ISAR Journal of Medical and Pharmaceutical Sciences
Volume 3, Issue 3, 2025 | Page: 15-23
Abbriviate Title- ISAR J Med Pharm Sci
ISSN (Online)- 2584-0150
https://isarpublisher.com/journal/isarjmps

Applications of High-Performance Computing (HPC) in Healthcare Diagnostics: A Systematic Review of AI-Driven Disease Prediction Models

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Article History
Received: 12.02.2025
Accepted: 06.03.2025
Published: 22.03.2025

Abstract: - This systematic review explores the applications of High-Performance Computing (HPC) in AI-driven disease prediction models, emphasizing the role of machine learning (ML) and deep learning (DL) algorithms in advancing healthcare diagnostics. HPC, by enabling rapid data processing and complex simulations, has become indispensable in analyzing large-scale medical data, such as genomic sequencing, biomedical imaging, and electronic health records (EHRs). Through the application of AI, particularly ML and DL models, healthcare systems can achieve more accurate disease predictions and personalized treatment strategies. These models, which learn from vast amounts of medical records and images, improve over time, becoming more precise in diagnosing conditions such as cancer and diabetes. This review assesses the effectiveness, scalability, and practical applications of HPC and AI in healthcare diagnostics, including drug discovery and disease progression modeling. We conducted a comprehensive literature search in multiple databases, including PubMed, Scopus, and IEEE Xplore, focusing on studies published between 2020 and 2025. After applying inclusion and exclusion criteria, 600 relevant studies were selected. The findings underscore the transformative potential of HPC and AI in healthcare, highlighting the accuracy and efficiency these technologies offer in disease prediction and treatment. Future research should focus on enhancing unsupervised learning algorithms and integrating HPC-enabled AI solutions into automated healthcare delivery systems, such as those supported by 5G networks and advanced neural networks. This review provides a critical overview of current advancements and sets the stage for further innovations in AI-driven healthcare diagnostics.

Keywords: High-Performance Computing, AI-driven disease prediction models, machine learning, deep learning, healthcare diagnostics, personalized treatment, genomic data, drug discovery.

1.0 Introduction

This review explores the transformative role of High-Performance Computing (HPC) and Artificial Intelligence (AI) in healthcare, particularly in diagnostics and disease prediction. With healthcare systems producing massive volumes of data from genomic sequencing, biomedical imaging, electronic health records (EHRs), and wearable devices, HPC has become essential for managing and analyzing these complex datasets (Uysal & Ozturk, 2020; Kong *et al.*, 2020).

The rapid growth of health data, alongside advances in simulation and modeling, drives the adoption of HPC. Effectively processing this data presents significant challenges in storage, management, and analysis challenges that HPC is uniquely equipped to address. In genomics, HPC enables researchers to analyze genetic data at unprecedented speed and scale, uncovering disease-related genetic variations and aiding in personalized treatment development (Xi *et al.*, 2019). HPC also plays a critical role in drug discovery and computational modeling. Traditionally resource-intensive, drug discovery is now accelerated through HPC-powered molecular dynamics simulations, offering detailed insights into drug-protein interactions at the atomic level, thereby reducing both time and cost (Bhatt *et al.*, 2021). Additionally, HPC-enabled computational models simulate biological systems and disease progression, informing treatment strategies.

The integration of HPC with AI in healthcare has grown substantially (Gorris *et al.*, 2021). Advanced AI techniques, especially deep learning, require significant computational power to process large datasets and complex neural networks effectively (Dhal & Azad, 2022). In biomedical imaging, HPC allows AI tools to rapidly analyze high-resolution images, enabling real-time, accurate diagnoses (Verma *et al.*, 2021). Moreover, the synergy

Cite this article:

Iluno, C., and Nwaogwugwu, C. J., (2025). Applications of High-Performance Computing (HPC) in Healthcare Diagnostics: A Systematic Review of AI-Driven Disease Prediction Models. *ISAR Journal of Medical and Pharmaceutical Sciences, 3*(3), 15-23.

between HPC, AI, and simulation has enhanced both the speed and quality of healthcare simulations (Rizk *et al*., 2019). Beyond clinical applications, HPC adoption provides valuable insights for healthcare business and strategic planning, offering a comprehensive understanding of current trends and future opportunities (Owais *et al*., 2019). However, the fast pace of technological advancements renders manual data analysis impractical (Abedi *et al*., 2020). This highlights the need for automated literature analysis frameworks to process vast scientific corpora and derive actionable insights for decision-making within the healthcare sector (Jiji *et al*., 2020).

