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APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CLINICAL PRACTICE

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) techniques into clinical practice has shown transformative potential in disease prediction, diagnosis, and patient care. This study explores current trends in the application of ML in healthcare, employing a qualitative research design with a focus on secondary data analysis. Findings reveal significant advancements in AI-driven solutions for health-related challenges, including early disease detection, personalized treatment planning, and epidemic control. Despite these strides, adoption in developing regions remain in its infancy, limited by data accessibility, technical expertise, and ethical concerns. The research highlights the efficiency of ML in processing vast datasets and generating precise, actionable insights, often surpassing human capabilities in speed and accuracy. However, it underscores the irreplaceable role of human empathy and patient interaction in medical care, presenting a critical limitation of current AI applications. Conclusively, while AI-ML holds immense promise to revolutionize global healthcare, achieving its full potential requires addressing infrastructural, ethical, and systemic barriers, particularly in resource-limited settings.

Keywords: Artificial Intelligence, Clinical Practices, Machine Learning Models, Health.

Introduction

Machine Learning is a subset of artificial intelligence that focuses on building systems that can learn from and make decisions based on data. AI-Machine Learning techniques aim to build machines as intelligent as a human brain. Algorithms are collections of mathematical operations that define the connections between variables and are the foundation of Machine Learning techniques (Qin et. al., 2019). Machine Learning is a technique for dataset is divided into training and testing data. The division is done in a ratio of 80:20 (training: testing) and runs simultaneously (Pillai & Kumar, 2021). The training data is used for evaluation purposes, and testing data is used for validation purposes (Osei et. al., 2021).

Machine Learning has facilitated the development of intelligent chatbots, digital health tools and applications that significantly change and redefine medical practice and clinical Practice (Cresswell & Sheikh, 2017). Such technologies have established proof of concepts in some medical fields, such as radiology, psychiatry, pathology, and ophthalmology which can be further used for early detection, prediction, diagnosis and management of different health conditions such as cancer, diabetes, tuberculosis including HIV/AIDS (Gwagwa et. al., 2020). AI-Machine learning applications in clinical practices assist health professionals and policymakers in making informed decisions to provide personalised patient care and improve clinical practices (Mittal et. al., 2022).

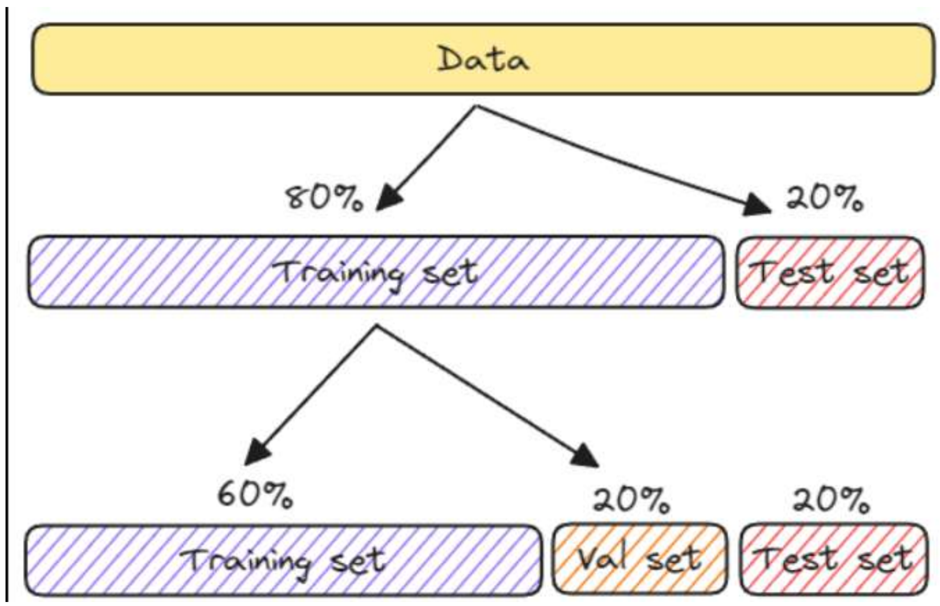

Figure 1: ML dataset splitting into Training and Testing (80:20) (Source: Madhuri, 2024)

