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Artificial Intelligence-Based Healthcare Technology: A Semantic Literature Review on Disease Diagnosis and Prediction Systems for Heart Disease, Diabetes, and Cancer Using Machine Learning and Deep Learning Algorithms

Ahmad Fauzan [a,1,*], Debi Setiawan [b,2]

[a,b] University Abdurrab
[1] AhmadFauzan@gmai.com*; [2] debisetiawan@univrab.ac.id
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Abstract

The rapid advancement of Artificial Intelligence (AI) has significantly influenced the development of intelligent healthcare systems, particularly in disease diagnosis and prediction. Machine learning and deep learning techniques have been widely applied to analyze complex medical data, enabling improved diagnostic accuracy and early disease detection. Despite extensive research in this area, existing studies are often fragmented, focusing on specific diseases or algorithms, which limits comprehensive understanding and cross-domain comparison. This study presents a semantic literature review of AI-based healthcare technologies for disease diagnosis and prediction, with a focus on heart disease, diabetes, and cancer. The review systematically analyzes recent peer-reviewed studies published within the last two years, examining employed datasets, machine learning and deep learning algorithms, evaluation metrics, and application contexts. A semantic categorization framework is adopted to identify relationships among disease domains, data types, algorithmic approaches, and performance indicators. The results reveal prevailing research trends, commonly used models, and emerging methodological practices, including the integration of hybrid models, visualization-based evaluation, and explainable AI techniques. Furthermore, this study highlights existing research gaps and challenges related to data heterogeneity, evaluation standardization, and real-world clinical applicability. The findings provide a structured overview of current advancements and offer valuable insights for future research and development of robust AI-driven healthcare systems.

Keywords: Artificial Intelligence, Disease Diagnosis, Decision Tree, Naive Bayes, Deep Learning, Neural Network, Semantic Literature;

1. Introduction

The rapid advancement of Artificial Intelligence (AI) has significantly transformed the healthcare sector, particularly in the areas of disease diagnosis and prediction [1], [2]. AI-based healthcare technology enables intelligent analysis of large-scale medical data, supporting clinicians in early detection, decision-making, and personalized treatment planning [3]. With the increasing availability of electronic health records, medical imaging data, and clinical datasets, AI techniques have become essential tools for improving diagnostic accuracy and predictive performance in modern healthcare systems [4], [5]. Among various medical conditions, heart disease, diabetes, and cancer remain the leading causes of morbidity and mortality worldwide [6], [7]. These diseases are characterized by complex risk factors, high prevalence, and substantial economic burden [8]. Early diagnosis and accurate prediction are critical to reducing complications and improving patient outcomes [9]. However, traditional diagnostic approaches often rely on manual analysis and rule-based systems, which may suffer from limitations in scalability, subjectivity, and predictive capability [10]. Consequently, intelligent systems based on machine learning (ML) and deep learning (DL) algorithms have emerged as promising solutions to address these challenges [11], [12]. Machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Logistic Regression, and Gradient Boosting have been widely applied to structured clinical data for disease classification and risk prediction [13]–[15]. These methods demonstrate strong performance in handling heterogeneous features and identifying hidden patterns in medical datasets [16]. Meanwhile, deep learning techniques, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have shown remarkable success in medical image analysis and time-series prediction, particularly in cancer detection, cardiovascular imaging, and chronic disease monitoring [17]–[19]. The integration of ML and DL approaches has further enhanced diagnostic accuracy and robustness in AI-driven healthcare applications [20]. Despite the rapid growth of AI-based diagnostic and predictive systems, existing studies are often fragmented, focusing on specific diseases, datasets, or algorithms [21]. A comprehensive understanding of technological trends, commonly used algorithms, and application domains remains limited [22]. Furthermore, variations in evaluation metrics, datasets, and experimental settings make it difficult to compare results across studies and assess their clinical applicability [23]. Therefore, a systematic and semantic-oriented literature review is essential to synthesize existing research, identify research gaps, and highlight future directions in AI-based healthcare technology [24]-[30]. This paper presents a semantic literature review on AI-based disease diagnosis and prediction systems, with a specific focus on heart disease, diabetes, and cancer. The review systematically analyzes published studies that employ machine learning and deep learning algorithms, examining their methodologies, datasets, performance metrics, and application contexts [25]–[27]. By providing a structured overview of current research trends and technological advancements, this study aims to contribute valuable insights for researchers, practitioners, and policymakers involved in the development of intelligent healthcare systems.

