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# Application of Artificial Intelligence in Healthcare: Trends, Challenges in Disease Diagnosis and Management

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***Abstract:*** This study thoroughly reviews the status of applications of artificial intelligence (AI) in healthcare, trends regarding AI usage for different disease types and problems that hamper their further progress. The study used a literature review and data analysis by locating relevant current articles on AI in healthcare through the PubMed database. The work analyzes AI use in cancer, cardiovascular diseases and neurological disorders as well as the bottlenecks in the real-world deployment of healthcare. The findings of the study indicate that, while AI has demonstrated the potential to improve diagnostic precision, several obstacles persist in relation to data privacy, ethical considerations, and model interpretability. In conclusion, this review offers an assessment of the current state of AI applications in healthcare and identifies key areas of concern that necessitate further investigation. By addressing these challenges, future innovations can be more effectively developed and broadly implemented, ultimately contributing to the advancement and optimization of AI-driven healthcare solutions.

***Keywords:*** Artificial Intelligence, Healthcare, Machine Learning.

## 1. Introduction

The usage of artificial intelligence (AI), which is one of the key instruments in healthcare across a wide array, from disease detection to tailor made treatments, has grown at an escalating rate especially with the rapid growth and changes experienced by the technology landscape today. Although the power of AI in healthcare is enormous, there are still significant voids to fill with respect to research (Patel et al., 2009). Original research is also skewed towards the roles of AI in specific high-burden diseases such as cancer (Murdoch & Detsky, 2013), cardiovascular disease and neurological conditions at the expense of understanding other diseases. Adding to this, many of the works highlight technical progression while overlooking data privacy, ethical questions and interpretability of the models developed using AI technologies that are equally crucial to wider adoption (Graham, 2016).

Current literature indicates that AI does well at handling large amounts of medical data, providing aids intended for doctors and helping work out treatment plans. In medicine alone, machine learning classification algorithms can extract important features out of complex data and generate precise diagnostic recommendations (Long et al., 2017). Despite the growing body of research on AI applications in healthcare, existing studies often focus on particular algorithms or diseases, resulting in a fragmented understanding of AI's potential and constraints in this context. Bridging these knowledge gaps is essential to gain a comprehensive view of AI's role in healthcare and provide targeted recommendations for future technological advancements. A holistic analysis of AI

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applications and their limitations will contribute to a more nuanced understanding of the field and support the development of innovative solutions that address pressing healthcare challenges.

While AI has been most commonly used in the medical field, this study hypothesized that there was no refined evaluation of its performance and applicability across different diseases (Ravi et al., 2017). This systematic review and analysis aims to comprehensively examine the current landscape and trends in AI applications within the healthcare sector. In doing so, the study seeks to identify potential technical obstacles that may hinder the effective implementation of existing AI technologies. Additionally, this research endeavors to explore avenues for technological advancement and to discuss strategies for enhancing the generalizability and efficacy of AI solutions in healthcare.

Therefore, the main aim of this study is to provide an overview of applications of AI in health based on the available literature, what are the deficiencies and under explored areas that have not been addressed by previous works and potential future directions (Murff et al., 2011). The objective of this study is to not only enhance AI technologies in the healthcare domain but also highlight these crucial themes for paving a way towards more realistic and broader deployment modes of AI applications within the context of healthcare. The findings of this study will be useful in facilitating the identification and filling of research gaps for the academic community as well as valuable reference for medical care in clinical practice.

## 2. Literature Review

The urgent requirement towards the application of artificial intelligence in the healthcare sector is quickly increasing, embracing diverse subfields from disease diagnosis to treatment decisions and patient care. First, it should be noted that the main AI techniques provide machine learning and natural language processing methods which are extensively implemented to process structured and unstructured healthcare data. It is possible to state that in the recent decade, AI has resulted as a highly productive solution in such areas as cancer, neurological, and cardiovascular diseases (Murdoch & Detsky, 2013; Kolker et al., 2016).

### 2.1. Background of Artificial Intelligence in Healthcare

AI systems are able to identify the causes and current states of diseases and provide doctors with the opportunity to make the right diagnosis and personalized therapy, and the entire healthcare sector benefits from the application of AI technologies (Dilsizian & Siegel, 2014). It is evident that in the past decade AI technologies, particularly deep learning techniques, have widely improved and are widely deployed in medicine for medical image processing, genomics, and EMR studies (Patel et al., 2009). For instance, CNN is deployed in the area of ophthalmology to typify disease diagnosis, while in the area of oncology AI technologies are used to guarantee cancer diagnosis in the early stages and establish the best treatment decisions (Long et al., 2017).

