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Exploring Artificial Intelligence in Healthcare: A Review

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Abstract

Artificial Intelligence (AI) is transforming healthcare by enabling advanced solutions in diagnostics, treatment planning, and healthcare management. This systematic review, conducted using the PRISMA framework, analyses existing studies to examine AI applications in healthcare, focusing on methodologies, datasets, performance, and challenges. Deep learning techniques such as convolutional neural networks (CNNs) for medical imaging and recurrent neural networks (RNNs) for disease progression prediction have shown strong results in radiology, oncology, clinical decision support, and drug discovery, improving diagnostic accuracy and personalized care. Supervised learning methods, including support vector machines (SVMs) and random forests, are commonly used for diagnostic tasks with labeled data, while unsupervised and semi-supervised approaches are applied when annotated datasets are limited. Hybrid models combining structured and unstructured data are increasingly adopted. Despite promising results, challenges remain, such as the lack of large, high-quality annotated datasets, data imbalance, privacy concerns, limited model generalization, and the black-box nature of deep learning models. Ethical issues and integration into clinical workflows further hinder adoption. Addressing these gaps is essential to enable trustworthy AI systems and improve real-world healthcare outcomes.

Keywords: Artificial Intelligence, Clinical Decision Support Systems, Explainable AI, Medical Imaging, Natural Language Processing.

Introduction

Artificial Intelligence (AI) refers to computational systems that simulate human intelligence to perform tasks such as learning, reasoning, and decision-making. In healthcare, AI enables the analysis of large volumes of medical data, supporting improved diagnosis, treatment planning, and patient management (1, 2). Healthcare itself involves the delivery of medical services aimed at maintaining and improving physical and mental well-being through diagnosis, treatment, and prevention.

AI technologies, including machine learning (ML), deep learning (DL), and natural language processing (NLP), are widely applied in healthcare for both clinical and administrative purposes (3). These techniques assist in analysing medical images such as X-rays, MRIs, and CT scans to detect diseases, including cancer and cardiovascular conditions (4). Deep learning models have demonstrated performance comparable to or exceeding that of human experts in medical image analysis. AI also plays a crucial role in predictive analytics and personalized medicine (5). By analysing electronic health records (EHRs) and patient data, AI models can identify patterns for early disease detection and risk prediction (6). Additionally, AI supports personalized treatment by integrating genetic, lifestyle, and environmental factors, particularly in areas such as oncology. Beyond clinical applications, AI enhances healthcare management through chatbots, automation, and resource optimization, improving efficiency and patient engagement.

Despite its potential, the adoption of AI in healthcare faces challenges such as data privacy, model interpretability, and ethical concerns. Figure 1 illustrates the overall architecture of AI in healthcare, including data collection, processing, and decision-making stages, highlighting how AI systems improve healthcare accuracy and efficiency.

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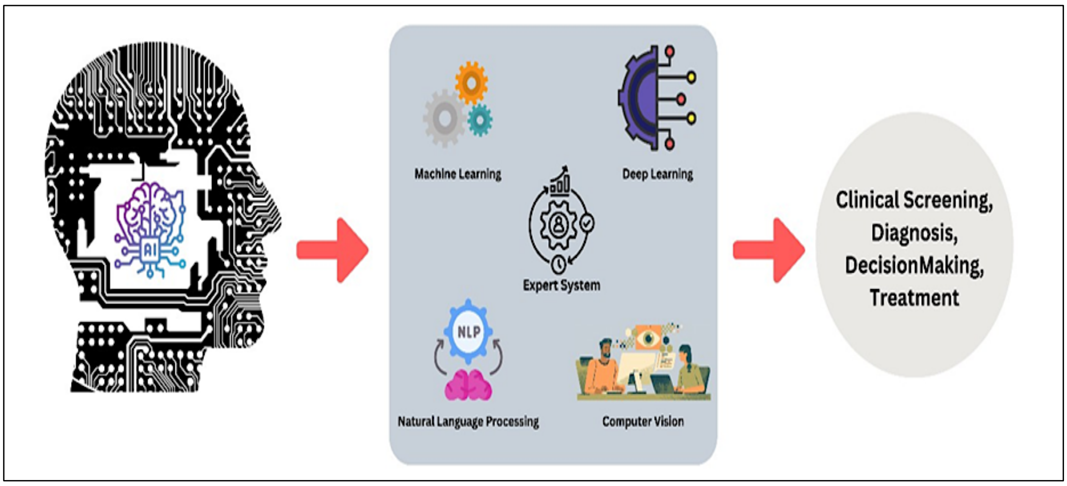

