A Comprehensive Review of AI in Healthcare: Exploring Neural Networks in Medical Imaging, LLM-Based Interactive Response Systems, NLP-Based EHR Systems, Ethics, and Beyond

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***Abstract* - The AI-based technologies used in healthcare systems have witnessed significant growth and innovation, as this growth is attributed to innovations in AI and rise in data collection in the healthcare sector. This survey paper provides a comprehensive overview of the diverse technological advancements reshaping the healthcare landscape. The reviewed topics include Medical Image Interpretation using Deep Learning, Generative AI-based Large Language Models (LLMs), Natural Language Processing for Healthcare Records to give a sense of what AI based systems look like in healthcare. For each of these topics, we've delved into their technical aspects and their applications. Through an overview of these cutting-edge technologies, this research aims to shed light on their current state, challenges, and potential implications for the future of healthcare. From enhancing diagnostics to improving patient care and accessibility, AI is poised to play pivotal roles in shaping the healthcare industry for years to come. Furthermore, this survey also delves into the ethical considerations surrounding these technologies.**

Keywords - AI, ML, Healthcare, Medicine, CNN, LLM, EHR

I. Introduction

The integration of Artificial Intelligence (AI) into tools and technologies used for healthcare has been growing steadily over the past decade. This paper presents a comprehensive survey of AI-based systems in healthcare like deep learning-based medical image interpretation, Generative AI-based Large Language Models (Gen-AI LLMs), and Natural Language Processing (NLP)-based Electronic Health Record (EHR) systems, etc..

In recent years, deep learning techniques have significantly transformed the field of medical imaging. The Paper delve into the ways in which deep neural networks are being employed for the interpretation of medical images, offering enhanced diagnostic accuracy and efficiency. The emergence of Generative AI and Language Models has opened up new possibilities for generating synthetic medical data, automating medical documentation, and facilitating data-driven decision-making. This paper explores the role of Gen-AI LLMs in healthcare applications. Natural Language Processing (NLP) plays a pivotal role in extracting valuable insights from Electronic Health Records (EHRs). Paper examines how NLP-based systems are transforming the way healthcare providers manage patient data, improve clinical decision support, and streamline healthcare workflows.

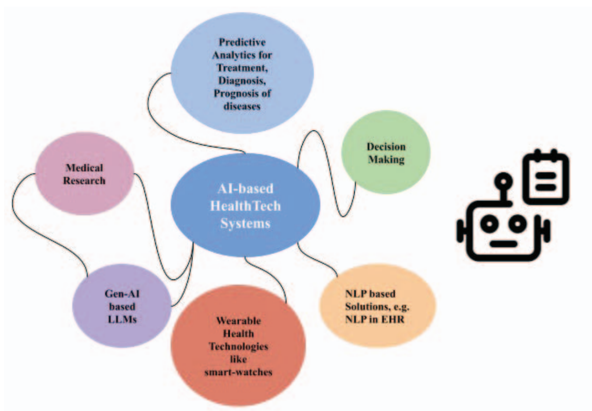

Fig. 1. Scope of AI in Healthcare

As given in Figure 1, AI holds great promises in healthcare, but it also presents several challenges, including data privacy, interpretability, and ethical considerations. This paper highlights both the opportunities and challenges associated with the adoption of AI in healthcare. To provide a comprehensive overview, a survey was conducted about the existing literature, encompassing research papers, case studies, and real-world applications. The findings presented in this paper are a result of analysis of these sources. As AI continues to make strides in healthcare, this paper concludes by emphasizing the transformative potential of AI-based systems and the need for continued research and collaboration to harness the full benefits of these technologies for improving patient care and healthcare outcomes.

II. AI Algorithms

In the fields of healthcare and medicine, the use of AI algorithms plays a pivotal role in enhancing the quality and

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efficiency of healthcare services. These algorithms are essentially sets of mathematical rules and procedures that enable machines to mimic human intelligence and perform complex tasks. The paper focuses on their significance within this specific domain.

AI algorithms are the driving force behind various AI applications within healthcare. For instance, in diagnostic processes, supervised learning algorithms can analyze vast datasets of patient information to assist in disease detection and treatment recommendation. Unsupervised learning algorithms can identify hidden patterns in patient data, aiding in personalized medicine approaches. Reinforcement learning algorithms can optimize treatment plans and resource allocation in real-time, while deep learning algorithms are instrumental in tasks like medical imaging analysis, where they excel at recognizing anomalies in X-rays, MRIs, and CT scans.

