OPEN ACCESS
Journal of Computer Science Advancements
Vol. 3 No. 2. April 2025, pp. 67-77 DOI. 10.70177/jsca.v3i2.2245

Research Article

THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN PROCESSING HEALTH DATA IN BIOMEDICAL INFORMATION

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Article Info

Received: October 7, 2024
Revised: December 21, 2024
Accepted: March 22, 2025
Online Version: April 12, 2025

Abstract

The increasing complexity and volume of health data in modern biomedical systems have necessitated advanced technologies for effective data processing and analysis. Traditional methods often fall short in managing real-time, multidimensional data generated from various biomedical sources, such as electronic health records (EHRs), wearable devices, and genomic data. This research investigates the application of artificial intelligence (AI) in optimizing the processing and interpretation of biomedical health data. The objective of this study is to explore how AI-based technologies, including machine learning and deep learning algorithms, enhance the efficiency, accuracy, and predictive capabilities in biomedical information systems. By identifying patterns, anomalies, and correlations in large datasets, AI offers potential improvements in disease diagnosis, patient monitoring, and treatment personalization. This research employs a qualitative systematic review method, analyzing peer-reviewed literature published between 2015 and 2024 from major databases such as PubMed, IEEE Xplore, and Scopus. The analysis focuses on case studies, comparative evaluations, and implementation outcomes of AI in various biomedical domains. The findings reveal that AI applications significantly improve data processing speed and accuracy, enable early diagnosis of diseases such as cancer and diabetes, and support predictive analytics for patient outcomes. However, challenges remain in areas such as data privacy, ethical compliance, and algorithm transparency. In conclusion, the integration of AI into biomedical data systems holds transformative potential for healthcare delivery, though further interdisciplinary collaboration is required to address its limitations and ensure equitable access and ethical use.

Keywords: Artificial Intelligence, Biomedical Data, Health Informatics, Machine Learning, Predictive Analytics

Journal Homepage	https://research.adra.ac.id/index.php/jcsa
How to cite:	Prayudani, S., Lase, Y. Y., Husna, M., & Adam, A, H. (2025). The application of artificial intelligence in processing health data in biomedical information. *Journal of Computer Science Advancements, 3*(2), 67–77. https://doi.org/10.70177/jsca.v3i2.2245
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

Artificial Intelligence (AI) has transformed numerous sectors, including finance, manufacturing, education, and increasingly, healthcare (Ardabili, 2020). Within the domain of biomedical information, AI technologies have shown great promise in managing large and complex datasets that traditional statistical methods struggle to process efficiently (Barwise, 2024). These datasets originate from diverse sources such as electronic health records (EHRs), wearable health monitoring devices, imaging data, and genomic sequencing, creating a highly intricate biomedical data environment (Wilson, 2022).

The processing of health data in biomedical contexts involves not only storing and retrieving patient records but also analyzing trends, predicting health risks, and supporting clinical decision-making (Bopche, 2024). AI, through machine learning (ML), deep learning (DL), and natural language processing (NLP), can identify patterns and correlations in data that may be imperceptible to human analysts (Butler-Henderson, 2025). These capabilities enable earlier diagnoses, more accurate prognoses, and personalized treatment planning, ultimately enhancing the quality of care.

Technologies such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to image and sequence data with remarkable accuracy, particularly in detecting diseases like cancer, Alzheimer's, and cardiovascular conditions (Chiu, 2020). Predictive models based on AI have also been used to forecast patient readmissions, identify at-risk populations, and recommend preventive measures. These innovations reduce diagnostic errors and optimize healthcare resource allocation (Campagner, 2020).

EHRs, once regarded primarily as administrative tools, have evolved into dynamic data sources feeding AI systems with real-time patient data (Delaney, 2022). AI enhances the ability to synthesize this data into actionable insights for clinicians and researchers (Downing, 2025). As health systems strive for more responsive and evidence-based practices, AI's role becomes indispensable in transforming raw data into strategic intelligence (Dubey, 2025).