Figure 1: Overview of AI in Healthcare

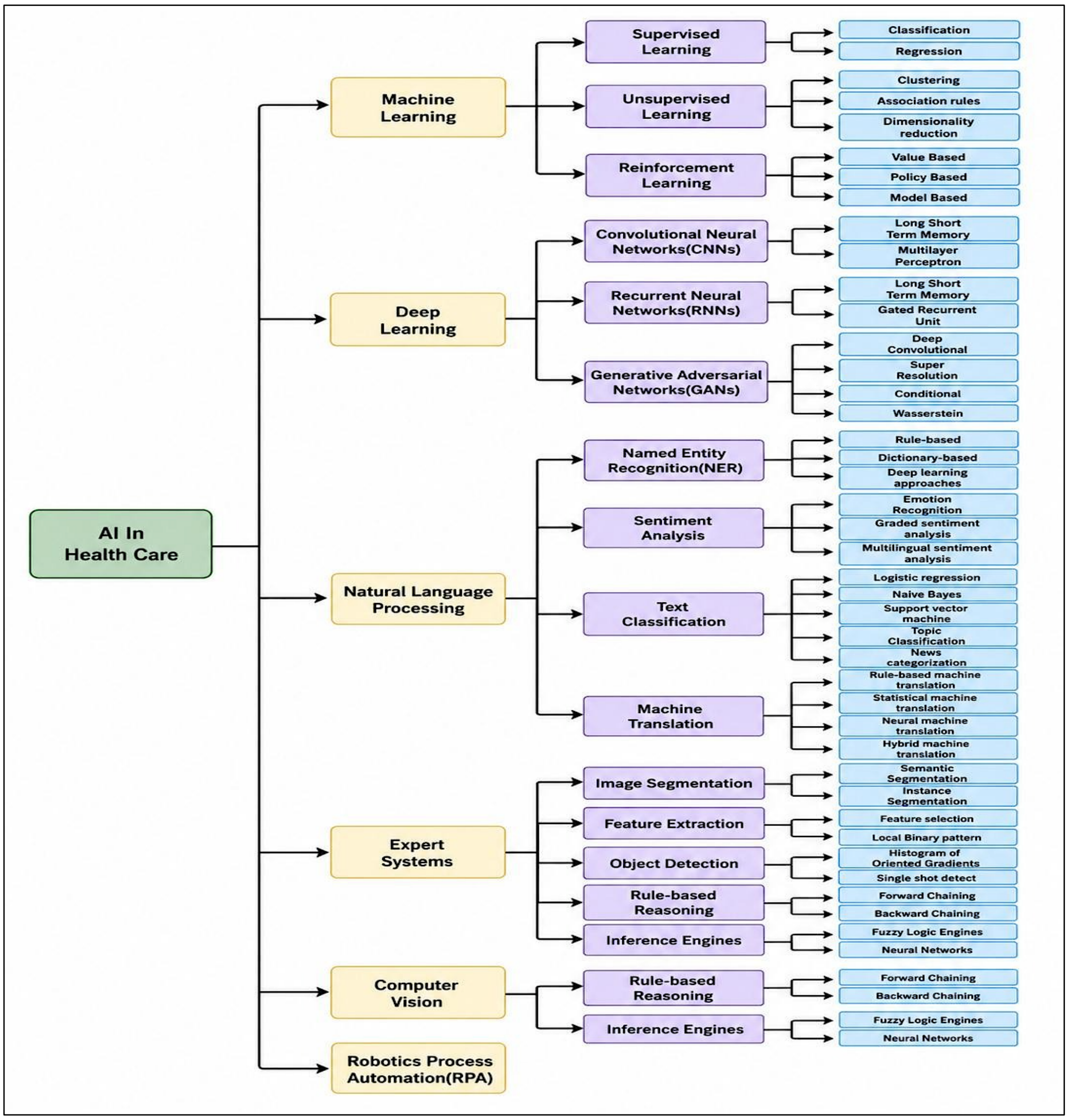

Figure 2: Methods and Techniques used in AI Healthcare System

The background study offers a thorough examination of the many approaches and strategies applied in the medical field. It focuses on using AI to enhance diagnosis, treatment, and patient care procedures. Key developments and approaches in AI healthcare are highlighted in Figure 2.

Machine Learning (ML)

Supervised Learning: Training models using labelled datasets with known right answers (outputs) is known as supervised learning as mentioned in Figure 3. Applications for this include classifying medical pictures (e.g., differentiating between benign and malignant tumours) and forecasting outcomes for patients (e.g., predicting if a patient will acquire a condition like diabetes).

$$y^{new} = f\,(x^{new}; \theta)$$

Unsupervised Learning: Involves algorithms learning on unlabelled data as mentioned in Figure 4. Finding previously unidentified risk factors for diseases or grouping patients who have similar medical records for targeted therapies are two examples of how this might be helpful in uncovering hidden patterns or groups in healthcare data.