### 2.2. Integration of Sustainable Development and Healthcare Technology

Currently, in the context of the growing attention paid to sustainable development at the global level, healthcare systems are beginning to incorporate sustainability principles. With this, the reduction of medical waste and the increased efficiency of resource use are far from the only factors. Thus, technologies are developed to enhance the overall sustainability of healthcare services by implementation of the hospitals, clinics, and other healthcare institutions throughout the country (Ravi et al., 2017). Furthermore, AI also helps in this by through shortening the timeframe previously required for diagnostics. As a result, it reduces the cost of medical examinations for patients, as well as more efficiently allocates resources, promoting the sustainability of healthcare services (Weingart et al., 2000; Graber et al., 2005). Simultaneously, AI also serves as a driving force for the development of healthcare technology. For instance, by processing vast amounts of patient health data, AI can tell that the patient is likely to suffer from a physical condition long before they start experiencing symptoms. As a result, healthcare management transitions towards a more proactive and preventative approach, not only reducing the need for substantial treatment resources but also significantly improving patients' overall quality of life over time (Murff et al., 2011; Neill, 2013).

### 2.3. Economic and Environmental Problems

While AI serves as the primary driver for the development of healthcare technology, the widespread implementation of AI in this sector can cause some related economic and environmental problems. In particular, the development and maintenance of AI systems require substantial financial investment, meaning that not every organization or individual will be able to afford their equipment. Moreover, according to who recognize that data processing requires a lot of energy, which can seriously damage the environment (Graham, 2016). Therefore, even though AI is expected to continue to develop healthcare; simultaneously, it is crucial to consider its environmental and economic implications and take measures to limit its development (Kayyali et al., 2013).

### 2.4. Debate and Research Gaps

AI has been recognized as an application tool in healthcare with remarkable opportunities. However, there is also a discussion about the limitations and challenges faced by the proposed solutions. Despite the high likelihood for AI to address diagnostic errors and promote and personal treatment, there remains an issue with the transparency and interpretability of AI. Specifically, models constructed using deep learning are known as black boxes, meaning that the processes of analysis and making decisions are not available for examination by human experts. As a result, recommendations offered by AI may not be trusted by healthcare professionals or contradict their judgement.

With the multiple benefits of AI, it is also known that such solutions raise significant ethical concerns. One of such concerns is that AI in healthcare is expected to utilize vast quantities of private healthcare data, and this may lead to risks of leakage, misuse of protected health information, and other threats. Additionally, issues that can be challenging to address are those related to the balance of patient’s and the system’s interests and the context of what decisions can be delegated to AI without any essential human supervision. In this way, even though a sufficient number of studies have been conducted on these issues, they remain underexplored. Thus, additional attention should be given to promoting studies where the analysis and examination of AI algorithms’ details are increased to make them more understandable and transparent to medical professionals, and methods to deal with the bias in data and processing are proposed. orientation efforts should also focus on studying the impact of AI on patient outcomes, processes of healthcare provision, and relationships between patients and valuable professionals.

## 3. Methodology

The main aim of this research is to describe the development trends of artificial intelligence technologies in the field of healthcare and explore how AI is used in different diseases and data types through statistical analysis of the related data. This study does not aim to construct certain machine learning models or carry out a predictive analysis. It aims to clarify the current status of the application of AI in the field of healthcare through descriptive statistics and trend analysis.

### 3.1. Data Sources

The main source of research data is the PubMed database. Research articles on AI and healthcare

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published in different time periods were received through a search using relevant keywords in PubMed. Relevant keywords used in the search processes are “artificial intelligence”, “machine learning”, “deep learning”, and “disease diagnosis”. The use of AI technologies in imaging data, genomics data, and electrophysiological data and what application trends each of the data types has across diseases such as cancer, neurological disorders, and cardiovascular diseases.

### 3.2. Data Analysis Methods

The main methods of the data analysis in this study are descriptive statistical analysis, trend analysis, and comparative analysis. The specific steps are as follows:
Descriptive Statistical Analysis: Excel was used to categorize and organize the received data,with number of articles on AI technologies are published each year and what the main disease types and data types are in them.

