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Ethical Challenges Presented by Advanced Artificial Intelligence in Diagnostics and Treatment Recommendations

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Abstract

The implementation of advanced artificial intelligence (AI) into the field of medical diagnostics and treatment recommendations brings forth a myriad of ethical challenges that necessitate prompt attention. This research explores six key areas of concern that encompass both technological and human factors. Firstly, the paper examines the need for Accuracy, Reliability, and Continuous Updates, emphasizing the significance of constant reflection of evolving medical knowledge and the prevention of severe consequences due to errors. Secondly, it delves into Data Concerns, such as biases in AI models, privacy, and the necessity for robust security measures. The third segment explores Transparency, Explainability, and Trust, shedding light on the vital role of understanding and faith in AI's decision-making process. Liability, Oversight, and Consent are analyzed as a fourth area, focusing on questions of responsibility, the debate surrounding human oversight, and patient

awareness. The fifth section concentrates on Human Aspects, examining the potential negative effects of over-reliance on AI, such as depersonalization of care and economic impacts on the medical profession. Lastly, the paper considers Accessibility, Equity, and Global Reach, addressing the imperative for AI diagnostic tools to be available equitably, without limitation to wealthy institutions. Collectively, the findings of this research emphasize the need for a proactive and comprehensive ethical framework that prioritizes patient well-being and preserves trust in the medical field as AI continues its advancement in healthcare.

Introduction

Medical diagnostics refers to the systematic process of identifying a medical condition or disease by its signs, symptoms, and from the results of various diagnostic procedures. This field encompasses a wide range of techniques and methodologies, including physical examinations, medical history analysis, and specialized tests such as blood tests, imaging studies (e.g., X-rays, MRI, CT scans), and molecular diagnostics. The primary objective is to determine the nature and cause of a patient's ailment to facilitate effective treatment planning. Medical diagnostics is an interdisciplinary domain, integrating knowledge from areas such as medicine, pathology, radiology, and bioinformatics to provide a comprehensive understanding of a patient's health status [1], [2].

The components of medical diagnostics can be broadly categorized into three main areas: clinical assessment, laboratory testing, and medical imaging. Clinical assessment involves the initial evaluation of the patient through physical examination and medical history taking. This provides preliminary data that guide the selection of further diagnostic tests. Laboratory testing includes a variety of biochemical, hematological, and microbiological tests that analyze samples like blood, urine, and tissue to detect abnormalities at the molecular or cellular level. Medical imaging, on the other hand, employs technologies such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) to visualize internal structures and functions of the body. These components often work in a complementary manner, providing clinicians with a multifaceted view of a patient's condition to arrive at an accurate diagnosis.

Imaging diagnostics are a cornerstone in modern medicine, providing clinicians with invaluable tools for the diagnosis, monitoring, and treatment of a wide range of diseases and conditions. Among the most commonly used imaging techniques are X-rays, Magnetic Resonance Imaging (MRI), and Computed Tomography (CT)

scans. X-ray imaging is one of the oldest and most frequently used diagnostic imaging techniques. It employs ionizing radiation to capture images of the internal structures of the body, particularly bones and certain soft tissues. X-rays are often used for diagnosing fractures, detecting tumors, and assessing lung conditions. However, due to the use of ionizing radiation, there are concerns about the potential risks associated with repeated exposure, particularly for pregnant women and young children.

Magnetic Resonance Imaging (MRI) is another widely used imaging modality that offers certain advantages over X-rays. Unlike X-ray imaging, MRI does not use ionizing radiation, making it a safer option for certain patient populations. MRI employs strong magnetic fields and radio waves to generate detailed images of soft tissues, including the brain, spinal cord, muscles, and joints. This makes it particularly useful for diagnosing conditions related to the nervous system, as well as for musculoskeletal and cardiovascular assessments. However, MRI is generally more time-consuming and expensive than X-ray imaging, and it may not be suitable for patients with certain types of implants or other medical devices [3].