This study seeks to investigate the emerging trends and applications of artificial intelligence (AI) and machine learning (ML) models in clinical practice, emphasizing their potential to enhance healthcare delivery through early disease detection, personalized care, and improved decision-making. Despite the growing adoption of AI-ML in global healthcare systems, significant gaps exist in developing regions, particularly Nigeria, where infrastructural deficiencies, limited technical expertise, and data accessibility challenges hinder widespread implementation. This paper aims to bridge these gaps by analyzing current advancements, identifying barriers to adoption, and exploring strategies to optimize AI-ML integration in clinical practices. The research also addresses the ethical considerations surrounding the use of AI in healthcare, such as data privacy, bias, and the absence of human empathy. Guided by these objectives, the study poses the question: How can AI-ML models be effectively leveraged to overcome healthcare challenges in developing countries while addressing ethical and operational limitations?

Review of Related Literature:

Clinical Practices machine learning solutions can be very advantageous to the treating patient by doctors, clinicians, researchers, and patients (Gwagwa et. al., 2020). Absolutely, it is fascinating how rapidly technology envolves and the innovative solutions that come from it. The advancement and application of machine learning have remained on the increase especially in its use in the clinical practices. Accordingly, organizations worldwide are leveraging AI-driven solutions and ML models to prove the clinical practices (Gwagwa et. al., 2020). Machine learning in the clinical sector is used in various ways and purposes including disease diagnosis, drug discovery, treatment planning, and effective patient care and so on. It can also help to identify patterns, detect anomalies and predict the outcomes, enabling the health professionals to make more accurate diagnoses and prescribe more personalised plans, resulting in improved patient care and recovery (Qin et. al., 2019).

Similarly, health institutions could take advantage by making identified and anonymous datasets easily accessible to researchers online, increasing the chances of benefitting from the emergence of research in AI-Machine models in clinical practices (Osei et. al., 2021). Health record like District health (DHIS) facilitates the availability within the clinical practice. However, such data are difficult to access for research purposes, bottlenecking the possibility of harnessing the data to enhance Clinical Practices in the region (Dabengwa et. al., 2022). Machine learning has been used to detect patients who were at risk of getting cancer or have a high risk of cancer recurrence. The platform analyzes large amounts of clinical and genomic data to recognize patterns that could help enhance patient outcomes (City of Hope, 2020). Records indicate that machine- learning models have been deployed in real-life settings to enhance clinical practices (Marufu & Maboe, 2017). One explanation for this could be that the datasets used may not be reflective of the reality on the ground since health facilities rarely make such data easily accessible to researchers (Marufu & Maboe, 2017).

The application of AI-Machine Learning in clinical practices started in the 1970s, with early applications focused on image recognition and diagnosis. For example, in 1974, researchers at Stanford University developed a computer program that could diagnose certain types of blood diseases with high accuracy (Shortliffe & Sepúlveda, 2018). In the 1990s, AI was used for speech recognition, natural language processing, and decision support systems in healthcare studies have shown that the application of IA-Machine Learning has improved clinical practices across the world in recent times (Marufu & Maboe, 2017). It is worth nothing that most developing countries in Asia, South America and Africa particularly Nigeria have a long history of re-emerging infectious disease outbreaks, which consequently overwhelm many health systems particularly the covid19, Ebola virus etc. which led to the deployment of machine learning to fight the diseases (Esteva et. al., 2019). Generally, machine learning can predict disease outbreaks which could assist clinicians in easily developing intervention measures, and preparing to fight the disease transmission (Bashshur et. al., 2016). Therefore, this study sought to investigate the current trends in the application of AI-machine learning models in the clinical practice. This study relied on a secondary data for the comprehensive review of the existing literature considered to be relevant to this study with the sole aim of reviewing the application of machine learning and the efficiency of clinical practice