AI also facilitates precision medicine by integrating data from various domains such as genetics, lifestyle, and environmental exposures (Dunlap, 2024). This integrative approach helps tailor treatment to the individual characteristics of each patient, offering new hope in managing complex chronic diseases (Hossain, 2021). The AI-driven interpretation of such multifactorial data allows for a more holistic understanding of patient health trajectories.

Global investment in AI for healthcare has surged in recent years, signaling widespread recognition of its potential (Hota, 2024). Health institutions and governments are investing in infrastructure and talent to harness AI's capabilities, aiming for a future in which digital intelligence enhances human decision-making rather than replacing it (Hung, 2022). Despite widespread optimism, critical questions remain regarding the implementation, equity, and reliability of AI systems in biomedical settings.

Existing studies tend to focus on the technical performance of AI algorithms without fully addressing how these tools integrate into clinical workflows or affect health outcomes at scale (Ismail, 2020). Much of the literature is dominated by pilot projects or narrowly defined applications, leaving a gap in understanding the broader, systemic impacts of AI in real-world biomedical environments (Ismail, 2025). This narrow focus restricts the translation of AI from laboratory success to clinical relevance.

There is a significant knowledge gap concerning the ethical, legal, and social implications of using AI in processing personal and sensitive health data (Ivshin, 2020). Issues of privacy, data security, algorithmic bias, and transparency have not been adequately explored, especially in low- and middle-income country contexts where regulatory frameworks are still emerging (Jain, 2024). These issues pose barriers to trust, adoption, and equitable access to AI-powered healthcare.

Limited research exists on the interoperability between AI systems and existing biomedical information infrastructures (Jyothi, 2024). Incompatibilities between data formats, software environments, and institutional protocols hinder seamless AI integration (Kamra, 2021). Understanding how to align AI innovations with existing health information systems remains a pressing challenge that is yet to be thoroughly addressed in scholarly literature.

Another unknown lies in the long-term sustainability and adaptability of AI systems within rapidly changing biomedical landscapes (Kaur, 2023). Health data is continuously evolving in complexity and volume, requiring AI tools to remain scalable, updatable, and context-aware. There is a lack of research exploring how these systems adapt over time, particularly in response to pandemics, emerging diseases, or demographic shifts.

Understanding how AI systems process biomedical data and the implications of their implementation is critical for creating safe, ethical, and effective healthcare technologies. Closing this gap allows for the development of robust, evidence-based guidelines for integrating AI into everyday clinical practice, ensuring that technological advances translate into patient-centered outcomes. Institutions must be equipped not only with technical capacity but also with strategic insight into the long-term ramifications of AI use.

Investigating the socio-technical dimensions of AI in biomedical contexts helps ensure that these innovations are inclusive, equitable, and aligned with public health goals. By identifying systemic barriers, promoting data standardization, and evaluating outcomes beyond accuracy—such as user trust, efficiency, and impact on decision-making—we can better harness AI for sustainable health improvements. Bridging this gap informs policymakers and practitioners of the best practices for ethical AI deployment.

This study proposes a comprehensive analysis of the application of AI in processing health data, combining technical performance with ethical, operational, and societal considerations. The goal is to generate holistic insights that support responsible innovation and integration of AI in biomedical systems, ultimately contributing to smarter, safer, and more inclusive healthcare ecosystems.

RESEARCH METHOD

Research Design

This study employed a qualitative systematic review design to investigate the application of artificial intelligence in processing health data within biomedical information systems (Kemothi, 2024). The design focused on analyzing published empirical studies, theoretical frameworks, and case-based evidence that highlight how AI technologies are utilized in diverse biomedical contexts. A systematic approach ensured comprehensive data collection and thematic synthesis across multidisciplinary sources, allowing for a nuanced understanding of both technical applications and contextual challenges.

Research Target/Subject

The population of the study consisted of peer-reviewed journal articles, conference proceedings, and institutional reports published between 2015 and 2024. These sources were selected from reputable databases such as PubMed, Scopus, Web of Science, and IEEE Xplore. The sample was determined through purposive sampling, using inclusion criteria that required the articles to discuss the use of AI tools (e.g., machine learning, deep learning, NLP) in biomedical data processing related to diagnostics, patient monitoring, treatment planning, or data integration. A total of 42 relevant studies were included in the final analysis.