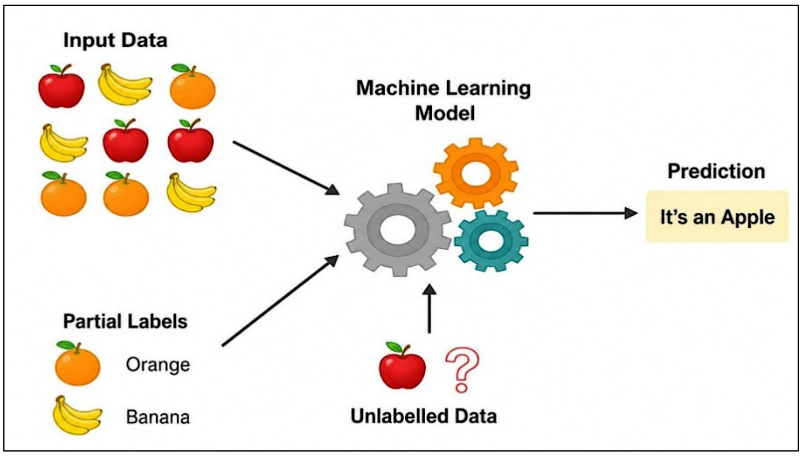

Figure 3: Work Flow of Supervised Learning

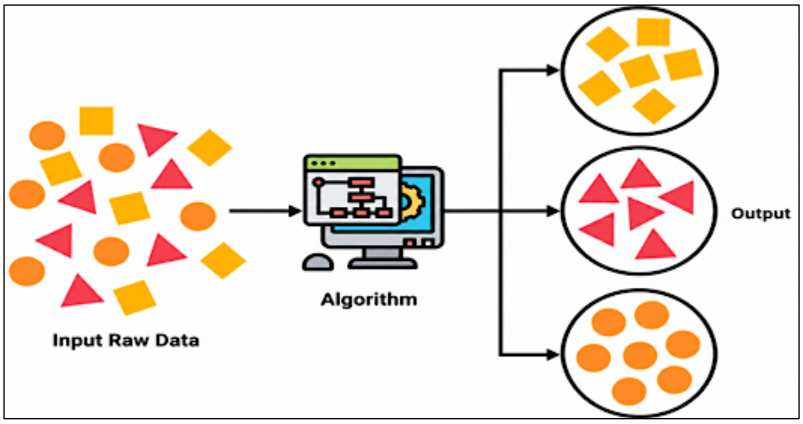

Figure 4: Procedure Chain of Unsupervised Learning

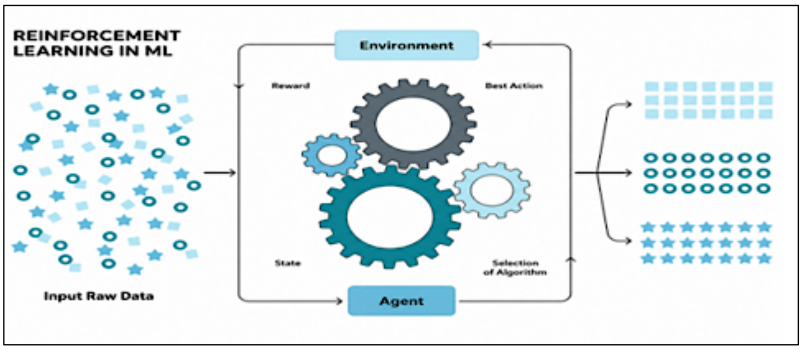

Figure 5: Process Map of Reinforcement Learning

Reinforcement Learning: Emphasizes rewarding algorithms for making the right judgments in order to train them to make a series of decisions. By continuously adjusting based on feedback, reinforcement learning is utilized in the healthcare industry to improve robotic surgery procedures and optimize treatment programs as mentioned in Figure 5 (7).

Deep Learning (DL)

Convolutional Neural Networks (CNNs): For image processing applications, convolutional neural networks, or CNNs, are widely utilized as mentioned in Figure 6. CNNs are quite good at automatically extracting characteristics in medical pictures, including radiology scan abnormalities, fractures, and malignancies.

Recurrent Neural Networks (RNNs): In order to handle continuous information, like timeseries data from devices used by patients (such as blood pressure or heart rate over time) or analyse patient medical records in order to forecast future health outcomes, recurrent neural networks, or RNNs, are frequently employed as mentioned in Figure 7.