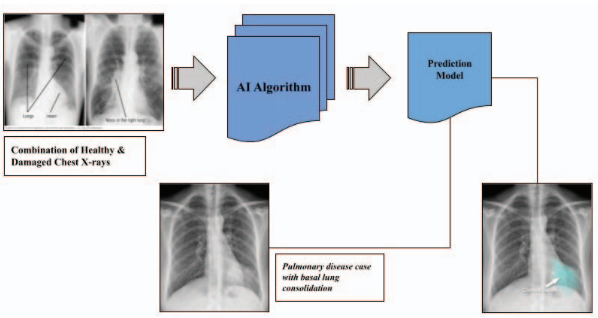

Fig. 2. Use of AI in finding anomalies in chest X-ray

These algorithms have the potential to revolutionize healthcare by enhancing the accuracy and consistency of diagnoses, improving the predictability of patient outcomes, and increasing the efficiency of medical procedures. As our research delves into the application of AI and automation in healthcare and medicine, it is crucial to understand the pivotal role that AI algorithms play in driving these advancements and improving patient care.

One widely used Algorithm in Medical Imaging is Convolutional Neural Network (CNN). It has been shown to be used for detection of Tuberculosis, Pneumonia, Prostrate Cancer [25] (Kumar, Soni, Khan, et al.), Depression Evaluation from EEG [26] (Ke, H, Chen, D, Shah, T, et al.), etc. Below we'll understand CNN and dive into mathematical foundations of CNN, and it's building blocks in Machine Learning.

CNNs are specialized neural networks designed to automatically and adaptively learn spatial hierarchies of features from input images. They excel in medical image interpretation due to their ability to capture intricate patterns and structures within images.

A. Mathematical Foundations of CNNs

At the core of CNNs lie convolutional layers, which perform convolution operations on the input data. A convolution operation between an input image I and a filter K is defined as follows:

$$S(i,j) = (I*K)(i,j) = \sum_m \sum_n I(i-m,j-n) \cdot K(m,n) \quad \text{--- (1)}$$

Where:

- $S(i, j)$ represents the output at position (i, j) after the convolution operation.
- $I(i - m, j - n)$ denotes the pixel intensity of the input image at position $(i - m, j - n)$
- $K(m, n)$ represents the filter coefficient at position (m, n) [27].

By utilizing multiple filters and applying non-linear activation functions (such as ReLU - Rectified Linear Unit), CNNs can learn complex features hierarchically, enabling the network to recognize intricate patterns within the input data.

B. Building blocks of CNNs

Basically, CNNs are inspired by the human visual system, designed to process visual data efficiently. The fundamental building blocks of CNNs include convolutional layers, pooling layers, and fully connected layers. Convolutional layers act as feature extractors, identifying patterns in the input data through filters or kernels. Pooling layers reduce the spatial dimensions of the extracted features, focusing on the most relevant information. Finally, fully connected layers analyze the high-level features, making decisions based on the learned representations. These layers work together in a hierarchical fashion, allowing CNNs to learn complex patterns and make accurate predictions.

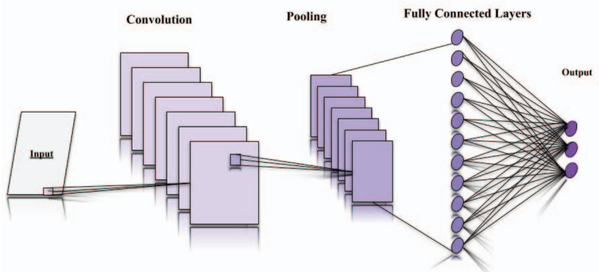

Fig. 3. CNN Block Diagram

C. CNNs in Medical Imaging

In medical image, CNNs are employed for tasks such as tumor detection, organ segmentation, and disease classification. These networks are typically deep, comprising multiple convolutional layers followed by pooling layers to reduce spatial dimensions and fully connected layers for high-level feature extraction. Additionally, techniques like transfer learning are often applied, where pre-trained CNN models (such as VGG16 or ResNet) are fine-tuned on specific medical datasets. Fine-tuning involves adjusting the network's weights using backpropagation with a lower learning rate, allowing the model to adapt its features to the nuances of medical images. Furthermore, advancements in CNN architectures, such as attention mechanisms and dense connections, have enhanced the network's ability to focus on relevant image regions and capture intricate details, making them invaluable tools in medical diagnosis and analysis.

