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The Role of AI in Modern Healthcare Innovations: A Literature Review

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Abstract:
The increasing accumulation and availability of health data, added to the recent progress in artificial intelligence, gave way to a more advanced health analytic tool and predictive models. The study derived its importance from AI tools and technologies' increasingly active role in modern healthcare innovation. The paper reviews the literature on AI applications in healthcare regarding identifying trends, challenges, and future developments of AI applications in health. This review throws light on some major aspects of healthcare, such as diagnosis, recommendation for treatment, design and delivery of a treatment plan, prediction of epidemic conditions regarding patients' care, and hospital management. Information was collated from various points in time. The paper reviews the current state-of-the-art research in AI and health, pinpoints trends and needs for better AI tools in health, indicates the way to advance this interplay, and discusses remaining AI challenges that must be overcome so that full benefits from health AI can be reaped.

Keywords: *Healthcare; Artificial intelligence; Machine learning; Deep learning; medical imaging and diagnostic; challenges; AI applications*

1. Introduction

Artificial intelligence (AI) is a branch of computer science in which human tasks long performed by humans are now taken over by machines [1]. AI is used in health care to inspire clinical decision-making, accelerate and improve the diagnostic process, and improve accuracy and efficiency. AI in healthcare is important given its efficiency and reliability in analyzing huge volumes of data, identifying patterns, and generating insightful information. AI, through ML and DL algorithms, will help in the early diagnosis of diseases, predict patient outcomes, and interpret results from diagnostic tests. This technology could improve therapy methods, reduce diagnostic errors, and improve patient outcomes [2]. Artificial

Intelligence (AI) is one technology that has the potential to address the growing issues facing global health systems, which is why practitioners and scholars are becoming more interested in it[3]. AI applications in healthcare span a wide gamut, including improvement in patient outcomes and experience, adding value, enhancement in quality and safety, facilitating evidence-based decision-making, and optimizing the effectiveness of the healthcare system. Human clinical practice-related diagnosis and treatment errors can be minimized using AI [4]. Diagnostics, treatments, care delivery, regenerative therapies, and precision medicine models are all set to be improved and revolutionized by innovations, including genomics, biometrics, tissue engineering, and vaccine industry breakthroughs [5]

The most important contribution of AI to the healthcare industry today is making diagnoses more accurate. The algorithms of machine learning, trained on large datasets, identify medical images like MRIs and X-rays with a high degree of precision, almost or even more so than that of human beings. Beyond this, AI algorithms can examine patient data to demonstrate trends and patterns indicative of a patient's future risk regarding specified disease types or complications, thereby facilitating treatment measures, including prevention with personal medication customized for a particular case. Expediting diagnosis reduces the margin for error while becoming more effective and timely treatment-oriented[6]. AI-powered remote monitoring systems allow patients' vital signs to be followed and monitored, warning medical professionals of any possible problems. It can decrease the need for in-person visits to medical facilities and result in better patient outcomes and earlier action. AI is also being utilized to enhance healthcare delivery through virtual consultations. Due to remote medical care, patients no longer need to visit a medical center to obtain treatment [7].

1.1. Motivation

Therefore, the objective of the systematic review is to give more attention to the various uses of AI and their underlying challenges in the healthcare industry. The survey provides an overall review through a systematic collection and evaluation of recent literature on how AI technologies handle healthcare concerns, improve patient care, and improve health outcomes. This review will also critically evaluate the obstacles and constraints when incorporating AI into healthcare procedures, including implementation and regulatory challenges to ethical and technical issues. This paper aims to present a balanced perspective that acknowledges the challenges and complex issues associated with the implementation of AI in healthcare. In doing so, the assessment seeks to provide a comprehensive picture.

The state of AI in healthcare today highlights areas of promise, ongoing challenges, and potential pathways for future research and implementation.

1.2. Paper Structure

The paper offers a methodical examination of AI techniques in healthcare and is divided into six sections. We present the motivations and research contributions in the 'Introduction' section. We review the research background and outline the primary research subjects in the 'Background' section. We examine relevant literature in the 'Related Work' section. The results and their causes are examined and discussed in the 'Results and Discussion' section. Finally, we summarise the entire content in the 'Conclusion' section.

2. Background

This systematic review would help advance the current discussion on best practices, limitations, and challenges that shape the effectiveness and influence the potential impact of AI in healthcare on both patient care and future global healthcare systems [8]. AI can completely change how we manage the operational facets of healthcare delivery, diagnose diseases, customize therapies for each patient, and monitor health status in real time. AI-powered diagnostic [9].

2.1. The Role of AI in Healthcare

This research attempts to uncover the role of AI in healthcare, with a particular emphasis on the following crucial elements (Figure 1), since it is extensively utilized in many healthcare domains to enhance patient health outcomes and deliver healthcare at a reduced cost.