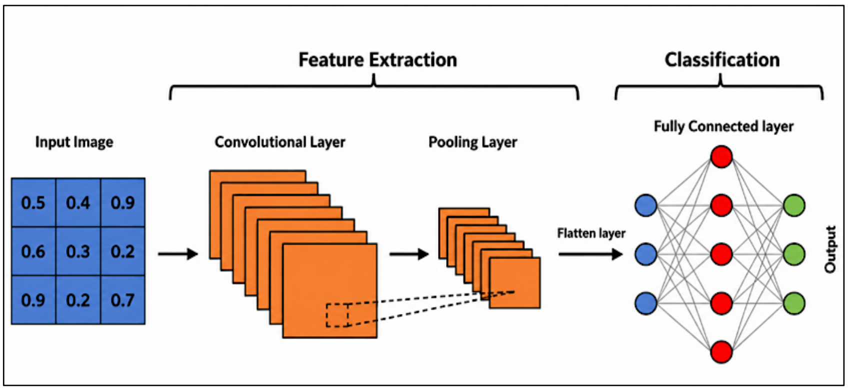

Figure 6: Task Flow of Convolutional Neural Networks

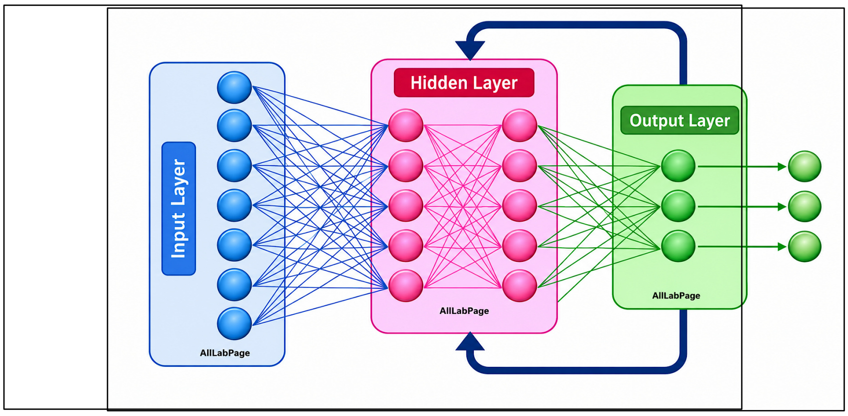

Figure 7: Process Pipeline of Recurrent Neural Network

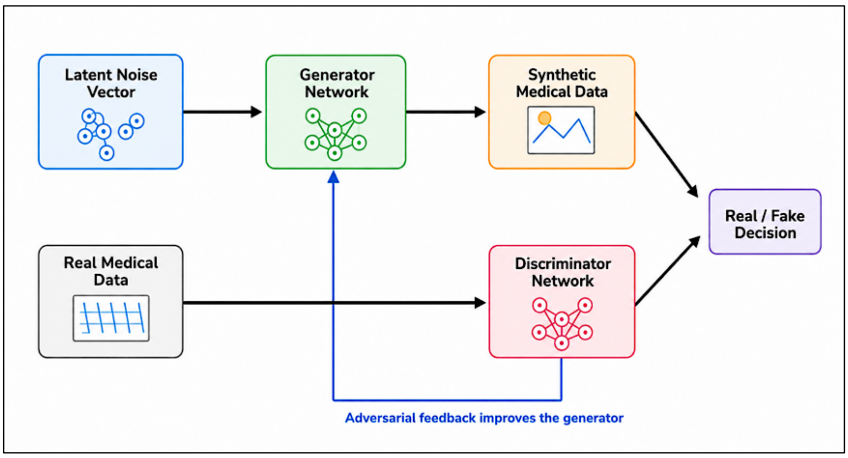

Figure 8: Progression Path of Generative Adversarial Networks

Generative Adversarial Networks (GANs): When real-world information is scarce or hard to come by, GANs are employed to create artificial medical data for AI model training. They can also produce realistic visuals for medical diagnostic tool training in imaging activities as mentioned in Figure 8.

Natural Language Processing (NLP)

Named Entity Recognition (NER): Aids in the recognition and categorization of particular textual elements, including patient demographics, drug names, symptoms, and illness names.

Sentiment Analysis: Used to assess patient happiness or identify any problems in patient care by examining the emotional content or tone of reviews, social media posts, and patient feedback.

Text Classification: Involves categorizing medical texts (e.g., EHR notes or research papers) into predefined categories (e.g., identifying whether a text is related to a particular condition or treatment) as mentioned in Figure 9.

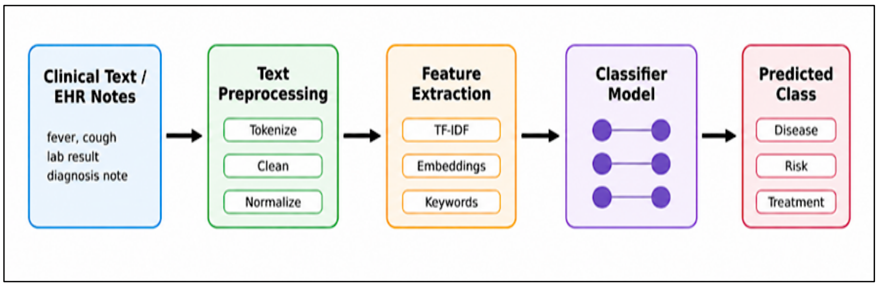

Figure 9: Process Flow Text Classification. Input text is converted into structured features and assigned to predefined healthcare categories

Machine Translation: Helps in translating medical content between languages, facilitating communication in diverse healthcare settings. Image Segmentation: Creates zones for medical photos to facilitate analysis. To separate and analyse tumours or other abnormality, for instance, a CT image can be segmented. Feature Extraction finds significant characteristics in medical images (such as edges, textures, and forms) that point to particular diseases, like identifying small calcium deposits in the breast cancer screenings. Object Detection finds and categorizes items in a picture, such as tumours, fractures, or indications of retinal disorders.

Expert Systems

Rule-based Reasoning: Uses a predetermined set of principles to simulate how humans make decisions. For instance, a system may provide possible diagnoses or treatment alternatives based on rules on the patient's symptoms, medical history, and test findings as mentioned in Figure 10.

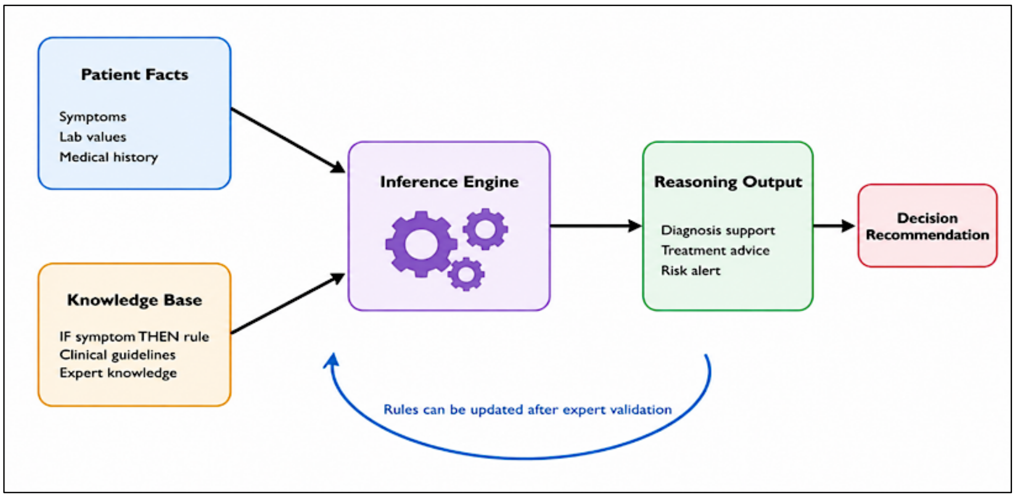

Figure 10: Process Flow of Rule-based Reasoning

Inference Engines: Analyse the knowledge base's rules to derive conclusions or offer suggestions based on the provided data (8).