Materials and Methods

The study adopts a descriptive, qualitative research approach to examine the application of AI and machine learning models in clinical practice. Data for this research were sourced from secondary materials, including peer-reviewed journal articles, books, conference proceedings, media publications, and reputable online resources. The selection criteria for these sources were based on their relevance, credibility, recency (published within the last decade), and their focus on the application of AI-ML in healthcare. Specific attention was given to studies addressing disease diagnosis, treatment planning, personalized care, and challenges in AI-ML adoption within developing regions. The analysis followed a content-analytic framework, which involved systematically reviewing, categorizing, and synthesizing information to identify patterns, trends, and gaps in existing literature. Key themes such as ethical considerations, technical challenges, data accessibility, and practical applications of AI-ML in clinical settings were identified and explored. This approach ensured a comprehensive understanding of the current state of AI-ML in healthcare and provided a basis for logical reasoning to draw conclusions and recommend strategies for addressing identified gaps.

Findings and Discussion

Artificial intelligence refers to computing techniques that mimic human intelligence’s support mechanisms, including cognitive technologies, natural language processing, deep learning (DL), adaptation, machine learning (ML), and sensory comprehension (Batani & Maharaj, 2022). Thus, AI focuses on making machines intelligent in performing a particular or general task (Phoobane et. al., 2022). The application of AI-Machine Learning in clinical practices started in the 1970s, with early applications focused on image recognition and diagnosis. For example, in 1974, researchers at Stanford University developed a computer program that could diagnose certain types of blood diseases with high accuracy (Shortliffe & Sepúlveda, 2018). The adoption of AI Machine learning in healthcare delivery has been on the increase with the potential to overhaul healthcare delivery and enhance patient outcomes

Machine learning is one of the most cutting-edge artificial intelligence techniques that can extract patterns from data without being explicitly programmed (Chen et. al., 2019). Machine Learning model uses advanced algorithms to gain valuable insights and can assist healthcare professionals to make informed decisions . Machine Learning algorithms can be trained using supervised learning, semi-supervised, unsupervised and reinforcement learning (Mbunge et. al., 2021). Advanced machine learning algorithms, including logistic regression, artificial neural networks (ANN), support vector machines (SVM), random forest (RF), decision trees, AdaBoost, Bagging and XGBoost, have been used to tackle different diseases. Machine learning has multilayer neural networks that automatically learn complex data representation (Thomford et. al., 2020). Machine learning models generally require huge datasets for training, and testing for effective decisions making for future occurrences (Chen et. al., 2021). Machine learning models can be pre-trained and have been used to detect different diseases in the health sector.

AI for healthcare encompasses many applications transforming patient care, medical research, and healthcare administration. Figure 2 shows the AI use in healthcare that one must know.

Figure 2: AI use in healthcare (Source: Divyesh, 2024)

MLMs and Clinical Practices

Absolutely, machine learning has indeed been making strides in the early detection and prediction of diseases. By analysis vast of data, machine learning algorithms can identify patterns and indicators that might be missed by traditional methods (Accenture, 2017). As a result of these approaches, different types of diseases have been detected but with diverse accuracy levels depending on factors such as the used algorithm, feature set, training dataset, and so on (Cresswell & Sheikh, 2017). It is important to note that machine learning models have played a crucial role in leveraging data to improve patient outcomes, enhance clinical decision-making, and optimize healthcare processes (Mbunge et. al., 2021). Machine learning models were designed to perform the complexities of healthcare data that often involve heterogeneous and high-dimensional information (Ellahham, 2020).

Machine learning has led to the development of new frameworks that offer significant benefits in clinical practice. Bishop & Nabney (2008), highlights the adoption of a Bayesian viewpoint, the use of graphical models, and the development of fast inference algorithms as key components of this new approach. Mavani et. al., (2022) presents a software framework for creating ensembles of learning systems, which can be distributed across different machines. Javaid et. al., (2022) discusses large-scale machine learning frameworks that support computationally expensive algorithms on big data processing platforms. Jamwal et. al., (2022) provides a survey of machine learning frameworks, comparing them based on various parameters such as modeling capability, interfaces, and community support. These frameworks collectively represent a significant advancement in the field of Artificial Intelligence (Bishop & Nabney, 2008).