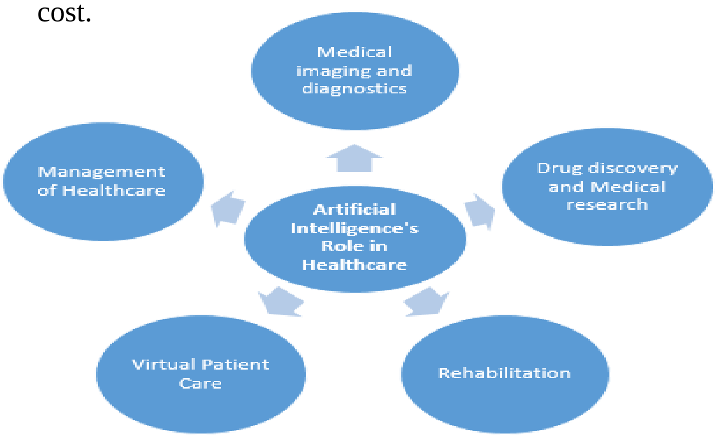

Figure 1: AI applications throughout the healthcare domain

- **Medical imaging and diagnostics**

AI is a potent image analysis technology that radiology experts are using increasingly to reduce diagnostic errors in the context of prevention and to diagnose various diseases early. AI has shown promising results in the early detection of diseases like pneumonia, eye disease, and skin and breast cancer using body imaging modalities. [10]. AI also influences medical diagnosis and clinical decision-making. It can process, analyze, and report vast data from many modalities for clinical decision-making and illness diagnosis [11].

•Drug discovery and medical research

AI is significant for managing big, complicated data in medical research. It helps create new drugs and combines different kinds of info. Additionally, it can help find scientific research projects [12]. ChatGPT, another AI-based technology, may be used in clinical trials to collect data and disseminate research information. Medical researchers can also benefit from a chatbot that uses ChatGPT to translate medical terminology. However, utilizing chatbots in medical research could raise further ethical concerns [13]. Notably, AI is used in vaccine research to review the spike proteins, which are the proteins that make up a virus. [14].

- Rehabilitation

Innovative uses of AI can be found in the realm of rehabilitation. It is a concept with both virtual (informatics) and physical (robotics) aspects. Perioperative medicine, brain-computer interface technologies, myoelectric control, symbiotic neuroproteins, and other rehabilitation areas all use machine learning. ML techniques have also been used in the musculoskeletal system. Rehabilitation activities were evaluated in treatment using an artificial cognitive application [15]. According to a recent analysis, AI holds promise for wearable technology integration in sports medicine. AI can enhance the functionality of injury prediction models, boost risk stratification systems' diagnostic accuracy, offer a dependable method for consistently tracking patient health data, and enhance the patient experience.[16].

- Virtual Patient Care

Intelligent wearable technology solutions for virtual care have made patient monitoring and management a reality and a component of care standards. Additionally, by employing wearable, non-invasive sensors, AI helps manage chronic conditions like diabetes mellitus, hypertension, sleep apnea, and chronic bronchial asthma. [17]. the significance of incorporating AI into bedside care in the context of COVID-19 and the upcoming pandemic after looking at experiences with new AI-enabled point-of-care technologies. Remote healthcare services are now required. [18]. AI-powered solutions also provide tailored

Health advice and notifications enhance patient involvement in their care and enable self-management of long-term diseases. This proactive approach to patient monitoring lowers hospital readmissions, improves care quality, and gives patients the tools to manage their health actively [19].

2.2.Fundamentals of Artificial Intelligence

Artificial intelligence is the capacity of computer systems to receive information accurately and learn from it to accomplish particular goals and tasks through adaptable change and the development of new applications. [20]. AI development aims to develop machines or software that can mimic human behaviour and thought processes, such as recognizing images, understanding language, solving problems, and making judgments based on trial and error. The most prevalent categories of artificial intelligence approaches are machine learning (ML), deep learning (DL), and natural language processing (NLP).

2.2.1. Machine Learning

A subset of AI is similar to the conventional statistical method in several ways. Using variable algorithms, it is focused on prediction and can distinguish between accurate and inaccurate classifications. It encompasses both supervised and unsupervised learning. To enhance predictions (particularly in classification or regression), supervised learning employs techniques like support vector machines (SVMs), k-nearest neighbour (KNN), decision trees (DT), and random forests (RF) to identify correlations between variables. Algorithms for unsupervised learning look for hidden or organic patterns or relationships in the data (particularly in grouping, extraction, and visualization) without using labels [21]. Machine learning algorithms can aid in the diagnosis of diseases by analysing data and applying disease-causing characteristics from electronic health records to anticipate the underlying causes of an ailment. When it comes to classification, prediction, and clustering tasks.[22]. Figure 2 depicts the overall machine-learning architecture, and the specifics of this stage are explained as follows:

Figure 2: Machine learning's overall architecture

1.Support Vector Machine (SVM): SVM is one of the most effective and reliable classification and regression algorithms in several application areas—a highly regarded and active study field among scientists. SVM is among the most well-known methods for improving the anticipated outcome [23].