Computed Tomography (CT) scans, also known as CAT scans, combine X-ray technology with computer processing to produce cross-sectional images of the body. This allows for more detailed visualization of internal structures compared to standard X-rays [4]–[6]. CT scans are commonly used in emergency situations to quickly assess injuries, as well as for the diagnosis of cancer, cardiovascular diseases, and various other conditions. Like X-rays, CT scans use ionizing radiation, which raises similar concerns about potential risks from exposure. However, advances in technology have led to the development of low-dose CT scans, which aim to minimize radiation exposure while still providing high-quality images.

Each of these imaging modalities has its own set of advantages and limitations, and the choice of which to use often depends on the specific clinical scenario. For instance, X-rays are quick and relatively inexpensive, making them suitable for initial evaluations and emergency situations. MRI, on the other hand, provides superior soft tissue contrast and is better suited for detailed examinations of complex anatomical structures. CT scans offer a middle ground, providing detailed cross-sectional images in a relatively short amount of time, but at the cost of higher radiation exposure compared to MRI.

Laboratory diagnostics are essential components of medical practice, aiding in the diagnosis, management, and monitoring of a myriad of health conditions. Blood tests, urinalysis, and biopsy are three common types of laboratory diagnostic tests that provide critical information for healthcare providers. Blood tests are perhaps the

most frequently conducted laboratory tests and can be used for a wide range of diagnostic purposes. These tests can measure various components of the blood, such as glucose levels, lipid profiles, and complete blood counts, to assess the overall health of an individual or to diagnose specific conditions like diabetes, cardiovascular diseases, and infections. Blood tests are also instrumental in monitoring the effectiveness of treatments and can be used in tandem with other diagnostic methods for a more comprehensive understanding of a patient's health status.

Urinalysis is another common laboratory diagnostic test that examines the physical and chemical properties of urine. This test is often used to diagnose and monitor conditions affecting the urinary system, such as urinary tract infections, kidney diseases, and diabetes. Urinalysis can provide information on a variety of substances present in the urine, including proteins, glucose, and red and white blood cells. It can also be used to detect the presence of illegal substances or performance-enhancing drugs. While urinalysis is generally non-invasive and poses minimal risks, it may not always provide a definitive diagnosis, necessitating further tests for a more accurate assessment [7].

Biopsy involves the extraction and microscopic examination of tissue samples to diagnose or rule out diseases, most commonly cancer. Biopsies can be performed on almost any tissue or organ in the body and are often guided by imaging studies for precise targeting. The procedure can be conducted using various methods, such as needle biopsy, incisional biopsy, or excisional biopsy, depending on the location and nature of the suspected abnormality. Biopsies are generally more invasive than blood tests and urinalysis and may carry risks such as infection, bleeding, or damage to adjacent structures. However, they are often essential for confirming malignancies and determining the stage and aggressiveness of cancers, thereby guiding treatment plans [8].

The choice between these laboratory diagnostic methods often depends on the clinical question at hand. Blood tests are versatile and minimally invasive, making them suitable for routine screenings and ongoing monitoring. Urinalysis is particularly useful for diagnosing conditions related to the urinary system but can also provide insights into metabolic and systemic diseases. Biopsies, although more invasive, are critical for diagnosing and characterizing tumors and other tissue abnormalities. Each of these tests has its own set of indications, contraindications, and potential complications, and healthcare providers must weigh these factors carefully when deciding which test to use [9], [10].

Molecular diagnostics represent a sophisticated subset of diagnostic techniques that focus on the analysis of biomolecules, primarily nucleic acids, to diagnose and monitor diseases, identify genetic mutations, and guide treatment decisions. One of

the most widely used molecular diagnostic methods is Polymerase Chain Reaction (PCR). PCR is employed to amplify specific DNA or RNA sequences, making it easier to detect the presence of pathogens, genetic mutations, or other specific markers. It is commonly used in infectious disease diagnosis, including the identification of viral infections like HIV and SARS-CoV-2, and bacterial infections such as tuberculosis. PCR is highly sensitive and specific but requires specialized equipment and trained personnel [11], [12]. It also serves as a cornerstone in forensic science, paternity testing, and genetic research.