Strategies in the Application of AI-Machine Learning Models in Clinical Practices

There are several ways in which Machine Learning Models are used in clinical practice. AI-Machine Learning is not new to the medical field, and the dramatic increase in the use of machine learning in clinical practices over the last ten years can be seen in various clinical Practice institutions where research and treatment are being provided (Mbunge et. al., 2021). Some of the strategies deployed in the application of machine learning in the clinical practice are presented below:

1. **Diagnosis of diabetes:** One of the most prevalent and dangerous illnesses is diabetes. It does not only harm a person's health in and of itself, but it also triggers several other severe disorders. Diabetes primarily affects the heart, nerves, and kidneys (Jeyaraman et. al., 2023). Therefore, Machine Learning, potentially saves lives by predicting and suggesting better options. A system that predicts diabetes may be constructed using classification algorithms like Naive Bayes, KNN, and Decision Tree. When it comes to the calculation and time, Naive Bayes has been proven most effective (Cobo et. al., 2011).

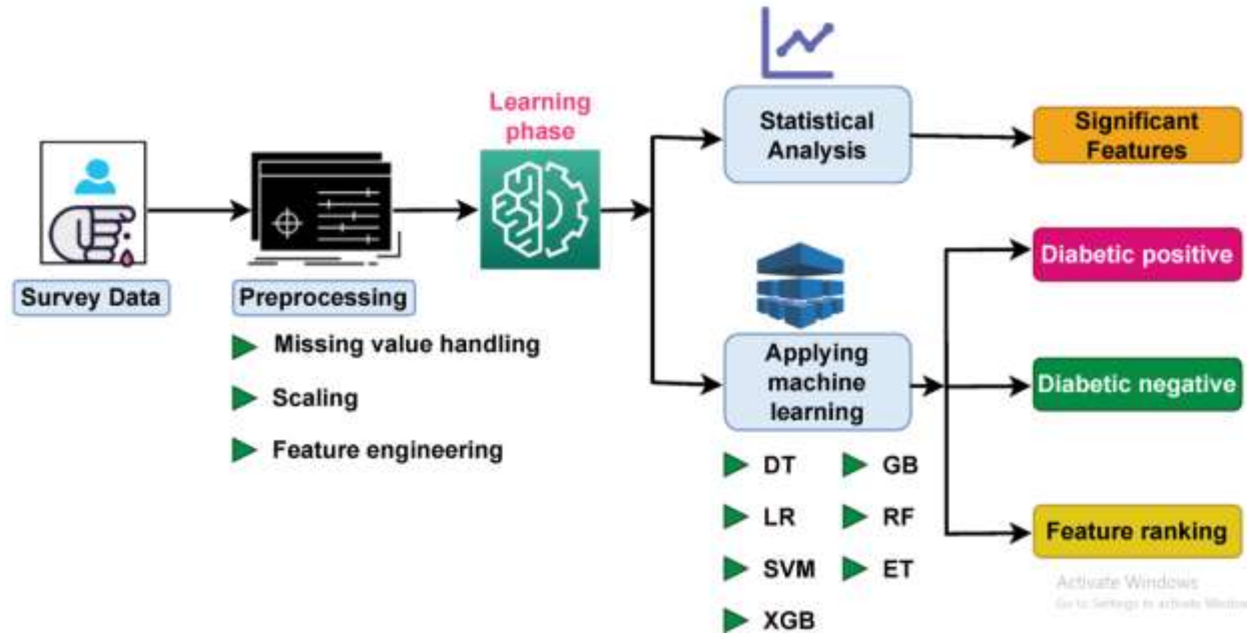

Figure 3: Machine Learning Model Architecture for diagnosis of Type-2 Diabetes Mellitus (Uddin et. al., 2023)

