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ORIGINAL ARTICLE

Medical diagnosis with neural networks

Diagnóstico médico con redes neuronales

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Abstract

Artificial intelligence, through the use of artificial neural networks, has become a relevant tool in the transformation of diagnostic and predictive processes in contemporary medicine. This study analyzes the application of artificial neural networks for disease prediction and diagnostic support, as well as their integration with telemedicine platforms. Using a structured methodology that includes data collection, preprocessing and feature selection, neural model design and training, validation, and continuous monitoring, significant improvements were identified in the early detection of complex diseases and in clinical risk stratification. The results demonstrate a reduction in errors associated with human factors, improved personalization of treatments, and optimization of healthcare resource utilization. In addition, the developed systems showed potential for continuous patient monitoring and dynamic adaptation of clinical recommendations. Nevertheless, the study highlights the need for ongoing validation and ethical, responsible integration to ensure clinical effectiveness and safety

Keywords: artificial intelligence; artificial neural networks; medical diagnosis; telemedicine; disease prediction

Resumen

La inteligencia artificial, mediante el uso de redes neuronales artificiales, se ha consolidado como una herramienta relevante en la transformación de los procesos diagnósticos y predictivos en la medicina contemporánea. El presente estudio analiza la aplicación de redes neuronales artificiales para la predicción y el apoyo al diagnóstico médico, así como su integración con plataformas de telemedicina. A través de una metodología estructurada que abarca la recopilación, preprocesamiento y selección de datos, el diseño y entrenamiento de modelos neuronales, su validación y monitoreo continuo, se identificaron mejoras significativas en la detección temprana de enfermedades complejas y en la estratificación del riesgo clínico. Los resultados evidencian una reducción de errores asociados a factores humanos, una mayor personalización de los tratamientos y una optimización en el uso de recursos sanitarios. Asimismo, los sistemas desarrollados mostraron potencial para el seguimiento continuo de pacientes y la adaptación dinámica de las recomendaciones clínicas. No obstante, se destaca la necesidad de validación permanente y una integración ética y responsable para garantizar su efectividad y seguridad clínica.

Palabras clave: inteligencia artificial; redes neuronales artificiales; diagnóstico médico; telemedicina; predicción de enfermedades

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INTRODUCTION

The accelerated development of artificial intelligence (AI) has driven profound transformations across multiple scientific domains, with a particularly notable impact on contemporary medicine. The increasing digitalization of healthcare systems, together with the exponential growth in the volume and complexity of available clinical data, has created a favorable environment for the adoption of advanced computational models capable of supporting diagnostic, prognostic, and therapeutic decision-making. Within this context, artificial neural networks (ANNs) have emerged as one of the most influential approaches in deep learning, owing to their ability to model complex nonlinear relationships and extract clinically meaningful patterns from heterogeneous data sources (Esteva et al., 2021; Topol, 2021).

Medical diagnosis represents one of the areas in which the application of ANNs has demonstrated the greatest potential, particularly in scenarios characterized by high information density, the need for timely decisions, and substantial interindividual variability. Numerous studies have shown that deep learning–based models can match or even surpass human performance in specific diagnostic tasks, especially in the analysis of medical images, biomedical signals, and multimodal data, thereby improving diagnostic accuracy and reducing variability associated with individual clinical judgment (Rajpurkar et al., 2021; Shen et al., 2021). This progress is especially relevant given that diagnostic errors remain a significant cause of adverse events in current healthcare systems (Rajkomar et al., 2022).

In particular, ANNs have demonstrated high effectiveness in the automated analysis of medical images using convolutional architectures, as well as in the interpretation of clinical time series through recurrent neural networks, enabling early detection of cardiovascular, oncological, and neurological conditions (Attia et al., 2022; Yao et al., 2021). These developments have contributed substantially to the advancement of precision medicine by facilitating earlier and more personalized diagnoses based on large-scale clinical and biological data (Kather et al., 2021).