Methodology

This study adopts a systematic review methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, consistency, and reproducibility in the selection of relevant literature. The review process follows structured stages, including identification, screening, eligibility assessment, and final inclusion of studies. Relevant articles were retrieved from major scientific databases such as IEEE Xplore, ScienceDirect, Google Scholar, and PubMed using predefined keywords, including “Artificial Intelligence in Healthcare”, “Machine Learning in Medical Diagnosis”, and “AI-based Healthcare Systems.” Additional sources, including IGI Global, Koreamed, IJAETI, and Sage Publishing, were also explored to ensure comprehensive coverage of interdisciplinary research, as summarized in Table 1. The distribution of selected articles across these sources is illustrated in Figure 11. A deduplication step was performed to eliminate overlapping records retrieved from multiple databases. From figure, X axis shows the Database, Y axis shows the Number of articles found from online source. This process involved manual and automated comparison of article titles, authors, and publication years to ensure that unique studies were included for screening (9). Although Google Scholar shows a higher number of retrieved articles compared to other databases, it is important to note that it aggregates results from multiple sources, which may lead to duplication. To ensure data accuracy, a systematic deduplication process was carried out by comparing titles, authors, and publication details across all retrieved records. Duplicate and overlapping studies were removed before the screening stage. As a result, unique and relevant articles were considered for further analysis.

Table 1: List of Research Articles Searched in Different Databases

Databases	Elsevier	MDPI	Springer	IEEE Explore	Wiley Online Library	ResearchGate	Springer Nature	Google Scholar	Other Sources
No. of Articles	6	9	12	19	2	2	2	38	12

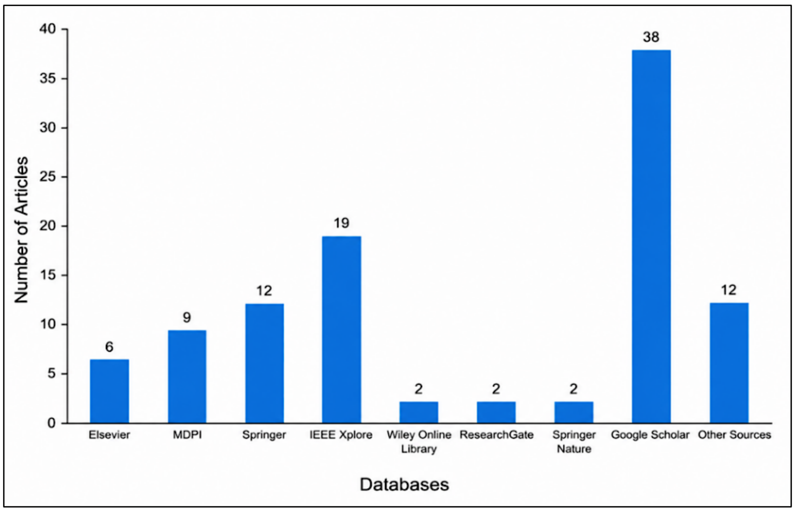

Figure 11: Graphical Representation of List of Research Articles

A structured search strategy was employed to retrieve relevant studies from databases including IEEE Xplore, ScienceDirect, Google Scholar, and PubMed. The search was conducted using Boolean operators and keywords such as (“Artificial Intelligence” AND “Healthcare” AND “Machine Learning”), (“Deep Learning” AND “Medical Diagnosis”), and (“AI-based Healthcare Systems” OR “Clinical Decision Support”). Additional filters were applied to include studies published between 2018 and 2025 and limited to peer-reviewed journal articles and conference papers. This systematic search approach ensures reproducibility and comprehensive coverage of relevant literature. A systematic screening process was followed to ensure the inclusion of only relevant and high-quality studies (10). The study selection process was conducted following the PRISMA framework to ensure transparency and reproducibility. Initially, a total of 102 records were identified from multiple databases. After removing 10 duplicate records, 92 unique articles remained for the screening phase. During the screening process, 10 records were excluded based on title and abstract, as they were not directly related to AI applications in healthcare. Consequently, 82 articles were considered for eligibility assessment. At the eligibility stage, 16 reports could not be retrieved or did not meet the inclusion criteria. The remaining 66 full-text articles were assessed in detail, out of which 1 article was excluded due to insufficient methodological validation. Finally, a total of 65 studies were included in the systematic review. This detailed breakdown ensures a clear understanding of the study selection process and enhances the reproducibility of the review.