Trend Analysis: R software was used to plot how trends of the application of AI technologies in different diseases and data types look across different time periods and how they change. Line charts and bar charts were created to show how research focuses and applications of AI change across different time periods.

Comparative Analysis: A comparative analysis of the application of AI technologies in different diseases and data types was conducted. The Chi-square test was applied to test how significant the differences in the application of AI technologies in different research areas were.

### 3.3. Tools and Materials

The software used for data analysis primarily includes Excel. The specific application is to use Excel for preliminary data collation and description statistics to sort the types and map drawings.

The main purpose of this study is to describe the history of the development of AI technology and its application in medical treatment more completely. Through descriptive statistics and comparison, the research trend of AI in various diseases and data types can be identified, providing data support and inspiration for the next step of research.

## 4. Results and Discussion

### 4.1. Results

Data used to be primarily based on traditional clinical activities such as screening, diagnosis and allocation of treatment before artificial intelligence systems were integrated into healthcare applications. This data was primarily gathered in the form of demographic details, medical records, e-records from devices used during treatment, examinations and clinical lab results (Murdoch & Detsky, 2013). But as AI is being integrated, a drastic change in the capabilities of handling medical data, especially in fields such as diagnostic imaging, genetic testing, and electrodiagnosis (Kolker et al., 2016).

Data from PubMed shows a substantial elevation of literature on diagnostic imaging and genetic testing; these rises arise out of the extensive use of AI in both. For instance, there has been an increase from 124,802 to 171,418 publications on-years consisting about genetic tests, reflecting the growing importance of AI in genomics and precision medicine (Gillies et al., 2016). Jha and Topol studies have shed light on the role AI can play in radiology imaging analysis, while Li et al. explored the application of AI in detecting abnormal genetic expressions, greatly advancing genetic testing technologies (Jha & Topol, 2016). The number of publications in the electrodiagnosis literature also increased, from 15,736 papers (2015) to just more than 7500 by year ending 2024. Even though electrodiagnosis is experiencing a somewhat slower rate in terms of AI growth compared to other

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fields, significant strides are done with the use of AI for localizing neural injury and analyzing electrophysiological electrical signals.

But as some disciplines have been on a decrease in literature volume. Between 2015 and 2024, the publications regarding Physiological monitoring & disability evaluation reveal a decrease. This is perhaps because scholarly research in these fields has centered predominantly on traditional modes of doing things, and hence AI's potential for penetration and evolution yet to be tapped (Graham, 2016). AI, offers vast potential as a tool for operational efficiency and improvement while its practical application in these specific fields is still limited by technological barriers and the complexity of data structures (Saenger & Christenson 2010).

In general, AI in medical data analysis is on the rise, most notably when it comes to high-dimensional tasks of analyses and processing. The fact that artificial intelligence has permanent implications for the healthcare industry is emphasized and how it improves diagnostic accuracy, efficiency and advances precision medicine on a large scale. Nonetheless, there are obviously wide ranging differences in the scope and depth of where AI is used between the medical fields covered in this study to which future focused research and technological breakthroughs will be still needed to fill some gaps.

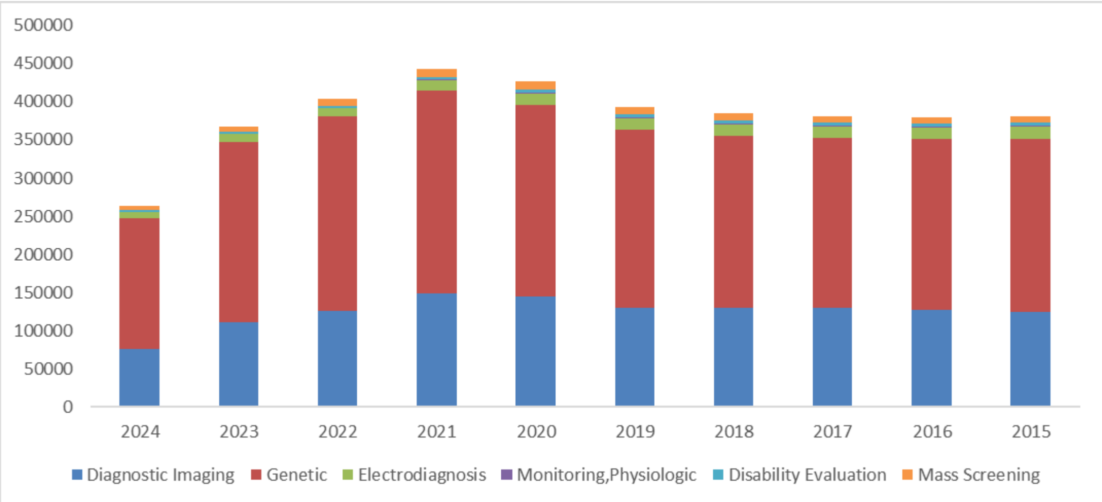


Figure 1: Comparison of Data Types in Diagnostic Techniques in AI Literature Based on PubMed Database