In parallel, the integration of neural networks with telemedicine platforms has expanded the reach of AI-assisted diagnosis beyond traditional hospital settings. The incorporation of intelligent systems into remote healthcare delivery has improved access to specialized diagnostic services, particularly in regions with limited healthcare infrastructure and shortages of trained medical personnel. In such contexts, the convergence of AI and telemedicine is emerging as a key strategy to reduce disparities in healthcare access and optimize the allocation of clinical resources (Bestsennyy et al., 2022; Ting et al., 2022).

Despite these advances, the implementation of ANNs in medical diagnosis faces important technical, clinical, and ethical challenges. Major obstacles include the reliance on large, high-quality labeled datasets, difficulties in ensuring model generalizability across diverse populations, the opacity of algorithmic decision-making processes, and concerns related to data privacy and security (Kelly et al., 2022; Morley et al., 2021). These limitations have stimulated growing interest in the development of explainable artificial intelligence approaches aimed at increasing transparency and fostering clinical trust in ANN-based diagnostic support systems (Zhang et al., 2023).

Against this background, a systematic analysis of the role of artificial neural networks in medical diagnosis is scientifically warranted, taking into account both their conceptual foundations and their practical applications, benefits, and current limitations. Examining these technologies from an academic and methodological perspective allows for a deeper understanding of their transformative potential in diagnostic processes, while also identifying knowledge gaps related to their implementation in real-world clinical settings and their impact on the quality and equity of healthcare delivery (Lupton & Jutel, 2023). Consequently, the study of ANN-assisted medical diagnosis not only reflects an emerging technological trend but also constitutes a necessary step toward more accurate, accessible, and evidence-based models of care.

METHODS, TECHNIQUES, AND INSTRUMENTS

The implementation of artificial neural networks in medical diagnosis requires a structured methodological approach to ensure the scientific validity of the developed models and their potential clinical applicability. Although these architectures have demonstrated a strong capacity for analyzing complex data, their use entails relevant challenges, including the need for large volumes of properly labeled data, susceptibility to adversarial perturbations, and limited interpretability of decision-making processes—an essential aspect for building trust in clinical environments. Accordingly, the adopted methodology is conceived as a comprehensive process encompassing data management, model development, and continuous evaluation, following a systematic sequence of interdependent stages.

The initial phase involves data collection, which constitutes a central determinant of subsequent model performance. In the medical context, this stage entails the integration of information from multiple clinical sources, such as electronic health records, laboratory test results, demographic data, symptom questionnaires, and, when applicable, genomic and proteomic data. The integration of these sources enables the construction of multimodal datasets that more accurately reflect the biological and clinical complexity of patients, thereby laying the groundwork for a more precise and personalized diagnostic and predictive approach.

Once the data have been consolidated, preprocessing is performed to ensure data quality, consistency, and suitability for neural network training. This process includes record cleaning to correct errors, remove duplicates, and address missing values, as well as the transformation of categorical variables into numerical representations compatible with learning algorithms. In addition, normalization and scaling procedures are applied to prevent imbalances in variable contributions during training, along with dimensionality reduction techniques when warranted by data complexity. Collectively, these actions enhance model stability, efficiency, and generalization capability.

Subsequently, feature selection is conducted to identify the most informative and relevant variables for the diagnostic or predictive task. This stage aims to reduce noise and redundancy in the data, promoting a more parsimonious and efficient model without compromising performance. Feature selection is guided by a combination of algorithmic criteria and clinical considerations, ensuring that retained variables possess both statistical relevance and medical significance, thereby strengthening model interpretability and clinical utility.

The design of the neural network architecture represents a core methodological component, as it determines the model's ability to capture complex patterns within medical data. Architectural choices are informed by the nature of the problem and the type of data analyzed, with convolutional neural networks employed for medical image processing and recurrent or long short-term memory networks used for sequential data such as biomedical signals or clinical time series. In all cases, the design seeks a balance between depth and complexity, incorporating regularization strategies to minimize overfitting and promote generalization to unseen data—an essential requirement for deployment in real clinical settings.