III. Medical Image Interpretation using Deep Learning

Medical imaging refers to the technologies used in medicine to create visual representations of the interior of the human body or to monitor its function. It is essential for diagnosing a wide range of medical conditions, from broken bones to cancer, and it plays a crucial role in guiding medical procedures and treatments. The advances in deep learning have made AI-based medical image interpretation possible and it is evolving as the paradigm of AI algorithms are evolving. The advances in high-performance computing have also made high-resolution data processing much easier for AI-based medical image interpretation systems.

A. Some Examples of Medical Image Interpretation using Deep Learning

Two examples demonstrate the potentials of AI-based medical imaging interpretation in disease diagnosis. The first of these is CheXNet [7]. CheXNet is a radiologist-level Pneumonia Detection system. It is implemented by a group of Stanford researchers. CheXNet uses a chest x-ray to diagnose 14 chest-related diseases. It uses 121 layers of convolutional neural networks. In 2017, the researchers tested the accuracy of CheXNet against radiologists and found that CheXNet performed significantly better at diagnosis than radiologists. The second comes from researchers at Seoul National University Hospital and College of Medicine [8]. They developed an AI algorithm known as Deep Learning-based Automatic Detection to analyze chest radiographs and detect abnormal cell growth, such as potential cancers. The algorithm's performance was compared with physicians and it turned out the algorithm outperformed physicians at detection. These two examples' superior performance compared to physicians highlights the remarkable progress AI is making in healthcare, offering doctors a powerful tool to enhance their decision-making processes.

TABLE I.

AI BASED MEDICAL IMAGE INTERPRETATION TOOLS & TECHNOLOGIES

Disease/Use case	Technology/Tool	Algorithm	Data
[11] Diagnosis of Appendicitis	AppendiXNet	3D residual network	646 Eligible CT scans
[12] Arrhythmia Detection	Computer Vision and Pattern Recognition	Convolutional Neural Networks	64,121 ECG records from 29,163 patients
[13] Pneumonia Detection	CheXNet	121-layer CNN	100,000 frontal-view X-ray
[14] Cerebral Aneurysms	HeadXNet Model	Neural Network Segmentation Model	818 Eligible CTA scans

B. High Level Abstract Design of AI-based Medical Image Interpretation System

To get the overall gist of how an AI software system operates in the context of medical imaging interpretation, we'll refer to the Fig. 4. The system diagram provides a visual representation of how the AI software system encompasses the processes of detection and training.

At its core, the Fig. 4 outlines the various components that constitute an AI-based medical image interpretation system. The Medical Imaging Database serves as the repository for diverse medical images, which are then processed through the Preprocessing Module. This module ensures that raw data is cleaned, normalized, and made consistent for analysis. Subsequently, the Feature Extraction Module extracts crucial image features, and these refined features are fed into the Deep Learning Model, a complex neural network architecture tailored for image recognition. The Training Module refines this model using labeled medical images, with iterative processes involving loss functions and optimization techniques, forming a crucial feedback loop.

This loop incorporates User Feedback, where medical professionals provide real-world input on the accuracy of interpretations, guiding the Training Module to continuously improve the model's precision. Once trained, the Inference Engine utilizes this model to interpret new, unseen medical images, predicting the presence of abnormalities with associated confidence scores. Meanwhile, the User Interface provides a user-friendly platform where medical professionals can interact with the system, visualize interpreted results, and offer feedback for continuous enhancement. The diagram captures the dynamic flow of data, the training process, and the vital interactions within the system, including the iterative feedback loop that ensures the ongoing refinement and accuracy of the AI-driven medical imaging interpretation system.