The data show that cancer, neurological disorders and cardiovascular diseases are the main target directions of researches in artificial intelligence (AI) for healthcare. The above diseases are common in AI literature generally because they raise large public health problems and applications of AI to these areas lead predictably, usually broad recognizes ideas to enhance timely diagnosis, implementation specific therapy strategies or final prognosis.

1.**Cancer (Neoplasms):** Cancer is one of the most researched areas in AI applications. AI technologies have been applied to various stages of cancer diagnosis and treatment such as in Image Recognition for successful detection; Pathology Analysis etc. The total number of AI-related publications on cancer increased between 2015 and 2024 with a slight decrease, down from level (149,724) in 2015 (105351). Even though a slow decline is predicted in 2024, the general trend will continue to be positive and indicate an increasing utilization of AI for improving advance cancer diagnosis (Somashekhar et al.,2017). For instance, imaged-based deep learning algorithms for a wide range of diseases and conditions, demonstrating the vast potential of AI in cancer detection (Esteva et al. 2017).

2.**Neurological Disorders (Nervous):** AI researches are also turning more towards neurological

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disorders, from neurodegenerative illnesses such as Parkinson's and Alzheimer's to epilepsy. From 2015 (34,079) to 2024 (35,952), the number of publications on this topic is increased. While that has come in small growth numbers, AI applications now have more nuance within this space. For example, Bouton et al. (2016) created an AI program to restore electric motor feature in quadriplegia people, highlighting how AI can be made use of for the betterment of human life.

3.**Cardiovascular Diseases (Cardiovascular):** Cardiovascular diseases make up the third largest category of AI research. Over the past few years, AI research in cardiology has been largely oriented towards cardiac image analysis and predictive modeling. According to statistics total publications related to heart diseases exceeded 68,571 compared with over all AI research during year 2015 where it has reached around 80,146. Arterys, an AI-based product made by a startup named after the cross-sectional view of arteries that MRIs provide, became the first such platform to receive FDA approval for automated cardiac MRI analysis (Marr 2017).

Research on AI in cancer, neurological and cardiovascular diseases has risen steadily from 2015 to 2024 with a steep increase. This is because these are diseases involved in the main causes of death worldwide, and early diagnosis to ensure individualized treatment automatically converts into benefits for patient care ( Saenger & Christenson 2010). There has been slower progress in AI research with regards to urogenital diseases and nutritional disorders. These are fields that you would find a comparatively smaller number of publications in, or they may simply have less research focus, data available for analysis and AI it is not as well applied here yet with underwhelming impact due to the applicability still improving.

Recent AI technologies including medical imaging analysis, data mining studies and machine learning have been increasingly important in research relating to cancer and cardiovascular dysfunction. Yet, in the case of chronic and rare diseases studies leveraging AI, technology-related challenges seem to hinder population-based investigations; thus reflecting a necessity for further research on these topics as well so that they can harness fully from what AI has brought into health care.