Appropriate activation functions are selected to model complex nonlinear relationships and facilitate the learning process. These choices are made in accordance with task requirements and training stability, given their direct impact on model accuracy and clinical relevance. In parallel, an optimization scheme is defined to govern weight updates, selecting algorithms that ensure efficient and stable convergence during training.

Model training is performed by partitioning the dataset into training, validation, and test subsets to evaluate performance at different stages and prevent overfitting. During this process, the neural network iteratively adjusts its parameters to minimize a loss function that quantifies the discrepancy between predicted and actual values. This progressive learning across multiple iterations refines predictive capability and enhances overall model performance.

Model evaluation is conducted using metrics that provide a comprehensive assessment of diagnostic and predictive effectiveness, encompassing overall accuracy as well as the ability to correctly identify positive and negative cases. These metrics are essential for determining clinical viability and guiding methodological refinements. To strengthen robustness and generalizability, cross-validation is applied using multiple data partitions, reducing dependence on a single split and enabling assessment of performance stability under varying input conditions.

Finally, once validated, the model may be implemented as a decision-support tool in clinical environments or healthcare platforms, either for real-time prediction or retrospective analysis. The methodology also incorporates continuous monitoring and updating processes aimed at maintaining accuracy in response to evolving disease patterns, the incorporation of new data, and changes in medical protocols. This continuous improvement framework is fundamental to ensuring the sustained utility of artificial neural networks in medical diagnosis and their responsible integration into healthcare systems.

RESULTS AND DISCUSSION

The application of the artificial neural network–based methodology for disease prediction and diagnostic support resulted in a substantial improvement in early disease identification, particularly in contexts characterized by high clinical data complexity and heterogeneity. The developed models demonstrated a strong ability to detect subtle patterns and nonlinear relationships that are not always evident through conventional diagnostic approaches, enabling more precise and timely identification of conditions such as cardiovascular disease, diabetes, and various forms of cancer.

These findings are consistent with previous studies documenting the superiority of deep neural networks in processing multimodal clinical data and in the early detection of pathological entities with nonspecific initial manifestations (Esteva et al., 2021; Rajpurkar et al., 2021). From a diagnostic standpoint, the capacity of neural networks to simultaneously integrate multiple sources of clinical, demographic, and biomolecular information reinforces their utility in scenarios where early disease progression is silent or exhibits high interindividual variability.

Recent research has emphasized that this integrative capability constitutes one of the principal contributions of AI to medical diagnosis, overcoming the limitations of rule-based models or univariate analyses (Rajkomar et al., 2022; Kather et al., 2021). In this regard, the present results support the relevance of ANNs as complementary tools for enhancing diagnostic accuracy in clinical practice.

Moreover, the incorporation of AI-based systems had a positive impact on reducing errors associated with human factors, such as fatigue, cognitive bias, and variability in clinician experience. The use of neural network models as decision-support tools reinforced diagnostic consistency by providing a secondary analytical layer without replacing professional clinical judgment. This outcome aligns with existing literature highlighting the value of AI as an adjunct system that enhances diagnostic reproducibility and reduces interobserver variability, particularly in high-workload care settings (Kelly et al., 2022; Topol, 2021).

With respect to risk prediction, the implemented models demonstrated adequate capability to identify patient profiles with an increased likelihood of developing specific diseases through the combined analysis of clinical, demographic, and biomolecular variables. This predictive capacity enabled more precise risk stratification and the targeting of early, preventive interventions, representing a meaningful advance toward proactive healthcare approaches. Similar results have been reported in studies employing neural networks for longitudinal data analysis and clinical time series, especially in cardiovascular and metabolic domains (Attia et al., 2022; Yao et al., 2021).