2. **The Proposed Method/Algorithm**

This study does not propose a new classification or prediction algorithm; instead, it employs a semantic literature review approach to systematically analyze existing Artificial Intelligence-based healthcare technologies for disease diagnosis and prediction. The proposed method focuses on identifying, categorizing, and synthesizing previous research related to heart disease, diabetes, and cancer that utilize machine learning and deep learning algorithms. Through this approach, the study aims to extract meaningful patterns, research trends, and technological insights from the existing body of literature. The review process emphasizes the semantic relationships among research objectives, datasets, algorithms, and performance evaluation metrics. By adopting a structured review methodology, this study ensures consistency, reproducibility, and comprehensive coverage of relevant publications. The overall method consists of literature selection, semantic categorization, and comparative analysis of AI-based diagnostic and predictive systems reported in prior studies.

2.1. Selecting a Template

This paper is prepared using the official IEEE conference template and the Tetrahedron Letters template by Elsevier, modified in Microsoft Word 2007 and saved as a “Word 97–2003 Document.” The template has been specifically designed for A4 paper size to ensure compatibility with the publication requirements of IJIIS proceedings. Authors must confirm that the correct template version is used prior to manuscript preparation. The use of an inappropriate paper size, such as US letter format, may result in formatting inconsistencies and non-compliance with the submission guidelines. The predefined template facilitates uniform presentation by incorporating standardized margins, column widths, line spacing, and font styles. These built-in specifications enable authors to focus on content development while ensuring automatic compliance with electronic publication requirements.

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3. Method

This study adopts a **semantic literature review methodology** to systematically analyze Artificial Intelligence-based healthcare technologies for disease diagnosis and prediction, focusing on heart disease, diabetes, and cancer. The methodology is designed to synthesize recent research findings, identify technological trends, and uncover research gaps related to machine learning and deep learning applications in healthcare. Unlike traditional systematic reviews, this approach emphasizes **semantic relationships** among research components, including disease types, data sources, algorithms, and evaluation metrics. The overall research methodology consists of five main stages: literature identification, screening and selection, semantic categorization, comparative analysis, and synthesis of findings. Each stage is described in detail to ensure transparency, reproducibility, and methodological rigor.

3.1. Literature Identification

Relevant literature was identified through comprehensive searches in major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and MDPI. The search strategy focused on peer-reviewed journal articles and conference proceedings published within the last two years to ensure the inclusion of up-to-date research developments.

Keywords and search strings were formulated by combining terms related to Artificial Intelligence, healthcare, disease diagnosis, disease prediction, machine learning, deep learning, heart disease, diabetes, and cancer. Boolean operators were applied to refine the search results and improve relevance. Only publications written in English were considered.

3.2. Screening and Selection Criteria

The initial search results were screened based on predefined inclusion and exclusion criteria to ensure quality and relevance. The inclusion criteria were as follows:

1. Studies applying machine learning or deep learning algorithms for disease diagnosis or prediction.
2. Research focusing on heart disease, diabetes, or cancer.
3. Articles published in peer-reviewed journals or reputable conference proceedings.
4. Studies reporting clear methodologies and evaluation metrics.

Exclusion criteria included:

1. Non-peer-reviewed articles, editorials, or opinion papers.
2. Studies lacking sufficient methodological details.
3. Research unrelated to healthcare or disease prediction tasks.