2. **Detection of Liver Disease:** The liver is one of the most essential parts of the human system that carries our metabolism. It is susceptible to cirrhosis, liver cancer, and chronic hepatitis (Sahlol et. al., 2020). Although it is challenging to forecast liver illness using vast medical data accurately, there have already been some notable changes in this field [31]. These distinctions are made by classification and clustering algorithms through the application of Machine Learning. It is possible to utilize the Liver Disorders Dataset or the Indian Liver Patient Dataset in clinical practice (Sahlol et. al., 2020).
3. **Control of Epidemic:** Talking about data analytics, professionals will have access to data from video streams, news websites, social media trends, and satellites. All the information might be processed by neural networks, which could then draw inferences about global pandemic outbreaks (Atomwise, 2021). Before they might do significant harm, dangerous illnesses may be managed with precise methods (Ibrahim & Tulay, 2023). It is crucial in third-world nations where there are no sophisticated medical systems. ProMED-mail, a reporting tool that operates online and keeps track of epidemic reports from around the world, will likely serve as the most outstanding example of this field (Kondo et. al., 2023). Today, machine learning model is widely used in food safety to assist in avoiding pandemic illness on farms.
4. **Management of Health Records:** Even with all these technological advancements, maintaining health data remains challenging. Support vector machines and OCR recognition algorithms might be used to categories records. The best examples are Math Works' ML handwriting recognition system and Google's Cloud Vision API (Chingombe et. al., 2022).

Benefits in Application of AI-Machine Learning Model in Clinical Practice

The application of AI machine learning in the clinical practice has been growing rapidly, with the potential to overhaul healthcare services and enhance patient outcomes. Absolutely, the intergration of AI and machine learning in the healthcare is poise for significant growth. Some of the benefits were presented and explained below which include:

1. **Predicting Diseases Outbreaks:** The data extracted from different electronic databases show that machine learning models have been used to predict disease outbreaks such as diarrhea, COVID-19, Ebola, malaria, typhoid, anemia, Tuberculosis and Zika, amongst others. For instance, a study conducted by Chingombe et. al.,(2022) applied convolution neural networks (CNN), support vector machines (SVM) and long-short-term memory networks (LSTM) to predict daily diarrhea cases in different provinces in South Africa using climate data. Also, a study by Deshpande (2020) used random forests to predict swine fever outbreaks using meteorological data. In addition, Ibrahim & Tulay, (2023) utilised COVID-19 datasets from Morocco, Sudan, Uganda, Rwanda, Cameroon, Gabon, South Africa, Namibia, Nigeria, and Senegal to predict the COVID-19 pandemic.
2. **Diseases Forecasting:** Machine Learning model has been used by clinicians to forecast disease outbreaks in many parts of the world. Machine learning models such as Convolutional Neural Networks (CNN), LSTM, Gated Recurrent Unit (GRU), and Bi-LSTM have been applied by various authors to forecast COVID-19 in Africa. For instance, a study by Ibrahim & Tulay (2023) applied deep learning models such as LSTM, CNN, and multilayer perception neural networks to forecast the spread of COVID-19 in Egypt and also to forecast lumpy skin disease occurrence based on meteorological and geospatial features.
3. **Diseases Detection and Diagnosis:** Early detection and diagnosis of diseases using emerging technologies are essential to reduce the potential consequences of late diagnosis. Deep learning algorithms such as CNN, GoogleNet, Inception, MobileNet, and DenseNet have been used for diagnosing, classifying, predicting, and prognosis of COVID-19 from chest X-ray images (Ibrahim & Tulay, 2023). A study by Pillai & Kumar (2021) developed a CNN-based deep neural network called CoroNet, for the detection and diagnosis of COVID-19 from chest X-ray images. Their study concluded that CoroNet can be used by radiologists and health experts to gain a deeper understanding of critical aspects associated with COVID-19 cases (Ibrahim & Tulay, 2023).