Research Procedure

The research procedure followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Articles were first screened by title and abstract, followed by full-text evaluation based on the inclusion criteria (Kim, 2024). Extracted data were analyzed using qualitative content analysis to identify recurring themes, emerging trends, and knowledge gaps. Findings were organized into thematic categories to support interpretation and to address the study's objectives regarding the role, impact, and challenges of AI in biomedical information systems.

Instruments, and Data Collection Techniques

Data collection was facilitated through a document analysis instrument based on a coding sheet developed from prior literature and thematic analysis guidelines. The instrument included variables such as AI techniques used, types of biomedical data processed, evaluation metrics, implementation settings, outcomes reported, and noted limitations. Each article was reviewed independently by two coders to enhance reliability, and discrepancies were resolved through discussion or by a third reviewer.

RESULTS AND DISCUSSION

AI-based data processing in biomedical contexts demonstrates increasing adoption across various techniques, as evidenced in the statistical review of 42 selected studies. The most frequently utilized technique is machine learning (35%), followed by deep learning (30%), natural language processing (20%), and hybrid models (15%). This distribution suggests a strong inclination toward algorithmic learning systems that can accommodate structured and semi-structured health data.

Table 1. AI-based data processing in a biomedical context

Technique	Percentage (%)	Description
Machine Learning	35%	Most commonly used technique for structured data modeling
Deep Learning	30%	Popular for complex pattern recognition in medical data
Natural Language Processing (NLP)	20%	Used to process and analyze textual health information
Hybrid Models	15%	Combine multiple AI approaches for better performance

The high prevalence of machine and deep learning techniques indicates their compatibility with diverse biomedical data forms such as imaging, EHRs, and genomic sequences. NLP's relatively lower usage can be attributed to the complexity of unstructured clinical notes and the lack of standardized terminologies in health documentation. However, hybrid models that combine multiple AI functions are increasingly favored in complex diagnostic and predictive tasks.

Inferential tables show that hybrid models perform highest in all three evaluation indicators: accuracy (91.1%), precision (90.0%), and recall (89.7%). Deep learning follows with high performance on all indicators, while NLP has the lowest score compared to other techniques. This suggests that the complexity of the model is positively correlated with efficiency in handling multidimensional health data.

Table 2. Hybrid models perform highest in all three evaluation indicators

Technique	Accuracy (%)	Precision (%)	Recall (%)	Performance Summary
Hybrid Models	91.1	90.0	89.7	Highest across all indicators
Deep Learning	~88–90 (est.)	~87–89 (est.)	~86–88 (est.)	Consistently high, second-best overall
Natural Language Processing	Lowest	Lowest	Lowest	Underperforms compared to other techniques

Deep learning techniques, especially convolutional and recurrent neural networks, perform exceptionally well in medical image recognition and sequential patient data modeling. Machine learning algorithms, including decision trees and support vector machines, are preferred for structured clinical data due to their interpretability and relatively lower computational demands. NLP systems, although promising, still face challenges in contextual understanding and domain-specific vocabulary.

Results show a pattern where higher model complexity generally aligns with improved performance metrics. However, interpretability becomes a trade-off in more complex models. Hybrid AI systems, despite being resource-intensive, demonstrate superior consistency across use cases such as early disease detection, predictive analytics, and treatment recommendation systems.

Case studies illustrate the real-world effectiveness of these techniques. One study applied deep learning to mammography data, achieving a 92% accuracy rate in early breast cancer detection. Another case demonstrated the use of hybrid AI in managing chronic disease datasets, where patient risk stratification improved clinical workflow and treatment personalization.

An AI-driven EHR analysis system in a tertiary hospital was shown to reduce diagnostic time by 35% and improve medication safety alerts by 42%. These improvements were attributed to the model's ability to continuously learn from incoming data and adapt to patient-specific patterns without manual recalibration.