2.Decision Tree (DT): A decision tree is a classification algorithm that builds a regression model in the shape of a tree. An associated decision tree is gradually built by dividing the data into smaller subsets. According to the parameters, data will be divided in this algorithm. The results of decisions will be given to us at the leaves, and data will be divided at the nodes.[24].

3.Naïve Bayes: One of the most used classification methods. Naïve Bayes is the simplest Bayesian network since it assumes only one parent node and a small number of independent child nodes. NB multiplies the individual probability of every attribute-value pair to use the probability classification algorithm. [25].

4.Linear Regression: The simplest and most popular methodology for determining the relationship between response variables and continuous predictors. Linear regression makes the assumption that there is a linear relationship between the predictor and target variables. [26].

5.Logistic Regression (LR): Logistic regression is mostly used to predict discrete class labels, as opposed to linear regression, which is used to predict continuous data. A logistic regression approach for classification tasks forecasts probability using two possible categories. In logistic regression, the label in a binary outcome between 0 and 1 is classified using a logistic function. [27].

6.K-Means: One popular unsupervised algorithm. Using the item mean value of each cluster, the K-means clustering method creates clusters. Where it can tackle well-known clustering problems due to its simplicity and speed. The K-means method divides data points into k clusters by minimizing the sum of the squared distances between the items and their closest neighbour set distance. [28]

7.Ensemble Methods: An ensemble learning method combines several classifiers to increase performance by producing predictions that are more accurate than those of a single classifier. Reducing prediction generalization error is the goal of using ensemble models. Ensemble modelling techniques are used in the majority of actual data mining solutions. Ensemble techniques mix various machine learning algorithms to produce predictions that are more accurate than those produced by a single classifier. The primary goal of the ensemble model is to increase its accuracy by combining multiple weak learners into powerful learners. As seen in Figure 3, the method generates forecasts by utilizing the combined output of individuals. [29].

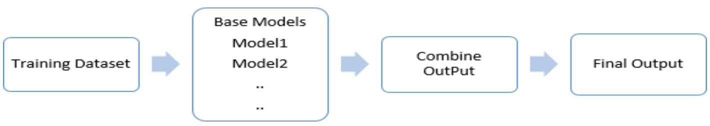

Figure 3: shows ensemble learning

2.2.2. Deep Learning (DL)

Deep learning (DL) is a subfield of artificial intelligence (AI) that has revolutionized numerous industries by enabling ground-breaking advancements in automation, predictive analytics, and decision-making. The healthcare sector employs DL to improve patient outcomes and operational efficiency through better diagnosis, individualized treatment plans, and expedited processes. One of deep learning's main benefits is its ability to extract features from unprocessed data [30] automatically. Deep learning algorithms have caused a significant change in medical image analysis, as they have been used increasingly in recent years to improve the diagnosis, management, and tracking of various medical problems [31]. Research has shown that the use of deep learning algorithms in healthcare imagery analysis has produced encouraging results, with high levels of accuracy in identifying and diagnosing various medical diseases. And making a variety of medical diagnoses [32]. Deep learning models frequently utilized include CNNs, RNNs, GANs, LSTMs, and hybrid approaches.

1.Convolutional neural network techniques CNNs are an important component of deep learning techniques for medical image processing. Their ability to automatically extract relevant features from complex medical images enables them to perform well in task localization, segmentation, and classification tasks. By recognizing intricate patterns and structures, CNNs may precisely detect abnormalities, diagnose cancers, and section organs in medical images. The hierarchical nature of CNNs allows for learning important properties at different levels, improving diagnosis and analysis. [30].

2.Generative adversarial network techniques: GAN techniques are crucial for deep learning algorithms used in medical image analysis. They may produce realistic-looking synthetic images, enhance datasets, and increase the precision and efficacy of diagnosis and analysis for various medical conditions. GANs consist of two neural networks: a generator and a discriminator. Through adversarial training, the generator learns to create realistic images, while the discriminator's role is to differentiate between real and generated images[33]. Not only has this creative method produced remarkably good images, but it has also demonstrated promise in improving image recognition. Adding GANs to recognition models can improve their performance and robustness, leading to more thorough and accurate models. [34].

3.Recurrent neural network techniques (RNNs) are crucial for capturing contextual information and temporal connections in healthcare analysis utilizing deep learning methods. RNNs do exceptionally well in jobs involving sequential or time-series data, like assessing dynamic imaging modalities or medical image sequences. [35].