Artificial Intelligence (AI), particularly in conjunction with Machine Learning (ML), is rapidly gaining prominence in various branches of medicine, including cardiovascular care (Nithya *et al*., 2020). Advocates suggest that AI has the potential to transform healthcare practices by harnessing advanced technologies capable of collecting highly detailed, diverse datasets and utilizing powerful computational tools to process and interpret this information (Guni *et al*., 2021). Central to this transformation is the creation and application of advanced clinical prediction models—tools, algorithms, or frameworks designed to improve, and possibly revolutionize, the processes of screening, diagnosing, and forecasting disease outcomes (Won *et al*., 2021).

These prediction models typically fall into two primary categories: diagnostic models, which estimate the likelihood that a patient currently has a specific condition, and prognostic models, which predict the likelihood of a patient developing a health outcome within a defined time frame (Sinagra *et al*., 2020).

The rapid advancements in machine learning have enabled the development of increasingly sophisticated prediction models using both structured data like; tabular datasets and unstructured data like, free-text notes in EHRs, medical imaging, and electrophysiological data) (Goenka & Tiwari, 2021). Leveraging these advances, AI has been employed across a broad spectrum of cardiovascular applications, such as automated detection of cardiac arrhythmias via electrocardiograms (ECGs) (Xu *et al*., 2020), early identification of aortic valve disease, and predicting survival outcomes in patients undergoing cardiac resynchronization therapy (Suresha *et al*., 2021).The rising implementation of AI-driven prediction models in cardiovascular healthcare, however, introduces new challenges. Medical professionals in this field must not only understand the benefits and potential of AI applications but also recognize their limitations when deploying them in clinical environments (Xu *et al*., 2021).

Diagnostic imaging plays a crucial role in medical decision-making, and many diagnoses rely heavily on analysis of images produced by advanced digital devices (Alfian *et al.*, 2018). The integration of AI into medical image evaluation has enabled automatic, accurate assessments, thereby decreasing the workload of healthcare providers, reducing diagnostic errors and delays, and improving the overall efficiency of disease detection and prediction (Jader & Aminifar, 2022). AI-based imaging analysis is a vital research area, involving sophisticated algorithms for disease prediction, diagnosis, and treatment planning, all of which significantly impact clinical decision-making (Ijaz *et al*., 2018).

Within AI, Machine Learning (ML) and Deep Learning (DL) represent two major subfields with extensive applications in healthcare, including disease diagnosis, drug discovery, and risk factor identification (Tigga & Gurg, 2020). The progress of big data and electronic health records has fueled the effectiveness of ML and DL methods. ML techniques encompass algorithms like neural networks and fuzzy logic, which are widely used for automating diagnostic and forecasting tasks (Momin *et al*., 2019). Deep learning, a specialized form of ML, differs from traditional neural networks by eliminating the need for manual feature extraction. Instead, DL algorithms automatically learn from raw data, making them especially powerful in medical image analysis tasks such as image fusion, segmentation, alignment, and classification (Kong *et al*., 2020).

Among these techniques, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are among the most commonly utilized for disease analysis and diagnosis. SVM is a classic ML method, while CNN, a type of DL architecture, excels in handling complex image data with high computational efficiency (Xi *et al*., 2019).The rapid development of computer-based technologies is revolutionizing many sectors, with digital healthcare being a significant area of innovation. These technologies help minimize human error, improve clinical outcomes, and support effective data tracking (Owais *et al*., 2019). Artificial Intelligence (AI), particularly through Machine Learning (ML) and Deep Learning (DL), plays a crucial role in diagnosing and predicting diseases, especially those requiring imaging or signal analysis (Bhatt et al., 2021), and identifying populations or regions with higher disease prevalence or risk behaviors (Xu *et al*., 2020).

ML has made notable progress in medical image analysis by automating feature extraction using advanced algorithms (Jiji *et al*., 2020). It includes supervised, unsupervised, and reinforcement learning (Mohan et al., 2019), with data preprocessing being essential for improving data quality and reducing errors (Taylor et al., 2018). Efficient image classification and enhanced algorithm performance are achieved through feature extraction and model training (Han *et al*., 2020).DL, a major subfield of ML, mimics human neural networks to analyze large datasets and extract features without manual effort (Bhatt *et al*., 2021; Chen *et al*., 2021). CNNs, a common DL model, have set benchmarks in image recognition challenges like ImageNet by significantly lowering error rates (Bharti *et al.*, 2021; Lu *et al*., 2022). Despite their computational precision, understanding trained DL models can be complex (Guni *et al*., 2021; Tigga and Gury, 2020).