DNA sequencing is another molecular diagnostic technique that has seen significant advancements in recent years. This method involves determining the precise order of nucleotides within a DNA molecule and is used for a variety of applications, including the identification of genetic mutations that may cause or contribute to disease. DNA sequencing can be applied to whole genomes or targeted to specific genes or regions of interest. It is instrumental in personalized medicine, allowing for treatments to be tailored to an individual's genetic makeup. For example, DNA sequencing can identify specific mutations in cancer cells, which can then guide the selection of targeted therapies. However, the technique is generally more time-consuming and expensive than other diagnostic methods, and interpreting the results often requires specialized expertise [13].

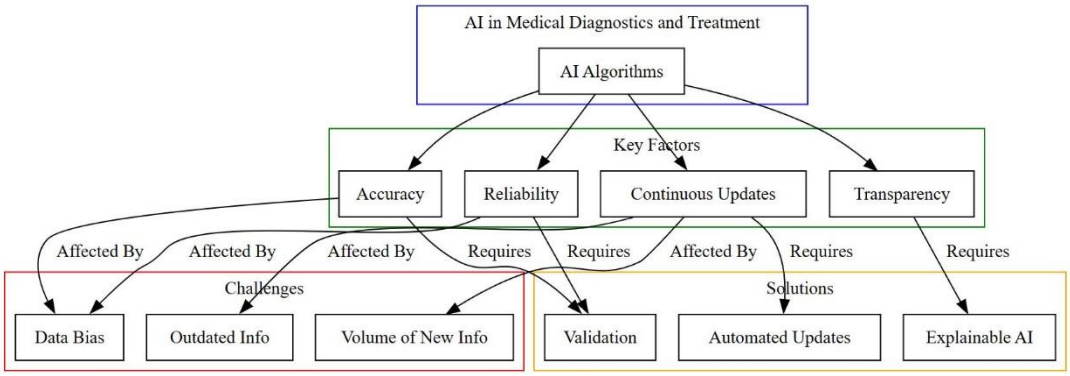
Microarrays are another molecular diagnostic tool that allows for the simultaneous analysis of a large number of genes or other molecular markers. In a microarray test, DNA or RNA samples are applied to a small, solid substrate where they bind to specific probes. This enables the simultaneous examination of thousands of genes to identify mutations, variations, or changes in expression levels. Microarrays are commonly used in research to study gene expression profiles in different diseases, and they have clinical applications in the diagnosis of certain types of cancer, genetic disorders, and other conditions. Like DNA sequencing, microarrays are generally more expensive and require specialized equipment and expertise, but they offer the advantage of high-throughput analysis [14]–[17].

The choice among these molecular diagnostic techniques often depends on the specific clinical question, the resources available, and the urgency of obtaining results. PCR is often favored for its speed and sensitivity, making it suitable for diagnosing acute infections or for applications where rapid results are crucial. DNA sequencing provides a more comprehensive view of genetic information but is usually reserved for cases where such detail is necessary for diagnosis or treatment planning [18], [19]. Microarrays offer the ability to screen a large number of markers simultaneously, making them useful for research and some specialized diagnostic applications

Accuracy, Reliability, and Continuous Updates

Ensuring the accuracy and reliability of Artificial Intelligence (AI) in medical diagnostics and treatment recommendations is of paramount importance, given the potential for severe consequences arising from errors or inaccuracies. AI algorithms, particularly those based on machine learning, are trained on large datasets to recognize patterns and make predictions or decisions based on new data. However, the quality of these decisions is heavily dependent on the quality and representativeness of the training data. Biases in the data, or the inclusion of inaccurate or outdated medical information, can compromise the reliability of the AI system. Therefore, rigorous validation using diverse and high-quality datasets is essential before deploying any AI system in a medical setting. Additionally, the algorithms must be tested for both sensitivity and specificity to ensure they are not only accurate but also reliable across a range of clinical scenarios [20]–[23].