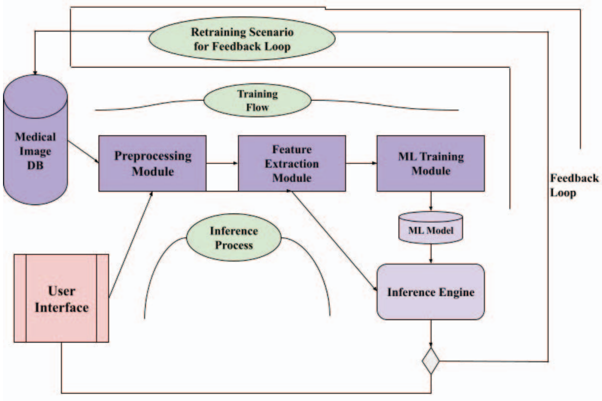

Fig. 4. Abstract Design of AI-based Medical Image Interpretation System

IV. GENERATIVE AI-BASED LARGE LANGUAGE MODELS (LLMS)

In recent months, there has been a rapid surge in Generative AI based LLMs like ChatGPT. These models are trained on extensive internet data. They have garnered widespread attention for their impressive capabilities in generating responses to human queries. The LLMs have been suggested for potential applications in healthcare due to their ability to process vast amounts of free-text medical data.

In one article, [19] i.e., 'The promise of large language models in health care' which is published in The Lancet, Authors have pointed out the issues with use of LLMs by the general public for their medical queries. Author says that LLMs have potential to incite harm, by referring to the use of LLMs chatbots for mental health issues and biases these chatbots hold.

One of the more worrying factors behind the use of LLMs by the general public is that if their usage becomes widespread, we might see a significant portion of the population displaying hesitancy to consult physicians, which has a direct impact on their health.

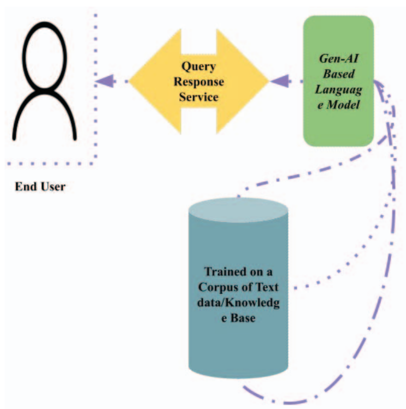

Fig. 5. Gen-AI based LLM Chatbot Services Abstract Flow

But despite these other concerns, LLMs have shown to be really useful in medical research. One example of this is example GatorTron, an LLM trained on more than 90 billion words of text from electronic health records. [20] This model can perform a comprehensive assessment across five clinical NLP tasks, which encompass clinical concept extraction, medical relation extraction, semantic textual similarity, natural language inference (NLI), and medical question answering (MQA).

As an example of the practical application of Large Language Models (LLMs), consider their role in the field of psychological counseling. A research project conducted at the University of Sydney has introduced a novel framework known as the AI-based Psychological Support with Large Language Models (Psy-LLM). [21] This framework is specifically tailored for question-answering in the domain of psychological support.

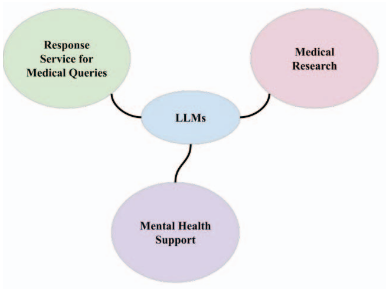

Fig. 6. LLM Use-Cases in Healthcare and Medicine

With both concerns and tremendous potential, these LLMs hold the promise to bring about significant changes in the healthcare sector.

V. Natural Language Processing in Electronic Healthcare Records Systems (NLP in EHR Systems)

Approximately 4/5th of total healthcare records exist in an unorganized style and AI can interpret and comprehend such data and can provide great insights into this data for clinical purposes. AI's capability to process natural language enables it to read, understand and learn clinical text from any source and identify, classify and code medical concepts and social notions.

Maintaining and keeping track of the patient's medical record can be done manually with the help of files or folders and paper-based reports and prescriptions. This type of method involves plenty of human assistance and can cost doctors a lot of time for searching a report or making judgments or providing insights of data to the patient since this data exists in an unorganized, handwritten, or hardcopies form. To overcome this challenge, hospitals use a system called EHR. EHR is the process of storing medical health records of individuals in digital form over static storage or cloud storage. This makes EHR accessible to anyone who wants to see it, especially doctors.