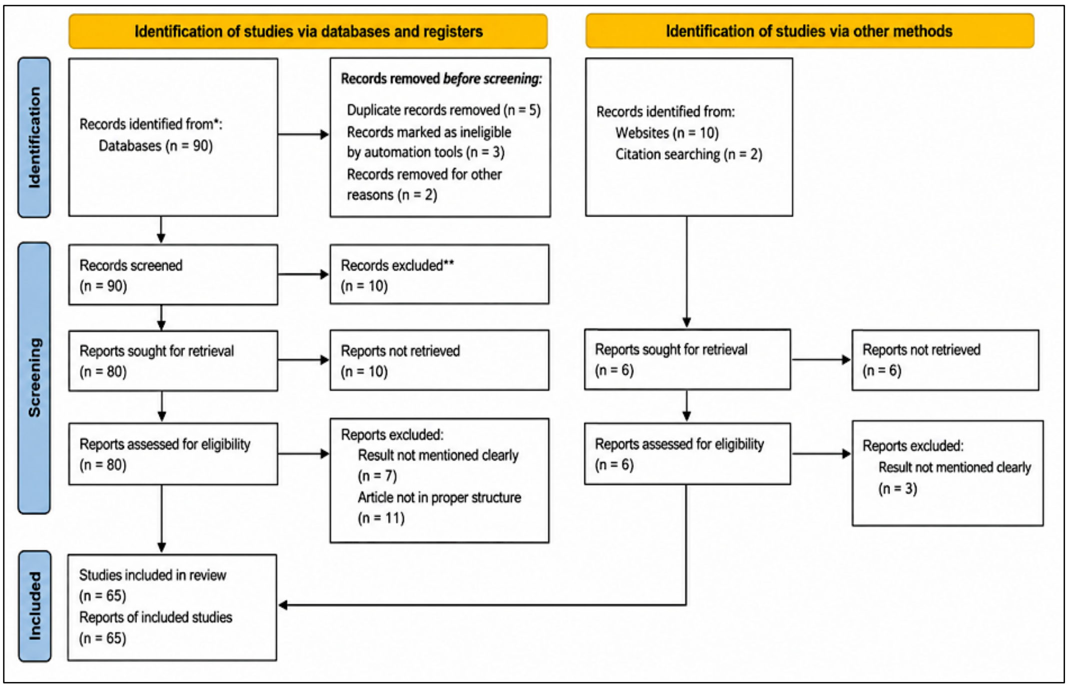

Figure 12: PRISMA Flowchart for Literature Review

The overall study selection procedure is represented using a PRISMA flow diagram Figure 12, which provides a transparent overview of the number of records identified, screened, assessed for eligibility, and included in the final analysis. This structured approach ensures methodological rigor and minimizes selection bias. Furthermore, the selected studies were analysed based on key parameters, including domain, research objectives, dataset, methodology, performance metrics, and identified challenges. These parameters, summarized in Table 2, provide a comprehensive framework for evaluating existing research and identifying gaps for future investigation.

Results and Discussion

The PRISMA-based systematic review highlights the growing impact of Artificial Intelligence (AI) in healthcare applications such as disease diagnosis, medical imaging, clinical decision support, and drug discovery. Deep learning models including CNNs and RNNs demonstrated strong performance in radiology, oncology, and disease prediction tasks, while machine learning methods such as SVM and Random Forest showed reliable results for structured clinical data analysis. The reviewed studies indicate that AI improves diagnostic accuracy, early disease detection, and personalized healthcare management. Hybrid models combining structured and unstructured healthcare data achieved better predictive performance compared with traditional approaches. However, challenges including limited annotated datasets, class imbalance, privacy concerns, lack of interpretability, and poor model generalization remain significant barriers to real-world clinical deployment.

Discussion for Problems and Challenges

The problems and challenges identified from the study are summarized here. These issues highlight key limitations and areas for improvement. They provide insight into the gaps in current research and potential directions for future work. A comparative analysis of selected studies is presented in Table 2, summarizing the techniques used, datasets, performance outcomes, strengths, limitations, and research gaps (11). This analysis provides a clearer understanding of the current state of AI applications in healthcare and highlights areas for improvement.

Recent studies on AI in healthcare can be organized into key thematic areas to provide a clearer analytical perspective. Significant progress has been observed in diagnostics and predictive analytics, where machine learning and deep learning models enhance disease detection and clinical decision-making using complex datasets (12). The integration of AI with blockchain has been explored to improve data security, privacy, and interoperability through decentralized data management. Additionally, AI-driven IoT healthcare systems enable real-time patient monitoring and support personalized care using data from wearable devices and sensors. At the same time, security and privacy remain critical challenges, leading to the development of robust frameworks for protecting sensitive healthcare data (13, 14). The emergence of explainable AI (XAI) addresses the need for transparency and interpretability in clinical applications, improving trust and adoption. Moreover, AI has demonstrated strong potential in drug discovery, accelerating the identification of therapeutic candidates through large-scale data analysis.

Ontology-based standardization improves interoperability by converting heterogeneous Electronic Health Record (EHR) data into a unified, structured format (15). Clinical information, such as symptoms and diagnoses, can be mapped to standardized vocabularies like SNOMED CT and Human Phenotype Ontology, ensuring semantic consistency across systems. For example, terms like "high blood sugar" can be standardized as "hyperglycemia," enabling uniform interpretation. This mapping allows seamless data sharing across healthcare platforms and supports efficient data integration for AI applications. Consequently, ontology integration enhances clinical decision-making, reduces ambiguity, and enables scalable, data-driven healthcare solutions (16).

Table 2: Comparative Analysis of Reviewed Studies

Domain	Techniques	Dataset	Accuracy	Evaluation Metrics	Strengths	Limitations	Research Gaps	Refs.
Disease Prediction	ML, SVM	Clinical dataset	High	Precision, Recall, F1-score	Early detection	Limited dataset	Needs scalability	(17)
Medical Imaging	CNN, DL	MRI/CT images	Very High	Accuracy, ROC-AUC, F1-score	High accuracy	Requires large data	Interpretability issue	(18)
IoT Healthcare	AI + IoT	Sensor data	High	Accuracy, Recall	Real-time monitoring	Security issues	Data privacy concerns	(19)
Blockchain + AI	ML + Blockchain	Distributed data	Moderate	Accuracy	Secure data sharing	High complexity	Scalability issues	(20)
XAI Systems	Explainable ML	Clinical/EHR data	Moderate	Accuracy, F1-score	Transparency	Lower accuracy	Trade-off between accuracy and explainability	(21)
Remote Monitoring	AI + IoT	Wearable sensor data	High	Accuracy, Recall, F1-score	Continuous monitoring	Data heterogeneity	Need for data standardization	(22)
Federated Learning	FL + AI	Distributed healthcare data	Moderate	Accuracy, ROC-AUC	Privacy preservation	Communication overhead	Improve model efficiency	(23, 24)
Healthcare Chatbots	NLP, AI Chatbots	Text/EHR data	Moderate	Accuracy, Precision	Faster response, accessibility	Lack of trust	Improve reliability and user acceptance	(25, 26)
Security Frameworks	AI + Cybersecurity	Network data	Moderate	Accuracy, Recall	Effective threat detection	Complex implementation	Real-time adaptability needed	(27, 28)
Drug Discovery	DL, ML	Biomedical datasets	High	Accuracy, ROC-AUC	Faster drug identification	Data dependency	Need for clinical validation	(29, 30)