Fig. 1. Accuracy, Reliability, and Continuous Updates in AI



The landscape of medical knowledge is not static; it evolves continuously with ongoing research and clinical experience. This dynamic nature of medical science necessitates the regular updating of AI models to reflect the most current understanding and guidelines. Failing to update these models could result in the propagation of outdated or even harmful medical practices. For example, treatment protocols for diseases like cancer or infectious diseases may change as new medications are developed or as resistance to existing treatments grows. An AI system that is not updated to reflect these changes could recommend outdated treatments, potentially leading to suboptimal patient outcomes [24].

The challenge of keeping AI models up-to-date is compounded by the pace of medical research and the sheer volume of new information generated. Traditional methods of updating algorithms, which often involve manual curation and retraining, may not be sufficient to keep up with the rapid advancements in medical science. Automated or semi-automated methods for updating AI models are being developed to address this issue. These methods may involve real-time data monitoring and the incorporation of new research findings as they are published, subject to rigorous validation processes to ensure the continued accuracy and reliability of the AI system [25], [26].

Another critical aspect of ensuring the reliability of AI in medicine is transparency. Medical professionals must be able to understand how a particular AI system arrives at its conclusions to trust its recommendations. This is particularly important in cases where the AI's recommendation diverges from standard medical practice or when unexpected outcomes occur. The concept of "explainable AI" is gaining traction in the medical community as a way to make the decision-making processes of AI systems more transparent, thereby allowing clinicians to better assess the reliability of the AI's recommendations.

Data Concerns: Bias, Privacy, and Security

The integration of Artificial Intelligence (AI) into healthcare brings with it a host of data-related concerns, including issues of bias, privacy, and security. One of the most pressing challenges is the potential for biased training data to result in AI models that make inaccurate or prejudiced decisions. Bias can be introduced at various stages, from data collection to data labeling and algorithm training. For instance, if an AI model for diagnosing skin cancer is trained predominantly on images of light-skinned individuals, its accuracy may be compromised when applied to individuals with darker skin tones. Such biases can have serious implications, including misdiagnosis and unequal access to healthcare services. To mitigate these risks, it is essential to use diverse and representative datasets for training and to rigorously test AI models for bias before they are deployed in clinical settings [27]–[31].

Data privacy is another significant concern, especially given the sensitive nature of medical data [32]. AI algorithms often require vast amounts of data to be trained effectively, and this data frequently includes personal medical records that contain sensitive information. The collection, storage, and use of such data must comply with existing privacy laws, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States. However, even with strict legal frameworks in place, the risk of data breaches remains. Unauthorized access to

medical data can have severe consequences, including identity theft and financial fraud, not to mention the potential for misuse of sensitive health information.

Security concerns are closely related to issues of data privacy. As healthcare systems increasingly adopt digital platforms, the potential attack surface for cyber threats expands. Data breaches not only compromise patient privacy but can also have implications for patient safety. For example, unauthorized alterations to medical records could lead to incorrect diagnoses or inappropriate treatment plans. Therefore, robust cybersecurity measures are essential to protect against unauthorized access and data tampering. These measures may include advanced encryption techniques, multi-factor authentication, and regular security audits. The challenges of data bias, privacy, and security are interconnected and often require multi-faceted solutions. For instance, efforts to reduce bias by collecting more diverse data could potentially conflict with the need to protect patient privacy. One possible approach to reconcile these competing needs is the use of differential privacy techniques, which allow AI models to learn from data without accessing the raw data directly. This can help to protect individual privacy while still enabling the AI to make accurate and unbiased predictions.

Transparency, Explainability, and Trust

Transparency, explainability, and trust are critical factors in the successful integration of Artificial Intelligence (AI) into healthcare systems. Many AI models, particularly those based on deep learning architectures, are often described as "black boxes" due to their lack of transparency. These models can make highly accurate predictions or recommendations but may not provide insights into the underlying decision-making process. In a medical context, understanding the rationale behind a diagnosis or treatment recommendation is not just a matter of intellectual curiosity; it is crucial for trust among clinicians, patients, and other stakeholders. Without a clear understanding of how decisions are made, healthcare providers may be reluctant to rely on AI-based recommendations, particularly in complex or high-stakes situations such as cancer diagnosis or surgical planning.