4.Long short-term memory techniques: (LSTM) approach's capacity to identify and represent sequential dependencies in the images makes it crucial for deep learning algorithms used in medical image analysis. Complex spatial and temporal patterns found in medical imaging frequently necessitate contextual knowledge. As a kind of recurrent neural network (RNN), LSTM is excellent at capturing temporal dynamics and modelling long-range dependencies, which makes it appropriate for applications like image sequence analysis, time series analysis, and disease progression modelling.

Table 1: The advantages and disadvantages of several ML and DL methods.

Method	Advantages	Disadvantages
SVM	It works better in high-dimensional areas has a lower chance of overfitting	- There may be difficulties in choosing an appropriate kernel solution function.
	It can be used for both classification and regression issues. Strong performance is demonstrated in the classification	When working with large datasets, training time may increase. When noisy data is present, performance may suffer. The general SVM technique is only capable of binary classification.
Decision tree	It is extremely intuitive and simple to comprehend and analyze. Preparing data is simpler. – supports a variety of data kinds, including category, nominal, and numeric. Missing values in the data do not affect decision tree	-Overfitting, or an algorithm with a high variance. Because it lacks an innate stopping mechanism, it can readily overfit and generate complex decision rules. – It is impacted by noise - training the model

	construction so that it can be used for classification and regression tasks.	frequently takes more time. – restricted regression performance.
Random forest	-It improves decision trees by minimizing overfitting and lowering variance, which raises accuracy. Effectiveness with both continuous and categorical variables is demonstrated. It manages missing values automatically and does not need human assistance. It is more resilient to noise than other methods.	-Compared to alternative methods, it is more intricate and computationally costly. - When determining a variable's relevance, it prioritizes variables or traits with a large range of potential values. -prone to overfitting, which is more likely to happen with this method.
K-Means	-Quite effective and simple to use - it has a great degree of flexibility, making it easy to adjust to changes. It works easily with big datasets and has a linear time complexity. K-means may be computationally faster than hierarchical clustering when there are more variables.	-The starting centroids are chosen at random - Noisy or outlier data cannot be handled. – produces clusters of uniform sizes even when the size of the incoming data fluctuates.
CNN	-Exhibits remarkable accuracy in image identification and classification tasks - automatically recognizes significant features without human oversight	-CNNs must have enough training data to function well. - CNNs typically have slower computation speeds – Lack of the ability to be spatially invariant concerning input data
RNN	-It is the finest illustration of long short-term memory. - It is especially useful for time series prediction because of its capacity to remember prior inputs.	-This neural network's computational procedure takes a long time. – Using an activation function to process lengthy sequences can become laborious and time-consuming.

5.Hybrid techniques Deep learning algorithms combined with other methodologies or data modalities are known as hybrid approaches, and they are crucial in medical image analysis. Deep learning has proven remarkably effective in tasks like classification and image segmentation. Interpretability problems or a lack of training data could be obstacles, though. Researchers can get around these restrictions and improve performance by implementing hybrid approaches. Hybrid approaches can overcome a lack of data or enhance interpretability. Better decision-making is also made possible by integrating several data modalities, such as physiological signals or medical imaging with written reports, to provide a more thorough understanding of the medical state. Finally, hybrid techniques in medical image analysis give medical practitioners access to more precise and dependable instruments for diagnosis, treatment planning, and patient care [36].

2.2.3.Natural Language Processing (NLP)

The computational area of evaluating, comprehending, and using natural language data. NLP is essential in the healthcare industry for extracting pertinent information from textual data, such as discharge summaries, clinician notes, and electronic health records. Text preprocessing, entity detection and identification, sentiment analysis, and information extraction are among the tasks that compose this field of work. Tokenization, stop word removal, and normalization are examples of preprocessing that ensures high-quality input for analysis. NER aids in extracting data from the text by assigning tags to illnesses, drugs, or procedures described in the text. The positive or negative attitudes of the patients mentioned in the narratives or the notes taken by the medical professionals about the patients can be determined by sentiment analysis, which also determines the attitude toward the therapy [37].

3. Related Work

In this section, we will examine some recent studies on using AI algorithms for healthcare analysis. The use of AI mechanisms in healthcare analysis is expanding due to developments in AI technology. Gupta and Katarya [38] thoroughly analysed the literature on machine learning-based social media surveillance systems for healthcare. Disease outbreaks, bad drug reactions, mental health, and vaccine hesitancy are just a few of the many issues covered by the 50 pieces of research the authors examined that were published between 2011 and 2021 and dealt with social media monitoring for healthcare. The review emphasized the potential of machine learning algorithms for sifting through enormous volumes of social media data and finding pertinent health information.