Ethical Issues on Application of Machine Learning in Clinical Practices

Studies revealed that there is a tremendous increase in the application of AI-Machine learning in clinical practice across the globe. As the healthcare system is transitioning from traditional to digital, more data is expected to be generated, which will further pave the way for the growing application of machine learning models for many purposes including the diagnosis, prognosis, drug designing, and many others (Ibrahim & Tulay, 2023). Studies and research are being carried out further to explore the possible applications of machine learning models in the healthcare system, but one aspect that is being overlooked in all this is the ethical aspect of using Machine Learning (Ibrahim & Tulay, 2023). It can be verified through a simple search on PubMed that when keywords such as ML and AI combined with medical science are used, we see an increasing trend in the number of publications. More interestingly, a sharp increase has been observed in recent years, but when these same keywords are combined with ethics, we do not see such a sharp increase and If we go back to 2013, we struggle to find publications describing ML's ethical side in medical sciences (Batani & Maharaj, 2022). Key ethical issues concerning the adoption and deployment of AI in healthcare include; Privacy and security, Bias and Fairness, transparency and explainability, autonomy and responsibility,and Accountability and liability (Harnessing Artificial Intelligence for Health, 2023, Grand View Research, 2021, Kaye et. al., 2019).

Factors Militating Against the Application of AI-Machine Learning in Clinical Practices

The authors discovered that factors mitigating against the application of AI-ML in clinical practices include;

i. **Lack of Security Measure:** Despite the potency of AI Machine Learning, there have been arguments from some quarters that the implementation of Machine Learning in clinical practices poses some challenges. For instance, Kumar et. al., (2023) pointed out that most of the data collected in for clinical practices are very sensitive or confidential information. This requires security measures to be applied or implemented by the machine learning developers. They further argue that machine learning algorithms are trained on large amounts of data without proper supervision and training; these algorithms can carry and propagate bias contained within the dataset which in turn may lead to negative consequences particularly in clinical practice.

ii. **Absence of Human emotions:** Absence of personal emotions in providing care to patients with chronic conditions requires inter-personal interaction to assess and diagnose, which might be difficult through Health interventions (Dubovitskaya, et. al., 2018). Though, AI mimics human intelligence, but the AI models lack emotions, an essential part of care which are mostly needed in clinical practice. Lack of emotions and interpersonal interactions presents a challenge to AI adoption in clinical practice. Lack of specialist knowledge and digital skills using digital health interventions to deliver healthcare services requires digital skills and training.

iii. **Technical Challenges**: One of the primary technical challenges is the need for robust and reliable algorithms. AI requires complex algorithms that can analyze and interpret large amounts of data to make accurate predictions. However, developing and validating these algorithms can be time-consuming and challenging, requiring significant expertise in machine learning and data science (Topol, 2019). Also, AI systems require robust and scalable infrastructure, specialized hardware, and software. These technical requirements can be costly, and organizations may not have the resources to invest in the necessary infrastructure (Ku et. al., 2018).

iv. Another technical challenge is the need for interoperability between different systems and platforms (Darzi & Yang, 2018). Healthcare organizations often use multiple software systems and data formats, which can make it difficult to integrate AI systems into existing workflows (Fong & Wong, 2017). Interoperability standards and protocols need to be established to ensure seamless integration of AI into existing healthcare systems.

v. **Lack of Trust**: patients cannot be expected to trust AI; a technology shrouded by mistrust immediately. AI-machine learning handles essential tasks, but is limited enough in its scope to leave the primary responsibility of patient management to human doctor (Cresswell & Sheikh, 2017). There is an ongoing clinical trial using AI to calculate target zones for head and neck radiotherapy more accurately and far more quickly than a human being. An interventional radiologist is still ultimately responsible for delivering the therapy but AI has a significant background role in protecting the patient from harmful radiation.

vi. **Medical Data Inconsistency**: Medical data are not always as precise and standardized as they need to be. There are gaps in records and inaccuracies in profiles and other shortcomings, therefore if the computed data is unreliable or current, there is a higher chance that the result will lead to incorrect treatment of the patient, which will further aggravate or worsen the patient"s condition of even causing death. Machine Learning is not the solution to every health issue. Given ML's value, it can be challenging to acknowledge when it is not the best way to solve a particular issue. However, predicting disease outbreaks can assist in clinical practice to develop intervention measures, and preparedness, understand disease transmission and most importantly enhance the community's resilience toward disease (Zhang et. al., 2021).