The issue of trust is closely tied to the need for explainability. If clinicians and patients are to trust an AI system's recommendations, they must be confident that the system's decision-making process is both sound and understandable. This is especially important in cases where the AI's recommendation diverges from established medical guidelines or from the clinician's own judgment. In such instances, the ability to scrutinize the AI's reasoning process can help to resolve any discrepancies and prevent misunderstandings that could compromise patient care.

Several approaches are being developed to improve the explainability of AI models, such as the use of attention mechanisms, local interpretable model-agnostic explanations (LIME), and counterfactual explanations, among others.

Ensuring that both patients and clinicians are aware of how an AI system makes its decisions can go a long way in preventing mistrust and fostering a collaborative healthcare environment. This involves not just technical solutions to improve model explainability but also educational efforts to help healthcare providers and patients understand the capabilities and limitations of AI. Clear communication is essential, possibly through user-friendly interfaces that can translate the AI's findings into terms that are easily understandable without specialized knowledge. This can empower patients to take a more active role in their healthcare and facilitate more informed discussions between patients and their healthcare providers [33].

However, transparency and explainability are not without their challenges. Making a complex AI model more interpretable can sometimes come at the cost of reducing its predictive accuracy. Moreover, there are ethical considerations around how much of the AI's decision-making process should be disclosed, especially when proprietary algorithms are involved. Balancing the need for transparency with the protection of intellectual property and the maintenance of competitive advantage is a complex issue that requires careful consideration.

Liability, Oversight, and Consent

Liability, oversight, and consent are critical considerations in the deployment of Artificial Intelligence (AI) in healthcare settings. One of the most pressing issues is the question of responsibility when AI-recommended treatments result in adverse outcomes. Traditional medical malpractice frameworks are not readily applicable to scenarios involving AI, as these systems do not possess legal personhood. Determining liability becomes complex when an AI system is involved in the decision-making process. Is the healthcare provider responsible for following an incorrect recommendation, or does the liability lie with the developers of the AI system? Resolving these questions necessitates a reevaluation of existing legal frameworks and may require the development of new laws or guidelines specifically tailored to the use of AI in healthcare.

The debate over the necessity of human oversight in AI-driven medical decision-making is another area of concern. While AI systems can analyze vast amounts of data more quickly and sometimes more accurately than humans, their lack of contextual understanding and ethical reasoning makes the role of human oversight crucial. Some argue that a "human-in-the-loop" approach should be mandatory, especially for high-stakes decisions such as cancer diagnosis or surgical planning.

This would involve a healthcare provider reviewing and approving any AI-generated recommendations before they are implemented. Others argue that in certain cases, the accuracy of AI systems may surpass human capabilities, and human oversight could introduce errors rather than prevent them. The appropriate level of human involvement is a subject of ongoing debate and may vary depending on the specific application and the level of trust in the AI system [34].

Patient awareness and consent are also essential when AI is used in healthcare. Patients have the right to know if and how AI systems are involved in their care, including the potential risks and benefits. This is particularly important given the nascent state of many AI technologies and the lack of long-term data on their effectiveness and safety. Informed consent procedures must be adapted to include information about the use of AI, and patients should have the option to opt-out of AI-based care if they so choose. However, this raises ethical questions about the equitable distribution of healthcare resources and the potential for a two-tiered system where only those who can afford it have access to the latest technologies.

The issues of liability, oversight, and consent are interconnected and often complex. For example, obtaining informed consent may be more challenging if the AI system's decision-making process is not transparent or easily understandable. Similarly, the question of liability could influence the level of human oversight deemed necessary, as healthcare providers may be more willing to rely on AI if clear legal frameworks are in place. These challenges require a multidisciplinary approach involving legal experts, ethicists, healthcare providers, and technologists to develop comprehensive solutions.