In a smart healthcare system, Jena et al. [39] also looked into how parameters affected the effectiveness of deep learning models for classifying diabetic retinopathy (DR). To classify diabetic retinopathy (DR), the researchers created a convolutional neural network (CNN) architecture with two branches using retinal fundus images. The proposed model includes two branches: one for classification and another for feature extraction. To estimate the severity of DR, the classification branch employs the relevant features extracted from the input image using a pre-trained model in the feature.

Extraction branch. Predicts the severity of DR using these characteristics. The results demonstrated that the recommended model had an accuracy of 98.12% when the optimal parameter combination was used. Patient outcomes could be improved by using the suggested system for DR early diagnosis and treatment.

Similarly, the authors of Vaccari et al. [33] addressed the problem of creating synthetic medical data for Internet of Medical Things (IoMT) applications by proposing a generative adversarial network (GAN) technique. Using their suggested method, the authors described how to generate various medical data samples, including both time series and non-time series data. They highlighted the benefits of using a Generative Adversarial Network (GAN)-based strategy, including the ability to produce realistic data that can improve the performance functionality of IoMT systems. The authors confirmed the effectiveness of their suggested method through tests using real medical datasets, such as electrocardiogram (ECG) data and healthcare imaging data. According to several criteria, the results showed that their GAN-based approach effectively generated synthetic medical data that closely matched actual medical data in terms of both appearance and statistical analysis. The authors concluded that their suggested method is useful for producing synthetic medical data for IoMT applications.

Purandhar et al. [40] suggest using Generative Adversarial Networks (GAN) to classify clustered healthcare data. The discriminator and generator networks are present in this study's GAN classifier. The discriminator distinguishes between real and fake samples, while the generator discovers the distribution of the underlying data. The scientists conducted their study using the MIMIC-III dataset derived from Electronic Health Records (EHRs). The results demonstrate how well and accurately the GAN classifier classifies patients' medical issues—illustrating the superiority of their GAN classifier by comparing it to traditional machine learning methods. The proposed GAN-based approach shows promise for early disease detection and diagnosis.

Wang proposed a hybrid deep learning model (CNN-GRU), X. et al. [41] for the automatic detection of BC-IDC+. The suggested model automatically predicts breast IDC (+) cancer using many CNN layers and GRU. The method yielded an average classification of 86.21% for ACC, 8.590% for PR, 85.71% for SN, 88% for F1, and 0.89 for AUC. When the output of the suggested model was compared to that of CNN-BiLSTM and other ML/DL models that are currently in use, CNN-GRU demonstrated a 4–5% increase in accuracy and a shorter processing time.

According to Ayandhi, G. et al. [42], a hybrid deep learning model can effectively predict breast cancer from mammography images. After the dataset was enlarged by preprocessing and augmentation, image features were extracted using the CNN. The LSTM was employed to capture temporal dependencies in the data. After that, the training set was used to train the hybrid deep learning model to predict the existence of breast cancer. The results show that, with a 96.8% accuracy rate on the testing set, the suggested hybrid deep learning model performed well in predicting breast cancer. Better patient Outcomes and reduced death rates may result from the suggested model's possible use as a tool for early breast cancer identification.

Tilborghs et al. [43] investigated semantic segmentation using (CNNs), the most sophisticated technique for several brain tumour segmentation problems, including the separation of the myocardium in cardiac magnetic resonance imaging (MR) images. Nevertheless, the expected division maps generated by such a standard CNN would not allow for an accurate comparison of local form attributes such as local layer strength. For instantaneous myocardial geometry and posture factor estimation, they provide a CNN. The parameters are linked to a suitable landmark-based mathematical geometry model. Semantic segmentation is used to aid with precise feature estimates and form adaptation. The error function enforces uniformity between integrated segmentation and estimated attributes. It is possible to ascertain regional myocardial properties quickly using the modified geometry model.

Sadik et al. [44] use customized U-Net to offer a new paradigm for COVID-19 detection. In addition to traditional methods, computer-aided diagnostic technologies are becoming increasingly important in the coronavirus disease-2019 (COVID-19) outbreak for the prompt and accurate detection of a sizable number of people. Using pulmonary computed tomography (CT), this study proposes an effective, accurate COVID-19 detection approach based on (CNNs). Initially, a customized CNN architecture dubbed SKICU-Net was constructed to detect and segment pulmonary regions in a chest CT scan by adding skip connections to the U-Net structure to compensate for the information loss caused by dimension shifting. The CT segments with insufficient data are eliminated using an agglomerative hierarchical method. Lastly, P-DenseCOVNet, a customized DenseNet structure, is effective for feature extraction and treating pneumonia and COVID-19 from broken chest slices. This structure overcomes the expense of strategical reasoning by adding a concurrent convolution layer pathway to the top portion of the traditional DenseNet framework, increasing effectiveness.