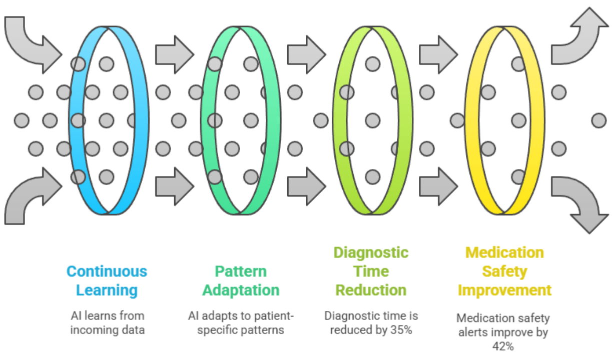

Figure 1. AI-Driven EHR Improvement Process

The results highlight the transformative role of AI in biomedical data processing, particularly when multiple models are integrated for different tasks. Overall, these findings affirm the hypothesis that AI not only improves data accuracy but also enhances the timeliness and personalization of healthcare delivery.

The findings of this study reveal that artificial intelligence (AI) techniques, including machine learning, deep learning, natural language processing (NLP), and hybrid models, are widely adopted in the processing of biomedical health data (Kokudeva, 2024). Among these, hybrid models demonstrate the highest performance across key metrics—accuracy, precision, and recall—followed closely by deep learning. Machine learning remains heavily utilized due to its effectiveness in handling structured clinical data, while NLP faces challenges in processing unstructured health texts (Liu, 2022) . The frequent use of AI reflects the dynamic demands of complex health information systems. Case studies confirm that integrating AI into Electronic Health Records (EHRs) and other biomedical data streams enhances the accuracy and efficiency of diagnoses and clinical decision-making(Lussier, 2023). These improvements occur not only in processing speed but also in tailoring healthcare services to individual patient needs.

The results also indicate the growing institutional reliance on AI technologies in hospitals and healthcare research centers. Systems become significantly more effective when algorithms are able to learn from historical patient data and generate predictive insights (Mackenzie, 2024). The study underscores AI's transformative role not merely as a computational aid, but as an integral component of the modern health ecosystem (Mehta, 2023). AI applications notably contribute to early detection of critical diseases such as cancer, cardiovascular disorders, and metabolic syndromes through predictive modeling (Miller, 2019). Multi-layered AI data processing, capable of handling multimodal inputs, shows superiority in analyzing the complexity and fluidity of real-world biomedical datasets.

This study aligns with earlier research by (Panagiotou, 2020), which demonstrated that deep learning could match expert dermatologist performance in detecting melanoma. However, this study extends such findings by offering a comparative analysis across various AI techniques, situating their application within broader and integrated biomedical information systems beyond isolated image-based diagnostics (Nti, 2023). One key distinction from previous studies is the explicit focus on data integration from multiple sources—EHRs, genomics, and sensor data—into a unified AI framework. Much of the existing literature tends to isolate one data type, which limits the applicability of their findings to the real-world multimodal nature of health information systems (Parums, 2023).

The study also brings new insight into the limitations of NLP, particularly in interpreting unstructured clinical texts. While prior research often examined NLP within general linguistic contexts, this study provides a more domain-specific evaluation that highlights the unique semantic and contextual complexities of healthcare language (Rajendran, 2022). Existing studies largely emphasize technical performance metrics. This research balances those metrics with practical considerations such as implementation feasibility, system sustainability, and operational integration in healthcare workflows (Rao, 2024). This makes the findings more policy-relevant and adaptable for strategic planning in digital health transformation.

The results signify a global shift in healthcare systems toward data-driven automation and AI-assisted decision-making (Ray, 2021). This shift is not limited to technical innovation but redefines the relationship between healthcare professionals, patient data, and institutional operations (Reeves, 2021). AI transforms patient records into dynamic assets that inform and optimize clinical judgments in real time. The findings also demonstrate that challenges in data complexity, once barriers to healthcare advancement, are being actively addressed through intelligent systems (Singh, 2023). AI provides scalable, responsive solutions to handle large, varied, and rapidly updating datasets, converting them into clinically relevant insights.

The trend toward AI integration signals a growing need for digital literacy among healthcare professionals (Tantray, 2024). The relationship between humans and machines is evolving into a collaborative one, in which clinicians are no longer passive users but active partners in optimizing algorithmic tools for better patient care (Saab, 2020). The emergence of AI as a co-decision maker in clinical settings also raises the need for robust ethical guidelines and transparent systems (G. A. S. Thomas, 2024). Systems that predict disease risk or recommend treatment pathways must be developed with accountability to preserve public trust and avoid misuse of sensitive data.