The diagnosis of diabetes is described as a very complex issue, which poses significant challenges in developing effective predictive models (31). There is a pressing need for accurate and timely illness forecasting in the healthcare sector, indicating that existing models may not be sufficiently responsive or precise (32). The increased volume of raw clinical data can lead to scalability issues, as the verification of new transactions on the blockchain can be time-consuming, particularly with certain consensus algorithms like Proof of Work (PoW) (33). The potential for malicious attacks to alter COVID-19 data collected from various sources raises concerns about the validity of AI learning and the overall integrity of the healthcare data (34). The latency in transaction approval on the blockchain can hinder the system's ability to handle large transaction volumes efficiently. Solutions like permissioned blockchains and sharding are suggested to address these scalability issues (35). The transition from traditional healthcare models to a decentralized, patient-centric framework requires overcoming resistance to change and ensuring compatibility with existing healthcare infrastructures (36). The simulations in the toy model demonstrate that even with defined parameters and instructions, AI systems can produce unpredictable results when datasets are altered or when certain groups are excluded. This unpredictability poses a significant challenge in ensuring reliable and equitable healthcare outcomes (37). A significant portion of the population lacks access to m-health systems due to financial constraints, lack of knowledge, and skills to use these technologies.

Developing resilient, precise, and secure methods for analyzing large datasets, especially in medical imaging and diagnostics, is crucial for future advancements in m-health (38). There is a need for comprehensive reviews and validations of AI models in conjunction with digital health tools to ensure their clinical efficacy and reliability (39). This paper discusses how artificial intelligence can complement physicians by improving diagnostic accuracy, treatment planning, and healthcare efficiency. It emphasizes the collaboration between human expertise and AI to achieve better patient outcomes (40). Some energy-efficient approaches for transmitting images over Wireless Sensor Networks (WSNs) do not account for network delay, which can be critical in healthcare scenarios (41). Patients in remote areas often lack access to timely medical care and monitoring, exacerbating health risks (42, 43). This review explains the applications of deep learning in healthcare, particularly in medical imaging, diagnostics, and clinical decision support systems. It also highlights challenges related to data quality, interpretability, and clinical implementation (44). Traditional healthcare systems often suffer from delays in data processing and response times, which can be critical in emergencies (45). Managing distributed data effectively across multiple edge nodes (46).

The COVID-19 pandemic highlighted the need for efficient and secure healthcare systems to respond to public health emergencies (47). Physicians may spend a significant amount of time on routine tasks, such as answering patient queries and providing basic information, which can limit their availability for complex cases (48). The lack of interoperability between different healthcare systems and databases hinders data sharing and analysis (49, 50). Traditional healthcare systems may lack transparency, making it difficult to track the movement of medical supplies, medications, and patient records (51). Remote and elderly patients may have limited access to healthcare facilities and healthcare professionals (52). Healthcare systems are increasingly targeted by cyberattacks, which can compromise patient data and disrupt critical services (53, 54).

Addressing potential biases in AI algorithms, ensuring responsible use of AI, and managing the impact on healthcare professionals and patients (55). Healthcare resources, including doctors, nurses, and medical equipment, can be underutilized or inefficiently allocated, leading to suboptimal patient care (56, 57). AI can help automate the process of mapping data from different sources to a common standard (58). Decision-makers need to be aware of the level of uncertainty associated with AI/ML-generated predictions and recommendations (59, 60). AAL systems need to be designed with a focus on the needs and preferences of older adults, requiring real-life testing and user feedback (61). Traditional methods like physical examinations can be ineffective in early detection, as heart disease often acts as a "silent killer" (62, 63). The article notes that patients often have limited autonomy in choosing or customizing AI-powered healthcare solutions. Empowering patients with more choices and control over their AI-assisted care is essential. The overall study defines the architectural process flow of AI with healthcare as mentioned in Figure 13.