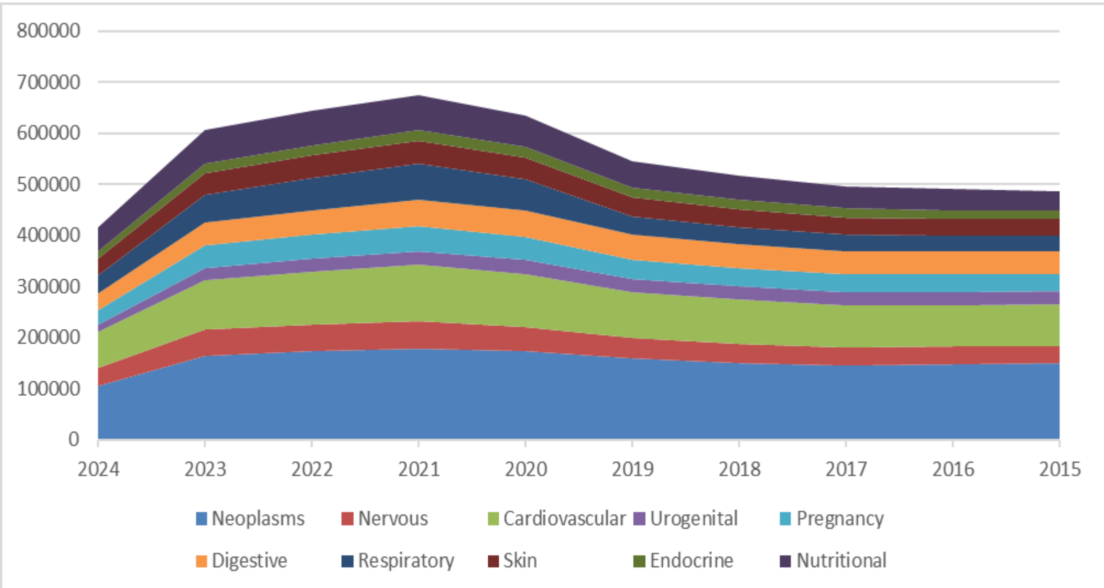


Figure 2: The Leading 10 Disease Types Analyzed in Artificial Intelligence (AI) Literature from 2015 to 2024

In healthcare, artificial intelligence technologies, particularly machine learning (ML), neural networks, and large language models (LLM), are gradually transforming the way healthcare is

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delivered. The machine learning algorithms face different scenarios in the medical data analysis to predict and focus on disease risk assessment, assisting diagnosis of a disease by providing information, optimizing treatment plans for patients. Statistical machine learning methods (like logistic regression, random forests and decision trees) are able to abstract key information from substantial amounts of data that can support clinical decisions. For instance, logistic regression is widely known to binary classification results like whether a patient got disease or nor (Witten et al., 2023). Using decision trees and random forests, they can generate hierarchical decisions rules making the wide range of classification/regression analysis it is enhanced to diagnosis accuracy (Breiman, 2021).

Deep learning models, such as neural networks have the ability dealing with complex non-linear relationships and are currently the main tools for medical image analysis. The multilayer structure of neural networks makes it possible to capture internal features of data deeply, which is crucial for tasks such as medical imaging analysis, pathology recognition in high-content screening images, and personalized treatment recommendations. Neural network models have excellent performance in processing medical imaging data, which can quickly address large-scale image analysis within milliseconds, thereby helping to enhance the efficiency of early disease diagnosis (LeCun et al., 2022).

The emergence of large language models (LLM) is a new milestone in medical data analysis. The trend has increased to 377 studies related to ChatGPT in 2023 compared with only 197 concerning Transformers published that same year, after the publication of ChatGPT. This means that large language models are gaining popularity among the medical field as a research topic. Models such as ChatGPT can handle complex text data to a very high level of competence, which makes them strong candidates for automating tasks like the organization of medical records or even guiding patients based on advice found in their profile information (Brown et al., 2020). A few examples to mention are the use of ChatGPT in developing personalized health recommendations, answering patient inquiries and serving as a medical education virtual assistant — all leading to improved overall satisfaction among patients (Radford et al. 2023).

Logistic regression remains the most cited machine learning algorithm based on data up to 2023 by journal distribution, and neural networks now have a similar number of citations over traditional ML; highlighting that traditional machine-learning methods remain highly relevant in healthcare. However, the emergence of new AI tools such ChatGPT and Transformers from the development large language models reveals significant areas of interest in both research and application. With LLM being further perfected and enhanced, it is anticipated that in more intricate healthcare use cases these other types of LLM will become even more prevalent (Johnson et al., 2023).