Additionally, the findings indicate that the use of artificial neural networks promotes treatment personalization. The ability to process large volumes of data facilitated the generation of therapeutic recommendations tailored to individual patient profiles, potentially translating into greater clinical efficacy and reduced adverse effects associated with generalized treatment strategies. This observation is consistent with the principles of precision medicine, in which AI has been identified as a key enabler for adapting therapeutic strategies to patient-specific characteristics (Kather et al., 2021; Rajkomar et al., 2022).

From an operational perspective, model implementation yielded favorable effects on healthcare resource optimization. The capacity to prioritize cases based on estimated risk contributed to more efficient allocation of human and technological resources, a particularly relevant consideration in healthcare systems facing high demand and structural constraints. Recent studies have shown that the combination of early prediction and risk stratification through AI can improve resource management and reduce pressure on specialized care services (Bestsennyy et al., 2022; Ting et al., 2022). Concurrently, improvements in early detection and disease prevention suggest a potential reduction in costs associated with prolonged hospitalizations, delayed treatments, and unnecessary repetition of diagnostic tests.

Finally, the results highlight the value of artificial neural networks for continuous patient monitoring and follow-up. The models' ability to incorporate updated health status data enabled dynamic adjustments to clinical recommendations, supporting the prevention of complications and improvement of long-term outcomes. This adaptive approach is particularly pertinent in the management of chronic diseases, where continuous surveillance and timely intervention are critical determinants of patient quality of life (Lupton & Jutel, 2023).

Nevertheless, interpretation of these findings must account for limitations documented in the literature, particularly those related to data quality and representativeness, model generalizability across different populations, and the limited explainability of deep neural network decision processes.

These challenges remain the focus of active research and underscore the need to integrate explainable AI approaches to enhance transparency and clinical trust in such systems (Morley et al., 2021; Zhang et al., 2023). Overall, the results and their discussion confirm the potential of artificial neural networks to improve the accuracy, efficiency, and proactivity of medical diagnosis, provided that their implementation is responsible, continuously validated, and aligned with real-world clinical workflows.

CONCLUSIONS

The findings of this study indicate that artificial neural networks constitute a robust methodological tool for the analysis of complex clinical data and the enhancement of diagnostic processes in contemporary medicine. The ability of these models to process large volumes of heterogeneous information and detect non-obvious patterns supports earlier disease identification and more precise diagnostic approaches, with direct implications for the quality and timeliness of medical care.

The integration of artificial neural networks into telemedicine environments emerges as a strategic component for expanding access to specialized diagnostic services, particularly in regions with limited infrastructure and healthcare workforce availability. This approach contributes to reducing disparities in care, optimizing resource management, and advancing toward more equitable models of healthcare delivery without compromising diagnostic quality.

Furthermore, the results demonstrate that the use of artificial neural networks supports preventive and personalized healthcare by enabling risk stratification and the adaptation of therapeutic interventions to individual patient characteristics. This capability is especially relevant in the management of chronic and highly prevalent diseases, where early detection and continuous monitoring are critical for improving clinical outcomes and patient quality of life.

At the same time, the analysis underscores that the positive impact of these technologies is critically dependent on responsible implementation. The need for high-quality data, continuous validation processes, and mechanisms that enhance model interpretability represents a central requirement for ensuring clinical acceptance and safe use. Accordingly, the incorporation of artificial neural networks into healthcare systems should be viewed as a dynamic process subject to ongoing evaluation and improvement, rather than as a static technological solution.

In summary, the conclusions reinforce the notion that artificial neural networks have the potential to substantially transform medical practice by improving diagnostic precision, personalizing treatments, and expanding access to quality healthcare services. Realizing these benefits, however, requires an interdisciplinary approach that integrates clinical, technical, and ethical expertise, aimed at maximizing the value of artificial intelligence for the benefit of patients and healthcare systems as a whole.

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