To improve predictive modelling and individualized patient treatment, this study explores the revolutionary effects of machine learning in diabetes healthcare. [45] uses various machine learning methods to predict and treat diabetic consequences, such as retinopathy, nephropathy, and cardiovascular diseases, and is centred on a dataset that includes 10,000 diabetic individuals. With an outstanding accuracy of 85.6%, the Random Forest algorithm outperforms Support Vector Machines (81.2%) and Neural Networks (79.5%). Furthermore, the Gradient Boosting model's impressive Area Under the Curve (AUC) of 0.92 highlights its reliability in predicting diabetic retinopathy. With an 88% sensitivity in identifying diabetic nephropathy early on, the Decision Tree model makes prompt treatment possible. The results of the study demonstrate how machine learning has the potential to transform the treatment of diabetes by increasing predictive accuracy and enabling early diagnosis.

N. Hallowell et al. [46] discuss the possible advantages and risks related to AI's interpretability and dependability from the standpoint of diagnostic instruments. AI may improve diagnostic output and accuracy, but it also runs the risk of eroding the skill sets of the specialized clinical profession. Instead of replacing human expertise, this study suggests using AI as an auxiliary technology.

Additionally, the role of ensemble classifiers over the XAI framework in predicting heart disease from CVD datasets was investigated by Pratiyush et al. [47]. The dataset used in the proposed study included 303 instances and 14 attributes with characteristics of category, integer, and real type attributes. The classification task was based on techniques like bagging, LR, naive Bayes, SVM, KNN, and AdaBoost.

According to Ricciardi et al.[48], they use machine learning methods (random forests, multivariate logistic regression, ADA-Boost, and gradient boosting) to analyse heart disease on computed tomography (CT) in older adults with chronic heart failure (CHF), coronary heart disease (CHD), and cardiovascular disease (CVD). The four-classification metrics that determine the study's outcomes are classification by tissue type, age, feature relevance, and overall classification score. Because of the effects, the random forest technique is superior since it gets the best classification performance across all analyses, and the total classification scores for all three situations are flawless: The AUCs are 0.936 for CHD, 0.914 for CVD, and 0.994 for CHF.

Sridhar et al. [35] proposed a novel method for reducing medical images without compromising their diagnostic quality. Recurrent neural networks (RNNs) and genetic particle swarm optimization with weighted vector quantization (GenPSOWVQ) are two components of the two-stage framework the authors presented. The RNN is used in the initial step to learn the contextual and spatial dependencies in the images, capturing crucial aspects to preserve diagnostic data. The GenPSOWVQ algorithm improved the image compression procedure in the second stage by choosing the ideal encoding settings. The experimental findings showed that the suggested approach significantly reduced image size while preserving good diagnostic accuracy. Large-scale medical image datasets can be stored, transmitted, and analysed more practically due to the effective and dependable method for medical image compression made possible by the combination of RNN and GenPSOWVQ.

Nancy et al. [49] presented a deep learning-based IoT-cloud-based smart healthcare monitoring system for predicting cardiac disease. The system collects patients' vital indications using wearable sensors and sends the signals to a cloud server for analysis. A deep learning model based on Convolutional Neural Networks (CNNs) is used to predict heart disease by training on a large dataset of ECG signals. The model is optimized by applying transfer learning techniques, particularly fine-tuning. On a real-world dataset, the proposed system's remarkable accuracy in predicting cardiac disease has been

Thoroughly examined. Furthermore, the model has the potential to identify heart problems early on, allowing for prompt intervention and therapy. The study concluded that the suggested method would be useful for monitoring and predicting cardiac disease in real-time, enhancing patient outcomes and lowering medical expenses. Moreover, Srikantamurthy et al. [50] suggested a hybrid method for correctly identifying benign and malignant breast cancer subtypes by histopathological imaging. Convolutional neural networks (CNNs) and long short-term memory

(LSTM) networks were used to integrate their strengths through synergistically transferred learning. The CNN first processed the histopathology images to extract pertinent features, subsequently transmitted to the LSTM network for classification and sequential analysis. To facilitate effective representation learning, the model leveraged pre-trained CNNs trained on large datasets by utilizing transfer learning. Patients with breast cancer may benefit from better diagnosis and treatment choices due to the suggested hybrid approach's encouraging outcomes in correctly differentiating between benign and malignant breast cancer subtypes.

4.Result and discussion

This part provides a detailed exploration and analysis of our study results, emphasizing the efficacy of different AI healthcare techniques. Our analysis fully addresses the research questions presented, offering comprehensive responses that advance knowledge and significantly contribute to the field.

RQ1: What are the challenges of using AI in healthcare?

We want to explore the challenges in healthcare. We found three main problems. They are governance challenges, social and ethical challenges, and technical challenges.

Table 2: Challenges facing AI in the healthcare field.