This screening process ensured that only high-quality and methodologically sound studies were included in the review.

3.3. Semantic Categorization Framework

After selection, the included studies were analyzed using a **semantic categorization framework**. Each article was mapped according to multiple semantic dimensions, including:

1. Disease domain (heart disease, diabetes, cancer),
2. Data type (structured clinical data, medical imaging, time-series data),
3. Algorithm category (machine learning, deep learning, hybrid models),
4. Specific techniques (SVM, Random Forest, CNN, LSTM, ensemble methods),
5. Evaluation metrics (accuracy, precision, recall, F1-score, AUC),
6. Visualization and interpretability methods.

This multi-dimensional semantic mapping enables cross-study comparison and highlights relationships that are not apparent in conventional narrative reviews.

3.4. Comparative and Trend Analysis

A comparative analysis was conducted to evaluate algorithmic performance trends and methodological preferences across different disease domains. The analysis focused on identifying:

1. Frequently used algorithms and their reported effectiveness,
2. Dataset characteristics and preprocessing strategies,
3. Common evaluation practices and validation methods,
4. Emerging trends such as explainable AI, hybrid models, and multimodal learning.

Visualization techniques reported in the reviewed studies, including confusion matrices, ROC curves, feature importance plots, and learning curves generated using Python-based tools, were also analyzed as indicators of methodological maturity and transparency.

3.5. Synthesis and Novelty Identification

In the final stage, findings from the comparative analysis were synthesized to identify research gaps, limitations, and future research opportunities. The novelty of this study lies in its **cross-disease semantic synthesis**, which integrates insights from heart disease, diabetes, and cancer studies into a unified analytical framework. This synthesis enables the identification of transferable algorithmic strategies and shared challenges across disease domains.

The methodological outcomes serve as a foundation for proposing future research directions, including the development of generalized AI models, improved explainability, standardized evaluation protocols, and real-world clinical deployment considerations.

Methodological Contribution

By applying a structured semantic literature review methodology, this study provides a reproducible and comprehensive framework for analyzing AI-based healthcare technologies. The methodology ensures alignment between research objectives, results, and discussion, while offering practical insights for researchers and practitioners seeking to advance intelligent healthcare systems.

4. Results and Discussion

This section presents the results of the semantic literature review and discusses the key findings derived from the analyzed studies. The discussion focuses on disease-specific trends, algorithmic performance, data characteristics, and visualization practices used to support model evaluation. The results are organized based on the targeted diseases—heart disease, diabetes, and cancer—while emphasizing cross-domain insights and technological convergence.

4.1. Distribution of Diseases and Algorithms

The semantic analysis reveals that heart disease, diabetes, and cancer are the most frequently studied diseases in AI-based healthcare research. Heart disease and diabetes studies predominantly utilize structured clinical datasets, while cancer-related research heavily relies on medical imaging data. This distinction significantly influences algorithm selection and model architecture.

Machine learning algorithms such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and Gradient Boosting are widely employed for heart disease and diabetes prediction due to their interpretability and robustness when handling tabular data. In contrast, deep learning models—particularly Convolutional Neural Networks (CNN)—dominate cancer diagnosis tasks, especially in breast cancer, lung cancer, and skin cancer detection using radiological and histopathological images.

The results indicate a clear algorithm–data dependency, where structured data favors classical machine learning models, and high-dimensional image data necessitates deep learning approaches. This finding confirms and extends previous studies by semantically mapping algorithm suitability across disease domains rather than evaluating them in isolation.

4.2. Performance Trends and Evaluation Metrics

Across the reviewed literature, accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) are the most commonly reported performance metrics. For heart disease and diabetes prediction, ensemble-based models such as Random Forest and XGBoost consistently achieve higher predictive performance compared to single classifiers. In cancer diagnosis, CNN-based architectures demonstrate superior accuracy, often exceeding 90% in controlled experimental settings.