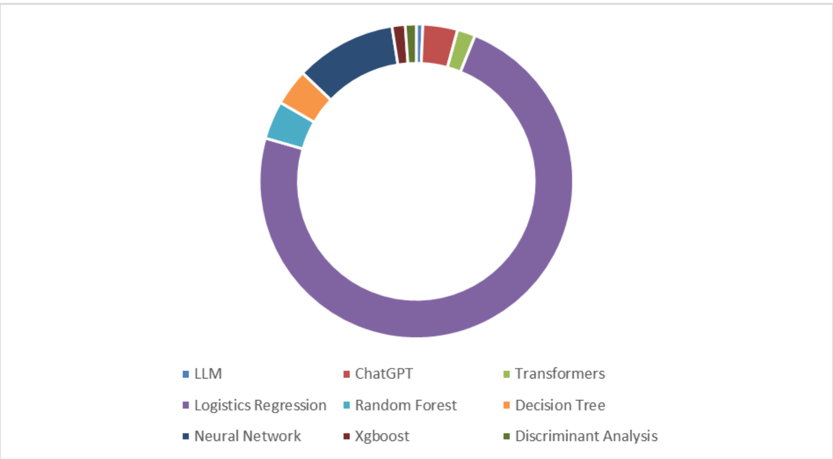


Figure 3: Applications of Artificial Intelligence in Healthcare: Machine Learning (ML) and Large Language Models (LLM)

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### 4.2. Discussion

The findings of this study show an increasing use of AI technologies in healthcare fields like cancer, neurological diseases and cardiovascular disease. The findings confirm the essential contribution that classical machine learning algorithms and neural networks continue to make for diagnosis and treatment of these disorders. Additionally, LLM has shown to be evolving at a great pace in the healthcare research and applications realm following ChatGPT, documenting a substantial promise for medical text processing, record analysis or patient consultation.

This study confirms the trend of AI in medical research, including traditional machine learning methods and deep learning models as other studies have shown since this is in line with our hypothesis. The rapid growth in the use of large language models has outpaced what many could have imagined; however, their integration into clinical work-flows still remains a challenge. Nonetheless, following research have pointed towards disruptively advancing technology of LLM while the implementation barrier is primarily based on issues such as data privacy or security and reaching a state which provides an acceptable rate for reliability.

These results add to existing medical AI research and corroborate the benefits of using these technologies to aid diagnosis or deliver personalized treatment. These findings provide additional information on early disease prediction, diagnosis and treatment optimization compared to conventional medical methodologies. This study serves to inform the potential ways in which AI could be deployed most effectively to drive positive health care improvements. These results help to quantify how AI is being applied by disease type in response recipients. While classic research may focus on a single technology, these results reveal the combined use of different AI approaches to solve and add value in realclinical cases.

Data sources are potentially limited in the generalizability of the results, although they consist of statistics where AI is applied —which however come from one database only. This data is not as reliable due to the differences in publication update speed and overall quality of data. The study was conducted primarily based on published literature, so the results might not provide a real time clinical data. The description of statistical methods limited the type of algorithms that were varied in optimization analyses, which did not explore performance differences or optimization potential of specific algorithms. These limitations suggest the need for broader and more diverse data sources to validate the study’s conclusions.

Subsequent studies will be required to elucidate how feasible the different AI engines are across specialties, and whether unencumbered large language models can serve as clinical decision aids. Flexible research necessitating a data-diverse approach and engagement in real-time analytics shall be an asset to mitigate existing limitations of research. Additionally, the further validation of AI applications in real-life clinical settings is critical to ensure that these technologies come up not only meeting but also maintaining the expected level of performance during practice. Researchers should also explore the ethical, legal, and social implications, alongside technical aspects, to foster more comprehensive and responsible AI deployment in healthcare.

## 5. Conclusion

The review highlights major applications of artificial intelligence in healthcare including the classic machine learning approach and more advanced ones such as neural networks and deep machines and large language models for a list of different diseases. Results underscore the sharp influence of AI technologies on disease screening, diagnosis, personalized treatment and discuss its huge utility in current major health diseases notably cancer, neurological disorders and cardiovascular pathologies. These technologies not only improve diagnostic accuracy and efficiency but also put a huge sum of money into healthcare spending cut, to give patients the best treatment experience.

Yet amidst the hopeful implications of AI integration within healthcare, there are also challenges related to data privacy and information reliability associated with employing it. This also suggests the promise for AI with applications to text through language models like ChatGPT. Full clinical integration requires further advances in technology and regulatory acceptance.

The study proposes the following: to further improve AI algorithm performance by optimizing the precision and robustness of these models with respect to complex medical data, while at same time aiming for improved usability and safety of AI in actual clinical practice so that it can positively disrupt healthcare services without adding new risks. On the whole, AI technology in healthcare is still developing rapidly. It has great potential to promote diagnose and treatment of disease quality improvement and will gradually become an important driving force for medical innovation in future years.

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