vii. **Lack of Human Empathy**: Another case against Machine Learning models in clinical practices is that machines cannot exhibit empathy (Chen et. al., 2019). A real-life medical professional is the only one who can guide a patient through a challenging treatment process, hold their hand when they get life-altering diagnostic news, occupy a young patient who is afraid of getting blood, or really care about their patients. Real world examples are used to trai n Machine Learning algorithms (Shortliffe & Sepúlveda, 2018). However, one of the essential components of high-quality clinical practices is empathy. It enhances patient happiness and encourages recovery. Although AI can perform various activities better than doctors, it cannot replace human beings. A closer examination of AI- Machine Learning solutions reveals that they operate most effectively in stable and predictable environments.

Managerial Implications of Machine Learning in Clinical Practice

Generally, it has been proven that the application of AI machine learning in the clinical practice has significant managerial implications that should be carefully considered. One of the primary managerial implications of AI-machine learning in clinical practice is the need for strategic planning and investment. Healthcare institutions must develop a clear strategy for the integration of AI-machine learning that aligns with their overall business objectives. These include identifying the specific AI-machine learning applications that are most relevant to their operations and investing in the necessary infrastructure and resources to support the technology. This includes having robust data governance and security frameworks in place to ensure patient data privacy and security (Alvarez-Rodríguez et. al., 2021).

Another implication is that healthcare organizations must develop new organizational structures and work processes to effectively integrate AI into their operations. This may involve retraining or hiring new staff with expertise in AI and related technologies, as well as redesigning processes to incorporate AI algorithms and decision-making (Chen et. al., 2021). Clinicians need to be trained in the delivery of AI-machine learning applications to make sure that they are used accurately and appropriately. This involves not only training in the technical aspects of using the technology but also understanding how it potentially impacts the patient and fits into the broader healthcare system. Furthermore, the adoption of AI in healthcare also requires a thorough understanding of ethical and social implications. Healthcare organizations must ensure that AI structures and systems are utilized and deployed in an accountable and just manner, taking into account issues such as bias, fairness, and transparency (Gutierrez, 2020).

Data privacy and security also involve significant managerial implications for machine learning applications in clinical practice. Healthcare institutions must ensure that their patient data is protected and that the use of machine learning complies with data privacy laws such as HIPAA. This requires careful management of how data is stored, accessed and shared, as well as the use of appropriate encryption and other security measures. Also, AI's use in healthcare can potentially impact the quality and costs of healthcare. Healthcare workers need to assess the financial and clinical implications of the application of machine learning and determine how to balance the benefits against its costs (Chen et. al., 2021).

Conclusion

This paper sought to reveal the current trends in the application of AI in clinical practice. It concluded that the current trends in AI-machine learning in clinical practice are breakthroughs and can results in tremendous benefits to humanity especially in the area of clinical practice.

This study highlights the transformative potential of artificial intelligence (AI) and machine learning (ML) models in revolutionizing clinical practices, particularly through advancements in disease prediction, diagnosis, and personalized patient care. However, the findings underscore several critical challenges limiting the widespread adoption of AI-ML. These include infrastructural deficiencies, lack of access to quality data, inadequate technical expertise, and ethical concerns such as privacy, bias, and the absence of empathy in AI-driven care.

To address these barriers, this paper proposes several actionable solutions. First, healthcare systems in developing countries must invest in robust digital infrastructure and data management frameworks, ensuring secure and accessible repositories for health records. Second, targeted capacity-building initiatives should be implemented to train healthcare professionals and data scientists in AI-ML applications, bridging the gap between technological advancements and practical implementation. Third, collaboration between governments, academic institutions, and technology providers is essential to promote the development and deployment of context-specific AI-ML solutions that account for local healthcare challenges and resource constraints. Lastly, ethical frameworks should be established to guide the use of AI-ML in healthcare, emphasizing transparency, fairness, and accountability while fostering trust among stakeholders.

By addressing these challenges and leveraging the insights provided by this study, AI-ML technologies can be harnessed to their full potential, significantly improving healthcare outcomes and bridging the global health equity gap.

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