthcare practitioners, technologists, and ethicists is essential for establishing a legal and ethical framework for AI in healthcare (Hosny & Aerts, 2019). Ensuring the alignment of AI advancements with patient safety and privacy may be achieved by fostering discussions and collaborations among stakeholders (Carter et al., 2020). It is essential to take into account the legal and ethical framework, as well as the definition and extent of health care services.The authors highlight extensive ideas, such as the UK's data-enabled health and care technology code and China's specific policy on health data security, which serve as important initial measures in addressing this complex topic (Greaves et al., 2018).Nevertheless, it is crucial to consider the legal, ethical, and various other dangers associated with AI technologies in order to fully realize their transformative potential. These challenges can be resolved by following established protocols and engaging in professional collaboration. This effort enables the healthcare system to reap the advantages of AI, while ensuring the preservation of patient privacy and adherence to ethical norms.

10.Discussion

This research specifically examines the latest findings on the use of artificial intelligence (AI) in healthcare, with a particular emphasis on how it affects the treatment of patients, as well as the early identification and diagnosis of medical conditions. AI has had significant success in illness detection, resource management, and cost reduction. Studies by Chen (2018), Dhieb et al. (2020), and Yu and Zhou (2021) have demonstrated substantial enhancements in the accuracy of diagnosing illnesses including cancer and heart disease. AI integration in health systems elevates the level of treatment from reactive to proactive, leading to enhanced patient outcomes. It also demonstrates the effectiveness of AI in data-driven contexts, as supported by Kaplan and Haenlein (2020) and Minz and Mahobiya (2017).

When comparing these findings to earlier studies, it becomes evident that recent advancements have significantly enhanced the effectiveness and impact of AI in this emerging field. However, there are still obstacles to overcome in terms of accessibility and integration (Comito et al., 2020; Bermardini et al., 2021). Initially, it is evident that AI is performing exceptionally in the field of healthcare, substantiated by concrete facts. Formally, it implies the presence of many effective exit tools, efficient performance, and instruments for personal care (Ribbens et al., 2014; Strachna and Asan, 2020). Policy proposals propose the necessity of implementing policies to promote the utilization of AI connection. It is also emphasized that these policies should be in line with ethical considerations, as stated by Aiken and Epstein (2020). From a social perspective, artificial intelligence (AI) has the potential to enhance services, particularly in populations who face challenges in accessing them. Nevertheless, it is crucial to evaluate the circumstances from the perspective of ethical decision-making (Ali et al., 2022; Chien et al., 2020). There are several limitations to consider in this assessment, including the possibility of bias in the selection of sources and the fact that the results may become outdated due to the fast-paced advancements in AI technology. Subsequent studies should investigate the enduring effects of cutting-edge areas on patient outcomes, taking into account the difficulties and moral dilemmas that arise in various situations. The primary emphasis should be on innovative regions, especially in the context of artificial intelligence in mental health and telemedicine. (Merhi, 2022; Kumar et al., 2023). This analysis highlights the significant impact that AI can have on healthcare, serving as a basis for future research and policy-making efforts to optimize the advantages of AI in this domain.

11. Conclusion

Artificial intelligence (AI) has made significant advancements in recent years, particularly in the healthcare sector. This review offers a comprehensive examination of artificial intelligence (AI), including its evolution, variety, emerging uses, and particular emphasis on its revolutionary capabilities in modern medicine. It highlights how AI, starting from its initial success in deciphering coded messages during World War II, has progressed to enable advanced applications like ChatGPT screening, leading to early detection of AIDS and other diseases. The review also acknowledges the role of unsupervised learning and advancements in genomics and generalized medicine in facilitating these developments. Reinforcement learning is used to enhance individualized treatment, while transfer learning enhances diagnosis when there is insufficient information available. Advanced natural language processing (NLP) techniques are employed to improve clinical documentation and facilitate communication between patients and physicians. Further validation in actual clinical settings is necessary to guarantee effectiveness and safety. Overall, the incorporation of artificial intelligence (AI) into the healthcare sector signifies a significant advancement towards enhanced efficiency, accuracy, and tailored medical treatments. This development holds the potential to revolutionize healthcare practices, enhance patient results, and effectively tackle critical medical issues, all while ensuring appropriate utilization of AI technology.

Author contributions

SMH, FI, and MSSS were responsible for conceptualization, fieldwork, data analysis, original draft writing, editing, funding acquisition, and manuscript review. MHHA, PKB, RA, and MRA focused on research design, methodology validation, data analysis, visualization, manuscript review, and editing. BH and M contributed to conceptualization, investigation, data visualization, manuscript review, editing, and proofreading. AS, RC, and ARS handled conceptualization, methodology validation, data analysis, investigation, manuscript review, funding acquisition, supervision, and editing. All authors have approved the manuscript after reviewing the final version.

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Competing financial interests

The authors have no conflict of interest.

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