Since data in EHR is stored in an organized way, it becomes easier for the doctor to search among the data. But this data mostly exists in textual form. Henceforth interpreting and learning it is a challenging task for a doctor because this data is growing exponentially. This problem can be solved by natural language processing(NLP). NLP is a subclass of AI that involves the understanding of human language by a computer, specifically how the computer can process and analyze the human language. In this process, by automating the access to the health record with EHR cloud storage and using AI to interpret the unstructured data efficiently, we can unleash hidden potential of this data. The figure shown below represents how EHRs, AI, automation can be put to work together. [17], [18]

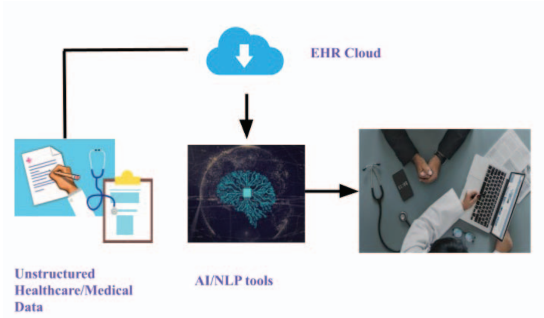

Fig. 7. NLP-based EHR System

By integrating AI with EHR, a patient's historical medical history can be analyzed in real-time aiding in faster and more accurate decisions. AI based EHR systems can help physicians with decisions like proactive interventions and personalized treatment plans, predicting health risks, identifying errors, etc.

A. Applications of NLP for EHR-based Use-Cases

There diverse applications showcasing the transformative impact of NLP in healthcare. The following table provides insights into key areas such as Pharmacovigilance, Clinical Research, Clinical Note Summarization, and Disease Status Identification. Each application harnesses NLP techniques to enhance various aspects of healthcare data analysis, from automating adverse drug effect detection to enabling efficient clinical research and disease status identification. Let's delve into the details of these applications:

TABLE II.

NLP for EHR-based Use-Cases

Application	Details
Pharmacovigilance	[29] **Pharmacovigilance** refers to the aim of **monitoring**, **detecting** and **preventing** adverse drug effects ((**ADEs**)) and other safety issues related to drugs & *EHR-Based Pharmacovigilance* relies on **data mining** of EHRs. **Methods & Techniques:** 1. Statistical analysis and ML automate ADE mining from EHR narratives. 2. State-of-the-art NLP methods show promise for ADE detection in EHRs. **Scope:** Integration into production pharmacovigilance .
Clinical Research	[32] Leveraging NLP allows **extraction** of valuable clinical insights from EHR narratives. This has **potential** in **clinical research** in **allergy, asthma, and immunology.** Cause this enables automated chart reviews* to identify patients with distinct clinical characteristics in clinical care, reducing methodological heterogeneity and clarifying biological heterogeneity. **Chart review is a previously recorded data to answer clinical queries.*
Clinical Note Summarization	**Clinical Note Summarization** entails the compression of health records to extract information that preserves the essential features of the original documents, with a focus on reported diseases. [30] **Methods & Techniques:** 1. Bag of n-gram based SVM, 2. Word Embedding based CNN, [31] 3. BERT based Neural Net [30]

	Leveraging these summaries has the following **advantages**, - **streamline** a physician's tasks, particularly during busy periods, [30] - enhancing **collaboration** among healthcare staff, - contributing to efficient **resource allocation**, - reducing the time spent reviewing extensive health records, etc.
Disease Status Identification	[33] - Automatically **spots** the **status of a disease** from EHRs - Relies on **supervised** and **semi-supervised** learning techniques. - It incorporates the use of **unstructured data** found in clinical notes and **structured data** from the patient record.

B. Challenges of applying NLP on EHR Data

Applying NLP techniques to EHR data presents numerous challenges, like accurate Clinical Entity Recognition, ensuring Privacy Protection, correcting Spelling Errors, dealing with the Lack of Labeled Data, detecting Negations, managing De-identification processes, and deciphering the multitude of Medical Abbreviations. [28]

Let's look at each challenge with a brief description for better understanding.

TABLE III.

CHALLENGES OF APPLYING NLP ON EHR DATA [28]

Challenge	Description
Clinical Entity Recognition	The accurate recognition of clinical entities within the text is a process crucial for understanding medical terminology and context.
Privacy Protection	Additionally, ensuring patient privacy and complying with healthcare regulations pose significant challenges, as sensitive patient information needs to be protected during the NLP analysis.
Spelling Errors	Medical document can have Misspelt terms due to clerical errors or OCR errors [28] and correction of such misplelt terms in medical texts, is essential for precise interpretation.
Lack of Labeled Data	Furthermore, the scarcity of labeled data specific to healthcare contexts hampers he development and training of NLP algorithms, making it difficult to achieve high accuracy levels.
Negation Detection	Detecting negations, since negation in text data causes sentences to have their meanings reversed.
De-identification	De-identification, or removing personally identifiable information from records, is essential for privacy but adds complexity to NLP tasks.
Medical abbreviations	The medical abbreviations can be misinterpreted by NLP. The wide array of medical abbreviations used in EHR data requires specialized handling to ensure accurate interpretation.