Governance challenges	effective governance is crucial to resolving ethical, trust, and regulatory concerns. Hospital-level active governance provides a chance to address these problems precisely with AI deployment and utilization.[51]. When implementing AI-powered apps, the governance framework should be all-encompassing to handle the clinical, operational, and leadership challenges [52]. The European Commission recently developed the Revealed Artificial Intelligence Act (AIA) to address the many risks associated with the social adoption of AI. These rules are designed to avoid or mitigate the negative effects associated with particular uses of technology while promoting AI use. [53].
Social and Ethical challenges	AI raises several ethical and social issues similar to those caused by excessive reliance on technology, automation, data usage, and problems with the usefulness of "telehealth" and assistive technologies. utilizing AI to make judgments, providing treatment, and operating medical equipment may present safety and dependability issues.
Technical challenges	there are some obstacles to implementing AI in healthcare, such as the inability to create and maintain IT infrastructure that supports the AI process, the higher expenses of storing and backing up data for research, and the high cost of enhancing data validity. Moreover, bias, brittleness (the propensity to be easily tricked), and inapplicability outside of the training domain are some drawbacks that AI systems may have [54].

RQ2: How will AI change healthcare in the future?

AI is fast-changing the future of healthcare. In this part, we'll discuss how AI can improve patient care. We'll also discuss how it can help during health crises, like pandemics, and how it affects public health.

Table 3: AI applications in the healthcare field.

Applications for Personalized Healthcare	One of the most exciting developments in AI healthcare is the tendency toward more individualized treatment. AI can handle much data about genes, health, and our daily lives. This means doctors can devise treatments that are just right for each person. It can help reduce side effects and improve how well the treatments work [55]. Future studies should examine the creation and verification of AI-powered instruments and algorithms for diagnosing, tracking, and treating medical conditions. This involves using machine learning to examine information from wearable technology, including activity levels, heart rate variability, and sleep habits.[56]
Improved Technologies for Treatment	AI can quickly find new medicines by looking at molecular and clinical data. This speed can reduce the time and cost needed to bring new drugs to the market [57]. These new changes could lead to clearer and more detailed images. They might even help catch illnesses early before symptoms appear [58].

Optimization of the Healthcare System	Optimization of the Healthcare System AI's revolutionary potential in healthcare has the potential to change both patient care and system effectiveness completely. To help patients recover better and stay alive, future AI tools will aim to spot diseases more quickly. They will customize treatments and make care more personal. AI can also help save money and make healthcare easier, especially for needy people [59]. AI's importance in responding to pandemics and other global health crises are becoming more widely acknowledged [60].

RQ3: What AI models are used in the healthcare field?

We checked out a bunch of research to see how machine learning and deep learning are used in healthcare. We gathered recent articles that focus on these techniques in the healthcare field. Key information and conclusions from these selected research studies are compiled and shown in Table 2.

Table 4: Various Studies of ML and DL Models in the healthcare field

RF	Year	Problem Statement	Objective	Algorithms	Dataset	Accuracy	Results	Pros	Cons
[61]	2024	Need for personalized treatment strategies in healthcare.	To discuss AI's role in advancing precision medicine.	AI-driven data analysis.	UK Biobank	92%	Improved patient-specific treatment plans.	Enhanced treatment efficacy.	Data privacy concerns.
[62]	2024	Challenges in discovering and developing drugs for Alzheimer's disease.	To explore AI applications in accelerating drug discovery for Alzheimer's.	Machine learning models.	ADNI	88%	AI models identified potential drug candidates more efficiently.	Accelerated drug discovery process.	Requires extensive data for training models.
[63]	2024	Early detection of skin cancer is critical yet challenging.	To review AI approaches in skin cancer detection and classification.	Convolutional neural networks.	ISIC	95%	Improved detection accuracy.	Early diagnosis and treatment.	Requires large datasets for training.
[64]	2024	Monitoring patient oral hygiene during orthodontic treatment is challenging.	To evaluate AI-driven remote monitoring technology for oral hygiene assessment.	Image recognition algorithms.	Custom Dataset	90%	Effective assessment of oral hygiene remotely.	Increased patient compliance.	Dependence on technology reliability.