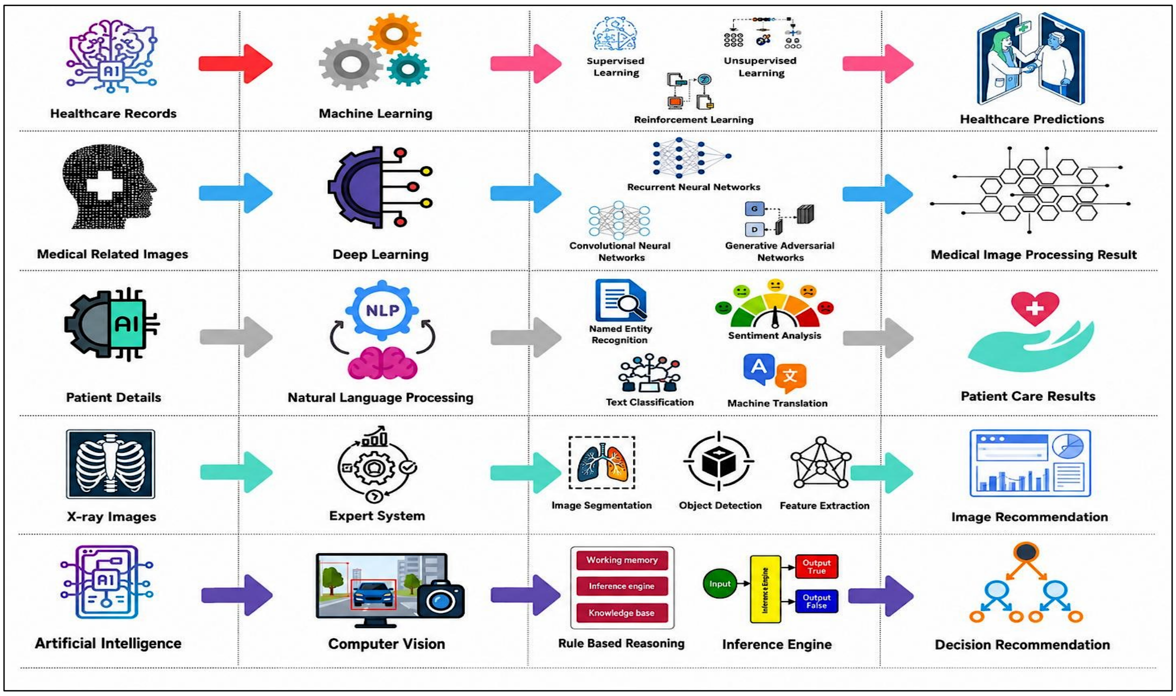

Figure 13: Architectural Flow of AI with Healthcare

Future Enhancement: Artificial intelligence (AI) is expected to significantly enhance healthcare by improving diagnostic accuracy, enabling structured data access, and strengthening predictive capabilities for better patient outcomes (64). However, achieving high accuracy remains challenging due to the complexity of diseases such as heart disease, diabetes, and cancer. The use of diverse, high-quality datasets and the integration of multi-modal data, including medical imaging, electronic health records, and real-time sensor data, can improve model generalizability and prediction performance (65).

Efficient data management is another critical factor in AI-driven healthcare. Limited interoperability across healthcare systems often restricts effective data sharing. Ontology-based approaches can address this issue by standardizing clinical data and improving data integration and accessibility. These frameworks also support the transformation of unstructured data into structured formats, enhancing the reliability of AI applications.

Future advancements should focus on improving predictive accuracy and real-time decision-making. The integration of continuous data streams from wearable devices and monitoring systems can enable timely interventions and personalized treatment strategies. Additionally, explainable AI (XAI) techniques can improve transparency and trust in AI systems, supporting better clinical decision-making. Advanced techniques such as deep learning and reinforcement learning can further enhance prediction capabilities by identifying complex patterns and adapting to patient data over time. Overall, improvements in data quality, model design, and interpretability are essential for developing reliable and efficient AI-based healthcare systems.

Conclusion

In conclusion, this study highlights the significant potential of AI to improve healthcare by enhancing diagnostic accuracy, treatment planning, and overall healthcare management. By reviewing various studies using the PRISMA framework, we identified important factors such as the areas where AI is applied, the methods used, the datasets involved, and how accurate AI models are. AI has shown great promise in fields like medical imaging, clinical decision-making, predictive analytics, and drug development. However, there are still several challenges that need to be addressed for AI to be more widely used in healthcare. One major issue is the availability and quality of data; many AI models require large, high-quality datasets, but these are often lacking due to concerns about privacy, data imbalance, and poor labelling. These problems can affect the accuracy and generalizability of AI models, making it hard for them to work effectively in different clinical settings or with diverse patient groups. Another challenge is the difficulty in understanding how some AI models make decisions, especially deep learning algorithms, which are often considered "black boxes." This lack of transparency makes it harder for healthcare professionals to trust AI tools and adopt them in practice. Ethical issues, such as bias in AI algorithms and concerns about fairness, are also important. If AI models are not carefully managed, they could contribute to existing healthcare inequalities. The study also points out several areas where more research is needed, including the development of clearer, more understandable AI models, better datasets, and standardized methods for integrating AI into healthcare systems. By addressing these challenges, future research can help create AI systems that are more reliable, fair, and useful for healthcare professionals. In the end, overcoming these barriers will lead to more effective AI tools, improving patient care and making healthcare delivery more efficient and equitable.

Abbreviations

AI: Artificial Intelligence, ANN: Artificial Neural Network, DD: Diseases Diagnosis, DN: Dynamic Update, DSS: Decision Support System, EE: Enhance Explainability, GNN: Graphical Neural Networks, KP: Knowledge Representation, PTP: Personalized Treatment Planning.

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Author Contributions

Priyadharshini U: Writing - Original Draft Preparation, Conceptualization, Methodology, Data Curation, Vijayan R: Writing – Reviewing and Editing, Supervision, Validation, Investigation.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability

Not Applicable.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the manuscript. All content generated through AI was critically reviewed, edited, and verified by the authors to ensure accuracy, originality, and compliance with academic standards. The authors take full responsibility for the integrity and validity of the final version of the manuscript.

Ethics Approval

This research did not involve experiments on live vertebrates, higher invertebrates, or human participants. Therefore, ethical approval and informed consent were not required. This manuscript does not contain any reproduced or adapted images. All figures and visual elements are original and created by the authors.

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