Healthcare's vast data output makes it ideal for AI applications, especially in medical imaging from X-rays, MRIs, CT scans, etc. (Uysal and Ozturk, 2020). AI-driven models enhance diagnostic efficiency and accuracy across medical fields (Chen et al., 2021; Kumar and Sungla, 2021). AI, encompassing ML and DL, allows systems to learn, improve, and generalize to new data (Wang *et al.*, 2022; Tazary *et al.*, 2021). DL aids automated diagnosis, reducing reliance on human interpretation and errors, and supports tools like computer-aided diagnosis (CAD) and disease segmentation (Tengnah *et al*., 2019; Ghafari *et al*., 2022). AI also aids in surgical robotics and improves decision-making through accurate healthcare data analysis (Matsuoka *et al*., 2020; Shabut *et al*., 2018).

DL's ability to recognize patterns enhances personalized care and early disease diagnosis, often surpassing traditional ML and human performance (Rajaraman *et al*., 2018; Jamal and Simon, 2021). Common DL models include CNNs, DNNs, DBNs, autoencoders, DBMs, DC-ELM, and RNNs, including variants like BLSTM and MDLATM (Cao *et al*., 2019).Recent innovations include RAGCN, which uses graph convolutional networks for region-based analysis in CT and MRI scans (Marwa et al., 2023; Bhosale and Patnaik, 2023), and LAPNet, which improves lesion detection in conditions like diabetic retinopathy through multi-scale analysis (Saha *et al*., 2021; Won *et al*., 2021).Overall, this review emphasizes the growing role of High-Performance Computing (HPC), AI, and ML in transforming healthcare diagnostics by enhancing accuracy, implementation, and efficiency in disease prediction and treatment planning.

1.1 Research Questions:

a. What Artificial Intelligence (AI) algorithms are most used for machine learning in healthcare diagnosis?

b. How do these AI algorithms compare in terms of accuracy, efficiency, and practical applicability in healthcare?

c. What are the main challenges in implementing High-Performance Computing (HPC), and its subsidiary machine learning for healthcare diagnostics and how have they been addressed in the literature?

d. What are the future opportunities for advancing High-Performance Computing (HPC) and AI algorithms in healthcare diagnostics and disease prediction models?

2.0 Methodology:

The methodology for this review entailed a comprehensive and systematic search of scholarly databases, including Scopus, Web of Science, and Google Scholar, to explore the use of High-Performance Computing (HPC) in healthcare diagnostics, with a particular focus on AI-powered disease prediction models. The review process adhered to the guidelines outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). As this study is based solely on previously published research, ethical approval and informed consent were not applicable.

2.1 Search Strategy:

To conduct a thorough and well-rounded literature search for this systematic review, the selection of appropriate databases was essential to gather a diverse and relevant set of studies. The primary databases utilized included PubMed, Scopus, IEEE Xplore, SpringerLink, Web of Science, and Google Scholar. A variety of keyword combinations were employed during the search process, such as "High-Performance Computing," "Healthcare diagnostics," "Artificial Intelligence (AI) driven disease prediction models," and "AI and machine learning in healthcare diagnostics." In addition to database searches, cross-referencing and software validation of key articles were performed to ensure comprehensive coverage. The search was limited to original research articles published between 2020 and 2025.

2.2 Inclusion Criteria:

The inclusion criteria were designed to capture and synthesize existing literature related to the themes of "High-Performance Computing (HPC)," "AI algorithms in healthcare diagnostics," "machine learning in disease prediction models," and "healthcare diagnostics." The review was further refined to include studies that met the following conditions:

(a) Analysis of how High-Performance Computing (HPC) is applied in healthcare diagnostics;

(b) Evaluation of the accuracy, scalability, and real-world implementation of various AI algorithms used in disease prediction models; and

(c) Identification of commonly used datasets, performance evaluation metrics, and case studies involving AI and machine learning in healthcare settings.

To be included, articles or data sources were required to report at least one indicator related to the use of HPC in healthcare diagnostics and AI-based disease prediction models.