[65]	2023	Need for personalized solutions in cardiovascular medicine.	To discuss the integration of AI in personalized cardiovascular treatments.	AI-driven modelling.	Open-heart	91%	Enhanced treatment personalization.	Improved patient outcomes.	Ethical considerations in AI use.
[66]	2023	Lack of interpretability in AI systems leads to mistrust among clinicians.	To propose a framework for interpretable AI in healthcare.	Interpretable machine learning models.	Not Applicable	N/A	Framework enhances clinician trust in AI.	Improved AI adoption in clinical settings.	Complexity in designing interpretable models.
[67]	2023	Understanding risks associated with AI implementation in healthcare.	To review and categorize AI-related risks in healthcare.	Literature review methodology.	Not Applicable	N/A	Identified clinical, technical, and socio-ethical risks.	Informs risk mitigation strategies.	Highlights the need for comprehensive risk assessment.
[68]	2021	Difficulty in diagnosing respiratory conditions through cough sounds.	To explore AI techniques in cough sound detection and diagnosis.	Machine learning classifiers.	Coswara	89%	Potential for non-invasive diagnosis.	Remote health monitoring.	Variability in cough sounds among individuals.
[69]	2021	Validation of AI models for sepsis prediction is necessary.	To validate the effectiveness of an AI-based sepsis prediction model.	Predictive modelling algorithms.	MIMIC-III	85%	The model showed varying accuracy levels.	Potential for early sepsis detection.	Risk of false positives/negatives.
[70]	2021	Analysis of X-ray images is time-consuming and prone to errors.	To assess AI solutions for X-ray image analysis.	Deep learning algorithms.	Chest X-ray14	94%	Enhanced accuracy in image interpretation.	Reduced diagnostic errors.	Potential for algorithmic bias.

RQ4: What are the advantages of using machine-learning techniques in healthcare?

The advantages of machine learning techniques include improved disease diagnosis accuracy, early disease detection, and therapy recommendations based on patient data. By learning about many forms of healthcare data simultaneously, such as genetic data, medical images, and clinical records, these prediction models can provide a comprehensive view of a patient's health. Identifying high-risk patients who require intervention, care, and resources to improve patient outcomes and the delivery of health services is another way that machine learning (ML) contributes to population health management [71].

4.1.RQ5: What are the advantages of using deep learning techniques in healthcare?

DL approaches in medical imaging have many advantages, including improved radiological procedures in healthcare, reduced diagnostic risks, and proficiency and accuracy in detecting abnormalities. Diagnoses and treatments can be completed more quickly by automating image analysis, saving the medical professional time spent on image analysis. Moreover, DL permits multi-modal fusion of data from other imaging modalities that cover different facets of patient evaluations for tailored therapy strategies. When working with large datasets, deep learning models can save significant time because deep learning algorithms can produce features without human assistance [72].

RQ6: What are the drawbacks of healthcare-related deep learning models?

DL in medical imaging has certain drawbacks, though, including the need for extensive data annotation, a significant amount of processing power, and the need to explain the models' output. To meet clinical needs and effectively improve patient outcomes, it is crucial to consider clinical validation and regulatory approval when developing DL models that function well across various patient groups and situations. Thus, compared to conventional ML techniques, deep learning models take longer to complete. Deep learning requires a large dataset [72].

RQ7: What Are the Drawbacks of AI in Healthcare?

Despite AI's demonstrated effectiveness in diagnosis and treatment, this medical technology has various known drawbacks. Physicians dispute that AI is progressively taking the place of medical personnel and worry that rather than advancing the medical field, AI may destroy it. AI tools are extremely expensive, require considerable training, and lack human empathy. The lack of reliable data, which is necessary for AI to keep "learning," also limits AI technologies in certain other fields. Furthermore, applications that use AI bring up concerns about privacy and data security. Hackers typically target health records during data breaches since they are important and susceptible. Maintaining the confidentiality of medical records is so essential. [73]. Furthermore, the algorithm's absorption of the relationships between patient characteristics and outcomes leads to the overfitting problem. Many factors influencing the results lead to this issue, which causes the algorithm to produce erroneous predictions [74].

5.Conclusion

AI can completely transform healthcare and disease diagnostics, moving the medical industry into a new era of precision and effectiveness. AI's rapid analysis of massive amounts of data can help with early detection, individualized care, and well-informed decision-making. Artificial intelligence (AI) systems can analyze medical images, including CT, MRI, and X-rays, to find subtle abnormalities the human eye could overlook. This facilitates prompt interventions to improve patient outcomes and help in the early detection of diseases. Additionally, AI can combine and evaluate patient data from many sources, assisting in the discovery of trends that might forecast the prognosis and risk of disease. AI has an impact that goes beyond diagnosis and changes how treatments are administered. AI can customize

Therapies based on individual features by evaluating genetic data and patient histories, increasing efficacy and reducing negative effects. Virtual health assistants with AI capabilities can help patients in real time by offering advice and support, eliminating the need for follow-up visits. AI has both exciting and revolutionary potential for the medical industry. More accurate diagnoses and individualized treatments will result from the capacity to process huge amounts of data, identify trends, and offer insights. Providing data-driven recommendations, improving decision-making and lowering errors will empower medical practitioners. However, this integration raises ethical and legal issues, like protecting patient privacy and preserving human supervision—appropriate integration and conformity to legal requirements. To ensure AI's responsible and efficient use in healthcare settings, it is crucial to balance its potential advantages and ethical considerations.

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