VI. SOME AI-BASED DISEASE MANAGEMENT USE-CASES FROM MEDICINE

There are numerous use-cases from medicine where we can use AI-based techniques. In medicine, AI is tackling complex challenges and can be used for diagnosis and treatment. Across cardiology, pulmonary medicine, endocrinology, nephrology, gastroenterology, and neurology, AI is reshaping the healthcare landscape. It aids in risk prediction for cardiovascular diseases, improves the interpretation of pulmonary function tests, enables continuous glucose monitoring for diabetes patients, forecasts the progression of kidney diseases, enhances diagnostic accuracy for gastrointestinal disorders, and offers intelligent solutions for seizure management and neurological assessments. [6]

For these use-cases, different kinds of data or lab test measurements are needed to come up with a prediction model. For example, for use-case, 'prediction of risk of cardiovascular disease', we'll need different data, ranging from weight and height to blood test results. As such, these use-cases also differ in terms of which stage of disease they lie, like, from diagnosis, prognosis and treatment. To highlight this, we've classified these use-cases on the basis of which stage of disease management they fall.

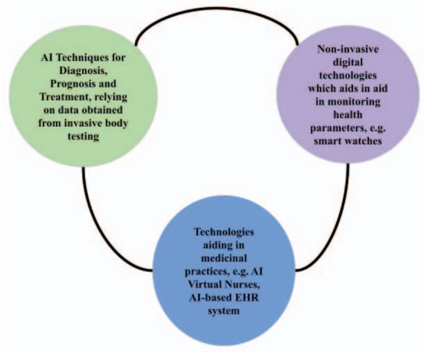

Fig. 8. Range of AI Use-cases across medicine and aiding in medicinal practices.

TABLE IV.

TABLE DEPICTING AI USE-CASES ACROSS DIFFERENT DISCIPLINES OF MEDICINE AND THEIR DISEASE MANAGEMENT STAGE. [6]

Branch of medicine	Use-case	Stage of Disease Management
Cardiology	**Prediction of risk** of cardiovascular disease for e.g. acute coronary syndrome and heart failure.	*Diagnosis*
Pulmonary Medicine	**AI-based software** shows a more accurate **interpretation** of pulmonary function tests and also serves as a decision support tool.	
Endocrinology	Continuous glucose **monitoring** helps diabetes patients to optimize their blood glucose control.	*Treatment*
Nephrology	**Prediction** of the decline of glomerular filtration rate in patients with polycystic kidney disease. **Establishing risk** for progressive IgA nephropathy.	*Prognosis*
Gastroenterology	Diagnosis of gastroesophageal reflux disease, atrophic gastritis.	*Diagnosis*
	Prediction of outcomes in gastrointestinal bleeding, the survival of esophageal cancer, inflammatory bowel disease, metastasis in colorectal cancer, and esophageal squamous cell carcinoma.	*Prognosis*
Neurology	**Intelligent seizure detection** devices for seizure management through permanent ambulatory monitoring.	*Treatment*
	Quantitative assessment of gait, posture, and tremor in patients with multiple sclerosis, Parkinson's disease, Parkinsonism, and Huntington's disease through **AI-based wearable devices**.	

As we can see, AI's diagnostic capabilities in cardiology and pulmonary medicine enable precise identification of diseases. Furthermore, its prognostic power in fields like cardiology and nephrology aids in predicting disease outcomes. In treatment management, AI supports continuous monitoring in endocrinology and offers valuable insights for neurological disorders. This classification reflects the nuanced and evidence-based roles AI plays in different stages of disease management, emphasizing its practical and targeted contributions in medicine.

Though there is a wide range of applications in the practice of medicine, there are also some digital applications that use AI and aid in medicinal practices. Some of them are Remote Patient Monitoring, Patient Health Record Management, Virtual Nurses, etc. These aforementioned applications help medical practitioners in fulfilling basic medical care either in virtual or in-person presence. The fundamental components of these applications consists of a whole combination of Surface-level or non-intrusive digital technologies that support the implementation of these applications. [10]

VII. Innovative Technologies Facilitating AI Integration in Medicine and Healthcare

In the fields of medicine and healthcare, some innovative technologies can be playing a key role or some are already playing that key role in facilitating the integration of Artificial Intelligence (AI). The intersection of these technologies and healthcare, with AI serving as a catalyst, is seen as a very innovative combination in the medical technology industry. These technologies are discussed below.