2.3 Exclusion Criteria:

The exclusion criteria for this review were as follows: all articles published before 2020, studies lacking experimental validation, and non-English language papers unless an English translation was available. Additionally, the following were excluded: (a) Articles or journals not related to the application of High-Performance Computing (HPC) in healthcare diagnostics; and (b) Publications focused on HPC but not addressing healthcare diagnostics or AI-driven disease prediction models.

2.4 Data Extraction:

Data extraction was independently performed by two reviewers using a standardized protocol. Relevant information concerning the use of High-Performance Computing (HPC) in healthcare diagnostics and AI-driven disease prediction models was systematically gathered from the selected research articles and journals. This review, focused on HPC applications in healthcare diagnostics, synthesized data on changes from baseline endpoints, which were either directly obtained from the original studies when available or calculated using AI algorithm outputs and machine learning predictions. These values were compared to baseline metrics to assess the effectiveness of HPC in healthcare prognosis and treatment.

2.5 Analysis:

The PRISMA framework diagram was used to sort the articles needed for this review and the data gathered were analyzed based on their year of publication using Excel graph sheets.

2.6 Expected Outcomes:

Machine learning, a subset of artificial intelligence, is an integral component of High-Performance Computing (HPC). HPC employs supervised and unsupervised algorithms, along with other AI-driven disease prediction models, to enhance healthcare diagnostics and provide accurate treatments for the benefit of human health. The integration of AI, machine learning, and HPC into the healthcare sector aims to improve efficiency, accessibility, accuracy, precision, and speed in delivering quality healthcare, while reducing human errors and limitations (Wang et al., 2022). The future of HPC, AI-driven disease prediction models, and machine learning largely relies on unsupervised algorithms, enabling machines to independently carry out medical prognosis and treatments through advanced automated systems and connectivity technologies, such as 5G networks and Convolutional Neural Networks (CNNs) (Marwa et al., 2023).

This review synthesizes research articles, review papers, and journals. Duplicate articles were meticulously identified and excluded to ensure the quality of the review. Abstracts of the selected papers were carefully analyzed to guarantee the relevance, quality, and accuracy of the literature included. The review was limited to papers published in the English language. A total of 9,551 articles and journals were initially extracted from the search. After applying exclusion criteria and removing duplicate records, 9,000 articles were excluded, resulting in 600 articles selected for further assessment.