Human Aspects: Depersonalization, Over-reliance, and Economic Impacts

The integration of Artificial Intelligence (AI) into healthcare raises important concerns about the human aspects of medical practice, including the potential for depersonalization, over-reliance on technology, and economic impacts on the medical job market. One concern is that an over-reliance on AI could diminish the human touch that is often crucial in healthcare settings. While AI systems can analyze data and make recommendations, they lack the ability to understand the emotional and psychological aspects of patient care. The absence of these human elements could result in a more depersonalized healthcare experience for patients. Moreover, excessive reliance on AI could erode diagnostic and clinical skills among healthcare professionals. If clinicians become accustomed to relying on AI for diagnoses and treatment recommendations, their own skills may atrophy, potentially affecting the quality of care, especially in situations where AI tools are unavailable or inappropriate.

Another human aspect to consider is the economic impact of AI on the medical job market. The automation of certain tasks, particularly those that are routine and data-intensive, could lead to job shifts or even job losses in some healthcare roles. For example, radiologists who primarily interpret medical images could see their roles evolve or diminish as AI algorithms become increasingly proficient at this task. On the other hand, the adoption of AI could also create new roles and specialties, such as experts in AI ethics, data scientists specializing in healthcare applications, and technicians to maintain and oversee AI systems. The net impact of AI on healthcare employment is still uncertain and is likely to vary by specialty and geographic region [35].

The potential for over-reliance on AI also raises ethical considerations. For instance, if an AI system is known to be highly accurate in diagnosing a particular condition, there may be a temptation to forego additional tests or second opinions, potentially leading to overconfidence and errors. This is especially concerning in complex or ambiguous cases where a multi-faceted approach to diagnosis and treatment is essential. Ethical guidelines and training programs may need to be developed to help healthcare providers navigate the complexities of integrating AI into their practice while maintaining a patient-centered approach.

Addressing these human aspects requires a balanced approach that integrates AI into healthcare in a manner that complements, rather than replaces, human expertise and compassion. This could involve the development of hybrid models of care where AI systems perform specific tasks but always in conjunction with human oversight. Training programs could also be developed to help healthcare providers adapt to new technologies while maintaining their clinical skills. Additionally, economic policies may be needed to manage the job transitions that could result from the widespread adoption of AI in healthcare, including retraining programs and social safety nets for those affected by job shifts.

Accessibility, Equity, and Global Reach

The integration of Artificial Intelligence (AI) into healthcare presents significant opportunities for improving diagnostics and treatment, but it also raises important questions about accessibility, equity, and global reach. One of the primary concerns is whether AI diagnostic tools will be universally accessible or whether they will be limited to affluent institutions and countries. High costs associated with the development, implementation, and maintenance of AI systems could create barriers to access, particularly in resource-limited settings. This could exacerbate existing healthcare disparities, both within countries and between high-income and low-income countries. For example, an AI system trained to diagnose skin cancer using

high-quality imaging equipment may be of limited use in rural areas or developing countries where such equipment is not readily available.

The issue of equity extends beyond the mere availability of technology to include considerations about the representativeness of the data used to train AI models. If AI systems are trained primarily on data from specific populations, their accuracy and utility may be compromised when applied to different demographic groups. This could result in biased or less effective care for underrepresented populations, further widening healthcare disparities. Efforts to make AI training data more inclusive and representative are essential to ensure that these technologies benefit a broad range of people.

Another aspect to consider is the global reach of AI technologies. While AI has the potential to revolutionize healthcare in resource-limited settings by automating complex tasks and improving diagnostic accuracy, the actual implementation of these technologies faces numerous challenges. These include not only financial constraints but also issues related to infrastructure, such as unreliable electricity and internet access, and human capital, such as the availability of trained personnel to operate and maintain AI systems. Partnerships between governments, non-governmental organizations, and private industry may be necessary to address these challenges and facilitate the deployment of AI technologies in low-resource settings [36]–[38].

Regulatory frameworks also play a critical role in ensuring accessibility and equity. Policies may be needed to regulate the pricing of AI technologies to ensure they are affordable for all healthcare providers, including those in resource-limited settings. Additionally, international standards could be developed to ensure that AI systems meet certain criteria for accuracy and equity before they are deployed in healthcare settings. These regulatory measures could help to ensure that AI technologies are both effective and accessible, thereby maximizing their potential to improve healthcare outcomes on a global scale.

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