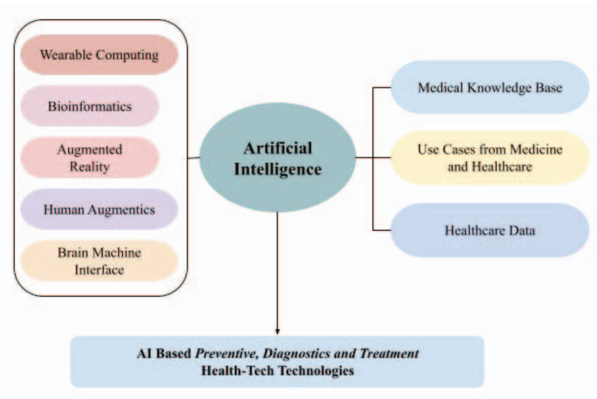

Fig. 9. Abstract roadmap of technologies facilitating AI Integration for Medicine and Healthcare

TABLE V.

Technologies where AI serving as catalyst for applications in medicine & healthcare

Technology	Definition	AI Relevance
Wearable Computing	[1] Field devoted to creating computer devices that can be seamlessly integrated into an individual's attire, aiding in various medical procedures and tasks. Often dubbed automation technology, wearable computing minimizes human intervention in performing procedures and processes.	Since, wearable health devices are instrumental in **health data gathering**, processing, **digital imaging**, these are incredible opportunities for **AI integration**
Bioinformatics	[2] It is blend of biology and information technology, involves the integration of biological data into information technology frameworks.	Makes use of AI techniques for **computational analyses** to generates insights
Augmented Reality	[3] AR integrates digital information into the user's real-world environment. It offers a new approach for treatments and education in medicine. AR aids in surgery planning and patient treatment and helps explain complex medical situations to patients and their relatives.	Have potential for use of AI for **optimization** of the **AR experience**
Human Augmentics	[4] Technologies that elevate human capabilities. Today human augmentics is implemented mostly in the form of devices. Devices that aid handicapped in performing tasks that otherwise would not occur without those devices.	Uses a great deal of AI to train devices for the real-world environment. It uses **data** and **ML** to attained those capacities.
Brain Machine Interface	[5] Uses electrical signals from the brain and interprets them for more insights and scientific understanding. electrical interference.	Uses AI to **train** the brain implantable chips to recognize **different brain activities** by their electrical signals.

Artificial Intelligence technologies are more applicable to problems where we're dealing with meaningful knowledge and data. Due to the proximity of the aforementioned technologies to data, these are highly suitable to use AI. This can lead to new and better solutions in healthcare by using AI to get important information from big sets of data. This mix of AI and these technologies can make healthcare more efficient and help us better understand medical issues. So, as AI keeps getting better, it can work hand-in-hand with these technologies to bring big changes to healthcare.

VIII. Ethical Considerations of Using AI in Healthcare

The use of AI in healthcare presents important ethical questions. One key concern is safeguarding patient privacy and data security since AI relies on sensitive medical information. Ensuring robust data protection and privacy compliance is essential. Another issue is making sure AI's decision-making processes are clear and accountable, especially as AI helps with medical diagnoses and treatments. Maintaining transparency in AI algorithms and understanding how they make decisions builds trust. Lastly, addressing biases in AI algorithms that could lead to unequal healthcare outcomes is vital. We must be careful when training AI to minimize bias and promote fairness to address these ethical concerns.