3.0 Result

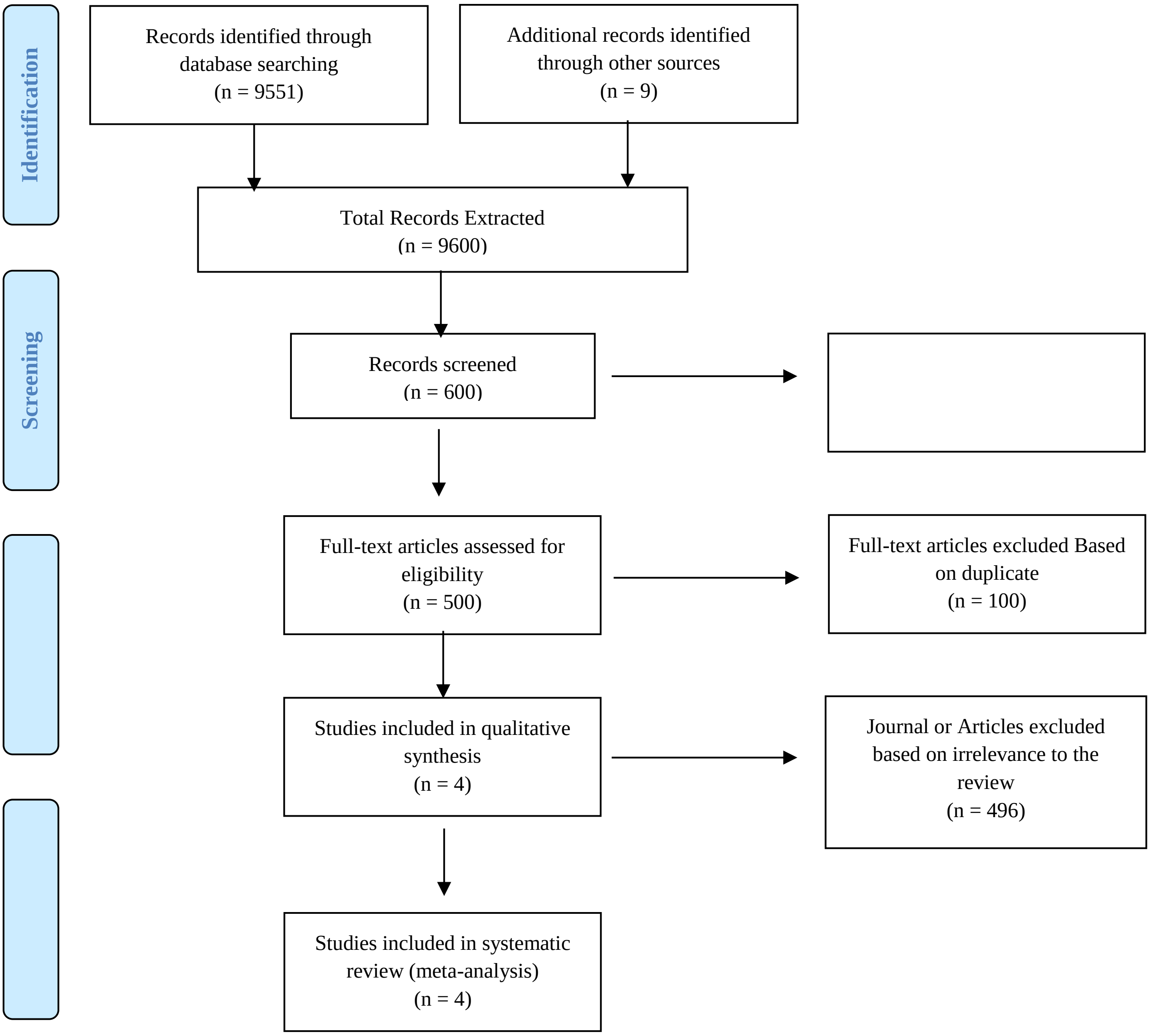

Fig. 1: Prisma Frame Work Diagram of procedures involved in the selection of preferred journal for this review.

3.1 Bar-chart representation of statistical data.

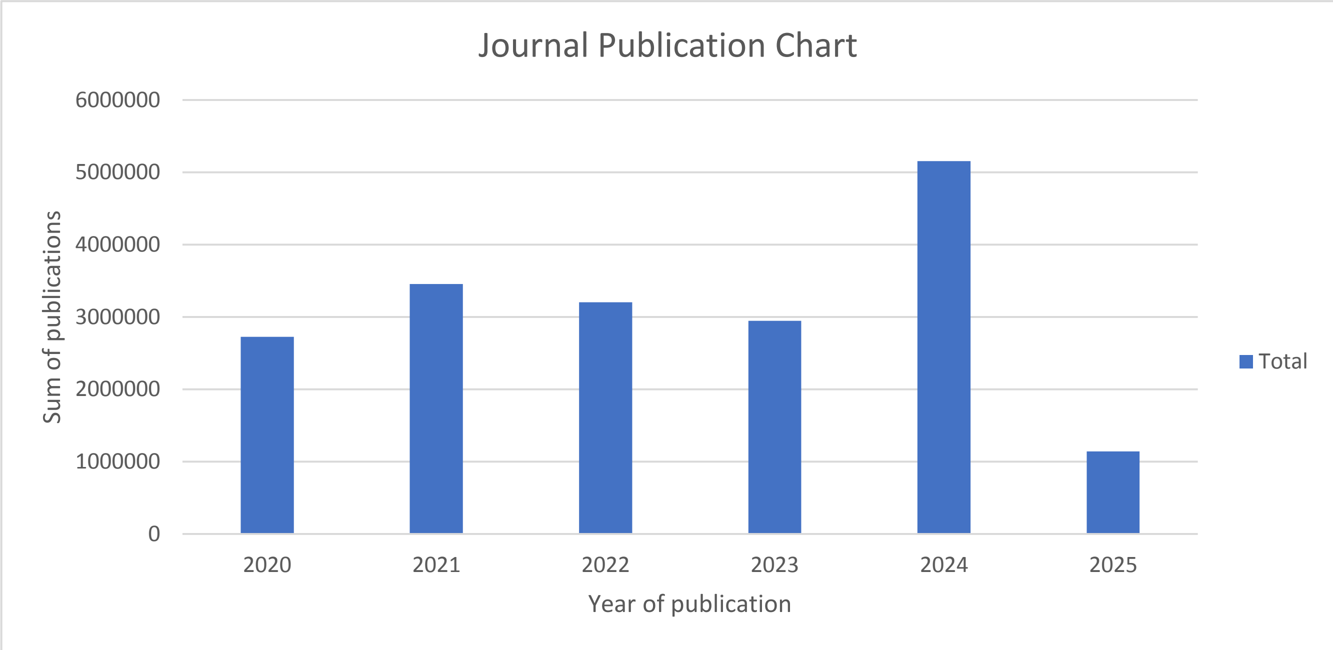

Fig 2: Bar chart representation of total number of article and journal publication for the last five years.