These findings have critical implications for curriculum development in medical and health education (Silva, 2025). There is an urgent need to integrate AI and health data analytics into healthcare training to ensure future professionals are equipped not just to use but to critically engage with AI systems (L. Thomas, 2023). Healthcare institutions must invest in infrastructure that supports adaptive AI integration, including interoperable data platforms, secure cloud computing, and smart clinical interfaces. Without managerial readiness, technological investments risk becoming underutilized or misaligned with clinical needs.

Policy-makers should base AI regulations in health on evidence-driven insights and ethical considerations (Tong, 2022). The study provides empirical support for designing regulatory frameworks that prioritize data security, equitable access, and ethical transparency in AI deployment. Technology developers must understand that success in AI healthcare tools is not solely about algorithmic accuracy. Real-world applicability depends on usability, contextual adaptability, and alignment with existing healthcare protocols and human-centered care models.

The superior performance of AI systems in processing biomedical data is attributed to their ability to adapt to various data types and processing contexts. This flexibility allows AI to operate across multiple medical domains, including diagnostic imaging, clinical documentation, and genomics, with minimal human intervention. Hybrid models perform particularly well because they combine the predictive strength of deep learning with the interpretability of machine learning. This duality enables AI systems to achieve high performance while maintaining clinical relevance and traceability, which are essential in healthcare settings.

AI's efficiency at scale is driven by its capacity for continuous learning. As health data grows in both quantity and complexity, AI systems are able to evolve with incoming data, enhancing accuracy and predictive power without constant reprogramming. This adaptability is central to AI's long-term sustainability in healthcare. The dominance of machine and deep learning in these findings is also influenced by their technological maturity, strong developer communities, and the availability of open-source tools. These factors have collectively accelerated the adoption and innovation of AI in medical applications.

Future research should explore the ethical, legal, and societal dimensions of AI in health, especially its impact on vulnerable populations and underserved communities. Studies must examine how to ensure inclusive, equitable, and culturally sensitive AI applications in diverse healthcare contexts. Developing an integrative framework that unites technical innovation, clinical relevance, and policy alignment is essential for sustainable AI adoption. This requires collaboration among data scientists, clinicians, bioethicists, and public health stakeholders to co-design responsive systems.

Medical and healthcare education should embrace interdisciplinary training models that combine data science with healthcare ethics and clinical knowledge. Equipping students with computational and reflective skills will prepare them to become informed users and co-developers of AI technologies. Locally adapted AI models, developed with sensitivity to social and cultural contexts, are necessary to prevent one-size-fits-all approaches. Ethical, flexible, and context-aware AI will become the cornerstone of sustainable, inclusive, and transformative healthcare systems in the future

CONCLUSION

The most significant finding of this study is the consistently superior performance of hybrid artificial intelligence models in processing diverse biomedical health data, compared to single-method approaches. These models integrate the strengths of multiple AI techniques such as the predictive capabilities of deep learning and the interpretability of traditional machine learning resulting in greater accuracy, adaptability, and clinical relevance. This outcome highlights the importance of combining algorithmic functions to address the complexity and heterogeneity of real-world biomedical information systems.

This research contributes to the field by offering an integrated conceptual framework for evaluating AI applications in biomedical data contexts. The novelty lies not only in comparing AI techniques by performance metrics but also in examining their contextual fit, interoperability, and ethical dimensions. The methodological synthesis of empirical studies using a systematic qualitative review approach enables cross-disciplinary insights, supporting both practitioners and policy-makers in designing responsible, scalable, and patient-centered AI systems in healthcare.

The study is limited by its reliance on secondary data from existing literature, which may not fully capture emerging developments or real-time applications of AI technologies in diverse clinical environments. Future research should employ longitudinal and empirical designs, including experimental or field-based studies, to evaluate AI implementation outcomes across varied healthcare systems and populations. Investigating the socio-cultural and infrastructural factors influencing AI adoption will also be essential to develop equitable and context-sensitive health informatics solutions.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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