However, the semantic review highlights that performance superiority is highly context-dependent, influenced by dataset size, feature selection, class imbalance, and validation strategies. Many studies report high accuracy without sufficient discussion of dataset bias or generalizability, particularly when using small or single-source datasets.

A notable trend observed in recent studies is the increasing use of cross-validation and external dataset testing, indicating a shift toward more reliable and reproducible evaluation practices. This evolution reflects growing awareness of clinical deployment challenges in AI-based healthcare systems.

4.3. Data Visualization and Graphic Model Support

An important finding of this review is the growing role of graphical model support and data visualization, particularly through Python-based tools such as Matplotlib, Seaborn, and Plotly. Visualizations are widely used to enhance model interpretability and support performance analysis. Common graphical representations include:

Confusion matrices to analyze classification errors,
Receiver Operating Characteristic (ROC) curves to evaluate model discrimination capability,
Feature importance plots for machine learning models,
Training and validation loss curves for deep learning models.

These visual tools provide intuitive insights into model behavior and are increasingly recognized as essential components of AI-based healthcare research. The integration of visualization frameworks supports transparency and facilitates communication between data scientists and medical practitioners.

From a novelty perspective, recent studies demonstrate a transition from static result reporting toward visual analytics-driven evaluation, enabling more informed interpretation of diagnostic and predictive models.

4.4. Cross-Disease Semantic Insights and Model Transferability

One of the most significant outcomes of this study is the identification of semantic similarities across disease domains. Despite differences in clinical context, heart disease, diabetes, and cancer share common challenges, including data imbalance, missing values, and the need for early prediction.
The review reveals that certain algorithmic strategies—such as ensemble learning, hybrid ML–DL architectures, and feature selection techniques—are transferable across diseases. For example, ensemble models effective in heart disease prediction are increasingly adapted for diabetes risk stratification, while attention-based deep learning mechanisms initially developed for cancer imaging are being explored in cardiovascular imaging.
This cross-domain transferability represents a key advancement in AI-based healthcare technology, supporting the development of more generalized and scalable diagnostic frameworks.

4.5. Novelty and Research Gap Discussion

The primary novelty highlighted by the results lies in the semantic integration of disease-specific AI research into a unified analytical framework. Unlike conventional reviews that focus on a single disease or algorithm, this study synthesizes findings across multiple disease categories, revealing convergence patterns and emerging best practices.

5. Conclusion

As outlined in the Introduction, this study aimed to provide a comprehensive semantic literature review of Artificial Intelligence-based healthcare technologies for disease diagnosis and prediction, with a particular focus on heart disease, diabetes, and cancer using machine learning and deep learning algorithms. The findings presented in the Results and Discussion chapter demonstrate that these objectives have been successfully achieved through systematic analysis and semantic integration of existing studies across multiple disease domains.

The results confirm the expected outcomes stated in the Introduction, namely the identification of dominant algorithms, data characteristics, evaluation metrics, and technological trends in AI-based diagnostic and predictive systems. Furthermore, the semantic mapping approach adopted in this study enables direct comparability across diseases and algorithms, thereby ensuring conceptual and methodological compatibility between the research objectives and the reported results.

Based on the findings discussed, this study provides a structured foundation for future research and practical applications. The identified convergence of algorithmic strategies across different diseases highlights the potential development of generalized and transferable AI models for healthcare. In addition, the increasing role of data visualization, explainable artificial intelligence, and hybrid machine learning–deep learning architectures suggests promising directions for improving clinical interpretability and decision support systems.

From an application perspective, the synthesized results support the prospective integration of AI-based diagnostic and predictive technologies into clinical workflows, particularly for early disease detection and risk stratification. Future studies are encouraged to extend the reviewed approaches by incorporating multimodal data, conducting large-scale external validation, and developing standardized evaluation and visualization frameworks. These advancements are expected to enhance the reliability, scalability, and real-world applicability of AI-driven healthcare systems.

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