Considering the chart above, 2024 has the highest number of journal publication on High-Performance Computing (HPC) in healthcare diagnostics and AI-driven disease prediction models. With a total publication of over 5000000 journals.

4.0 Discussion:

AI-driven disease prediction models and machine learning technologies are increasingly becoming pivotal in healthcare for providing more accurate insights into various disorders and diseases (Saha et al., 2021). Given AI's ability to interact effectively with image data, it has seen widespread adoption in disease diagnosis and prediction. Machine learning algorithms, along with big data sourced from medical records and wearable devices, are essential tools for deploying AI models within the healthcare system (Li *et al.*, 2022). These technologies help improve disease diagnosis, classification, decision-making processes, walking aids performance, optimal treatment choices, and ultimately contribute to longer and healthier lives (Li *et al.*, 2023). AI significantly accelerates medical analysis and diagnosis. For example, it can detect tumors in medical images, allowing pathologists to diagnose diseases at an earlier stage and initiate treatment, instead of waiting for tissue samples to be sent to a laboratory (Chee *et al.*, 2019). AI-based algorithms also play a crucial role in identifying undiagnosed patients and rare diseases, providing opportunities for earlier diagnosis (Moen *et al.*, 2019).

Machine learning (ML) and deep learning (DL) techniques are increasingly applied in diagnosing heart diseases (Lu *et al.*, 2022). With the availability of various medical imaging techniques, such as CT scans, ECGs, and echocardiograms, deep learning has proven to be effective in analyzing cardiovascular data (Khan *et al.*, 2021). Coronary atherosclerotic heart disease, a common and debilitating condition, has been studied using SVM and ANN methods to diagnose heart diseases such as Arrhythmia, Cardiomyopathy, Coronary Heart Disease (CHD), and Coronary Artery Disease (CAD) (Nordin *et al.*, 2023). The SVM model achieved accuracy rates of 89.1%, 80.2%, 83.1%, and 71.2%, respectively, while the ANN model achieved 85.8%, 85.6%, 72.7%, and 69.6% accuracy for the same conditions (Keenan *et al.*, 2021). In another study, researchers used Naïve Bayes, SVM, and Decision Tree models to predict CHD from the South African Heart Disease dataset, enhancing prediction rates for CHD (Moen *et al.*, 2019).

AI has also shown promise in predicting and diagnosing brain diseases (Burgos & Colliot, 2020). Advanced machine learning and deep learning techniques are applied in the early diagnosis of neurodegenerative diseases such as Alzheimer's and Parkinson's diseases, as well as brain tumors, which are often challenging to detect in their early stages (Das *et al.*, 2021). AI can process vast amounts of brain signal data to uncover insights that are not immediately apparent to human observers (Jia *et al.*, 2019). One of the most commonly used algorithms for such disease detection is deep learning-based convolutional neural networks (CNNs). Similarly, AI algorithms are being utilized to detect and predict breast cancer at early stages. Early detection is crucial for effective treatment of breast cancer, a leading cause of death among women (Min *et al.*, 2023). For example, the Wisconsin Breast Cancer Dataset (WBCD) is frequently used for investigating machine learning methods for breast cancer diagnosis. The least-squares support vector machine (LSSVM) algorithm achieved 98.53% accuracy in diagnosing breast cancer using this dataset (Min *et al.*, 2023). Other algorithms, such as a hybrid fuzzy-artificial immune system combined with a k-nearest neighbor algorithm, achieved 99.14% accuracy, and an SVM algorithm with feature selection achieved 99.51% accuracy (Yu *et al.*, 2022; Lamba et *al.*, 2022).