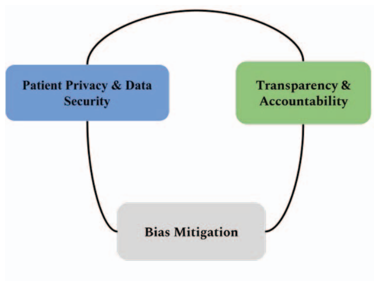

Fig. 10. Key Issues in AI Ethics

A. Challenges around Privacy and Security

There are various challenges around patient privacy, either from private technology companies or clinical laboratories, where these institutions are doing innovative things in Research and Development but they lack a foresight for maintaining privacy protections for public health data. Issues like corporate interests, monetization of data, and insufficient legal penalties pose challenges to maintaining privacy standards. [24] There are some rules and regulations around data sharing of patients' confidential information, like 1996 American legislation, HIPPA, i.e. Health Insurance Portability and Accountability Act. But such privacy laws worldwide face challenges due to varying standards, inadequate enforcement, and struggles to keep pace with technological advancements. Issues like data breaches, cross-border data transfer, complexity, and gaps in protection pose drawbacks, requiring more nuanced regulations to safeguard patient privacy effectively.

In addition to privacy concerns, biases are inherent challenges in the foundational aspects of healthcare technologies.

B. Key Biases posed by AI Algorithms while Addressing AI Ethics within Healthcare

Sample Biases in Training Data: ML models, especially supervised ones [22] (Gaonkar, Cook, Macyszyn et al., 2020), are limited by biases present in training data. Ethical concerns arise when these models are implemented in situations they were not appropriately trained for, leading to unreliable predictions. This concern can be addressed by aligning the distribution of training data with the target population.

Annotating Biases from inconsistently labelled data: Human-Induced Data Labeling Biases refer to biases introduced into datasets when humans label or annotate data. In the context of healthcare, these biases can arise from variations in how healthcare professionals, such as physicians, diagnose and treat patients with similar symptoms. For instance, when two physicians encounter a patient with identical symptoms, their treatment choices may differ based on their individual experiences, expertise, or personal biases. If machine learning algorithms are trained on these physicians' data, they can inherit these biases and replicate the divergent treatment patterns. [22] Consequently, the algorithms may provide different recommendations for the same patient depending on the source of training data, highlighting the impact of human-induced biases on machine learning outcomes in healthcare.

Automation Bias from AI-driven Decisions: As quoted [23] by Kathleen L. Mosier and Linda J. Skitka in Proceedings of the Human Factors and Ergonomics Society Annual Meeting, "The availability of automation and automated decision aids feeds into a general human tendency to travel the road of least cognitive effort." When this meta-philosophy to AI-driven decisions made by clinicians, it may cultivate excessive dependence on these technologies, potentially resulting in misleading conclusions. Consequently, this over-reliance could jeopardize patient safety and well-being.

IX. Conclusion

AI-based systems are already demonstrating real-world applications, improving diagnostic accuracy, and enhancing patient outcomes. AI systems provide valuable data-driven insights, supporting more personalized treatment plans and efficient resource allocation. Beyond patient care, AI has the potential to enhance cost-efficiency in healthcare delivery, optimizing processes and reducing administrative burdens. Safeguarding patient privacy is paramount as AI systems handle sensitive data.

The progress in AI healthcare systems hinges on interdisciplinary collaboration among experts in various fields. Ethical guidelines and regulatory frameworks must be established to govern AI in healthcare. AI systems should be designed with a patient-centric focus to enhance patient experience and well-being. Recognizing that the impact of AI in healthcare will evolve, ongoing research is crucial for continued innovation. Healthcare systems must adapt to emerging AI technologies and integrate them effectively. As AI can address healthcare challenges globally, efforts should be made to ensure AI in healthcare contributes to global health equity, addressing disparities in access to healthcare resources.

In the future, for holistic advancements in AI-based healthcare systems, it requires innovative approaches such as enhanced privacy protection for health data sharing, improved feedback mechanisms to mitigate biases, and the implementation of health protocols to ensure patient well-being. Additionally, it is imperative to focus on enhancing the interpretability of AI algorithms, allowing healthcare professionals to understand and trust the decisions made by these systems. Moreover, continuous research and development efforts should aim at creating adaptable AI frameworks capable of evolving alongside the rapidly changing healthcare landscape.

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
Gen-AI	Generative Artificial Intelligence
LLM	Large Language Models
EHR	Electronic Health Records
CNN	Convolutional Neural Network
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
NLP	Natural Language Processing

Note

All the figures presented in paper are created by authors, The X-rays shown in figure 2 are taken from following these two sources, 1. Chest X-Ray, Mayo Foundation for Medical Education and Research (MFMER), 2. Chest X-ray - Pulmonary disease - Basal lung consolidation, Radiology Masterclass, Department of Radiology, New Hall Hospital, Salisbury, Wiltshire, UK

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