Despite these advancements, challenges remain in applying AI, deep learning, and machine learning in disease diagnosis and prediction (Das *et al.*, 2021). One significant challenge is the large volume of data required to train these models, which is not always available, especially for rare diseases. Additionally, labeling data, which necessitates expertise and can be time-consuming and costly, presents a major hurdle (Nasir *et al*., 2022). To address this, techniques such as data augmentation, which artificially increases the size of the dataset, can be employed (Campos *et al.*, 2019). Another challenge is the complexity of deep learning models, which can be reduced using techniques like pruning, quantization, and low-rank factorization, which help maintain model performance while reducing computational resources (Tong *et al*., 2020). The analysis of low-contrast images is also a challenge in medical imaging, with techniques like Histogram Equalization (HE) being used to enhance contrast and improve image quality (Ahmed *et al.*, 2022; Suh *et al*., 2023).

Machine learning and deep learning can analyze large medical datasets such as patient records, imaging studies, and laboratory results to identify patterns that may be unnoticed by human clinicians (Ricke *et al*., 2020). This leads to more accurate and efficient diagnoses and enables the development of personalized treatment plans based on a patient's medical history (Joshi *et al.*, 2023). It is critical, however, to ensure that the data used to train these models is diverse and unbiased to avoid any potential inaccuracies or discrimination in diagnoses (Magalhaes *et al.*, 2021).

Looking ahead, machine learning and deep learning algorithms will continue to evolve and become increasingly integrated into the healthcare industry, improving disease prediction and diagnosis (Pagono *et al*., 2023). These technologies can analyze genomic data to identify genetic markers for various diseases, leading to more precise and personalized treatment plans (Johnson *et al.*, 2018). Additionally, predictive models for disease progression and treatment responses are also being developed, enabling physicians to identify high-risk patients early and provide more effective interventions (Shameer *et al*., 2018; Gantam & Sharma, 2020). As these techniques advance, they are poised to revolutionize patient care, leading to improved outcomes and more effective healthcare solutions.

5. Conclusion

This review emphasizes the transformative role of High-Performance Computing (HPC) in AI-driven disease prediction, enhancing diagnostic precision and computational efficiency (Srivastava *et al.*, 2021). Although challenges such as infrastructure limitations and regulatory approval persist, future progress in integrating artificial intelligence with HPC offers significant promise for personalized medicine and early disease detection (Faieq & Mijwil, 2022).

Deep learning and machine learning techniques possess immense potential to revolutionize disease diagnosis and prediction. In this context, the accuracy and reliability of diagnoses are critical to effective treatment (Li *et al.*, 2022). AI has demonstrated remarkable accuracy in detecting image-based diseases and predicting treatment outcomes, including survival rates and treatment responses (Joshi et al., 2023). The massive volume of image data requires sophisticated processing capabilities, provided by AI methods, to ensure timely, reliable, and precise results (Coenen *et al.*, 2018). In medical diagnostics, factors such as detection accuracy, effective treatment planning, and ensuring patient well-being are essential (Afshar *et al.*, 2020). AI encompasses a vast range of data, algorithms, advanced computing techniques, neural networks, and emerging methods that continue to evolve to meet medical needs (Lu *et al.*, 2022).

This study aims to explore the performance of AI techniques in diagnosing and predicting various diseases. The results show that Support Vector Machines (SVM) perform exceptionally well in predicting heart diseases (Savas, 2022). Supervised deep learning networks, particularly conventional neural network (CNN)-based models, are widely used due to their high accuracy and rapid image recognition capabilities, especially for diagnosing respiratory, lung, skin, and brain diseases, leading to significant results (Suh *et al*., 2023). In breast cancer diagnosis, combining KNN with other networks like SVM enhances diagnostic accuracy (Chen *et al*., 2019). Therefore, deep learning and machine learning, with their impressive experimental results in detecting and classifying medical images, play a critical role in the success of diagnosing various diseases (Tong et al., 2020). In essence, AI-based methods optimize medical systems for diagnosing and predicting conditions by utilizing various resources efficiently.

With the rapid advancement of AI technologies, the objective diagnosis of diverse diseases will soon become a streamlined process, reducing the workload for doctors (Lamba et al., 2022). This review, focusing on the application of HPC in healthcare diagnostics, concludes that AI, particularly through machine learning (ML) and deep learning (DL), is integral to achieving HPC in medical diagnostics and treatment. These technologies are essential for future improvements in efficiency and accuracy. Ultimately, the full potential of AI algorithms could mark a new era in the medical field, where most diagnoses and treatments are conducted effectively and efficiently by AI-powered systems without the need for human intervention, assistance, or supervision.

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