The Role of Unsupervised Learning in the Healthcare Sector Considering Three Application Examples

Group Report

Data Mining and Predictive Analytics MT413

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1 Introduction

Machine learning (ML), a discipline rooted in mathematics, statistics, knowledge analytics, and data processing, defies a concise definition due to its interdisciplinary nature (IBM, n.d.). It is a distinct subset of artificial intelligence (AI) that enables the computer to find an algorithm to approximately solve the problem by deriving patterns from large amounts of data (Alanazi, 2022). ML encompasses subfields like supervised, semi-supervised, unsupervised, and reinforcement learning (Verma & Verma, 2022). Unsupervised learning, the focal point of this essay, excels in uncovering patterns in unclassified and unlabeled data (Raza & Singh, 2021). Unlike supervised learning, it avoids the manual effort of maneuvering pre-classified data, addressing scalability issues by grouping unlabeled data based on patterns (Verma & Verma, 2022). These models offer robustness and versatility, serving as a foundation for tasks such as data compression, dimensionality reduction, and noise reduction (Miller, 2023).

In the healthcare sector, whose AI market is predicted to grow with a projected Compound Annual Growth Rate (CAGR) of 41.4% between 2020 and 2027 (Meticulous Market Research Pvt, 2020), the application of unsupervised revolves around the effective utilization of vast amounts of unstructured data, hindering the optimization of patient care, resource allocation, and medical research (Eckhardt et al., 2023). In healthcare, the increasing adoption of ML is intrinsically linked to the surge in data generation and processing power. Many healthcare organizations have already implemented or are planning to implement ML solutions (Alanzi, 2022).

The following essay will first provide a brief overview of unsupervised learning´s evolvement and application in the healthcare sector. Furthermore, three application examples of unsupervised learning will be examined. Lastly, the efficiency gains of this technology and the challenges of using unsupervised learning in medicine will be discussed.

2 Evolvement of Unsupervised Learning in the Healthcare Sector

The marriage of healthcare and data-driven technologies has brought forth a paradigm shift in the healthcare landscape. Among these, the utilization of unsupervised machine learning algorithms has catalyzed transformative changes in the understanding, management, and delivery of healthcare services (Raza & Singh, 2021). Being able to discern hidden relationships and structures from unlabeled data, unsupervised learning creates insights that were hitherto inaccessible (Eckhardt et al., 2023). The evolution of unsupervised learning is a testament to its growing significance in the healthcare sector, as it endeavors to revolutionize various facets of medical science, from diagnostics to patient care and drug discovery (Raza, & Singh, 2021).

Forming the bedrock of unsupervised learning in healthcare, the theoretical foundations of unsupervised learning are cluster analysis, dimensionality reduction, and autoencoders (Awotunde et al., 2022). The theoretical evolution of unsupervised learning algorithms has been marked by the refinement of these methodologies, often guided by empirical evidence and experimental validation (Verma & Verma, 2022).

Unsupervised learning has found application in the healthcare sector through a multitude of avenues. For instance, clustering algorithms have been instrumental in identifying patient cohorts with similar disease profiles, thus enabling tailored medical interventions (Khalid et al., 2018). Dimensionality reduction techniques have streamlined the analysis of high-dimensional medical data, rendering it more amenable to interpretation (Awotunde et al., 2022). Autoencoders, on the other hand, have been leveraged for feature extraction, contributing to the efficiency of medical image analysis (Latif et al., 2019).

3 Application of Unsupervised Learning in the Healthcare Sector

In the following, three concrete application examples of unsupervised learning along the patient journey, starting from segmentation until treatment payment, in the healthcare sector are discussed, explaining their relevance within the industry.

3.1 Patient Segmentation in Both Theory and Practice

A first important example of unsupervised learning involves its ability to analyze large amounts of unlabeled patient data (Yan et al., 2019). In turn, these insights can provide new decision-making tools increasing the efficiency of resource deployment, enabling tailored treatments, and warranting superior patient outcomes (IBM, n.d.). For example, algorithms such as k-means or hierarchical clustering offer useful approaches to differentiate patient's contingent on their individual attributes or medical records (Desai, 2023). Subsequently, previously undiscovered patterns can discover new insights, leading to a more accurate assessment of patients' wants and needs (Davenport & Kalakota, 2019).

To illustrate, the next section will highlight two specific use cases of unsupervised learning in patient segmentation followed by a paragraph highlighting possible business approaches. First, unsupervised learning could facilitate the process of effectively allocating intensive care unit (ICU) beds. In most hospitals, ICU beds are of limited capacity due to the associated high costs, especially if they are not efficiently occupied (Sinuff et al., 2004). Consequently, this often leads to bottlenecks which became especially evident during the COVID-19 pandemic (Sen-Crowe et al., 2021). Understanding the need for improved systems of patient prioritization, a group of hospitals enrolled in a study to leverage the clustering capabilities of unsupervised learning by classifying patients regarding severity and duration of residence (Zampieri et al., 2019). Consequently, these hospitals optimized bed utilization, reduced waiting times and, most importantly, provided better patient outcomes (Zampieri et al., 2019). Second, in another use case, unsupervised learning could be integrated into mental health care. Currently, the sheer number of treated patients every day per doctor has often rendered personal contact with patients suboptimal which is especially detrimental to appropriate mental health care and patient involvement (Pedrelli et al., 2020). Thus, a team of scientists utilized unsupervised learning to cluster patients about mental health concerns and requirements (Gold et al., 2022). On balance, the first results have shown that not only the possibilities of personalized treatments were improved but also patient engagement and satisfaction (MIT Jameel Clinic - AI & Health, 2020).

Notwithstanding these specific use cases in patient segmentation, several companies have decided to implement unsupervised learning beyond scientific research. For example, the AI platform Apixio harnesses previously unexploited, unorganized medical data such as patient charts, records, and billing information to provide new insights into patient risk scores for provider groups and insurance companies (Apixio, n.d.; Japsen, 2023). Other major players such as UnitedHealth Group´s Optum, which offers a wide array of healthcare analytics and consulting services, have also expressed their interest in unsupervised learning to identify high-risk patient groups and design targeted care programs (Lawson, 2023; Optum, n.d.). On balance, the versatility of unsupervised learning in patient segmentation, as shown in various studies, offers several avenues for implementation and is expected to be significantly expanded in the coming years.

3.2 Medical Imaging Through Microsoft InnerEye

Machine learning algorithms are increasingly used in image analysis within the healthcare sector. Unsupervised learning is particularly relevant in this area. For example, it is used for image segmentation or anomaly detection where deviations in the brain structure are detected by comparing them with a large amount of unlabeled training data. In this context, the Microsoft InnerEye Toolkit progressively applies the method of self-supervised learning, which is a subset of unsupervised learning defined by the concept that the model is trained on data to predict parts of the input data, where the labels are automatically generated from the input data itself (Microsoft, 2023).

Microsoft's InnerEye Deep Learning project was introduced in 2020 as an open-source toolkit for analyzing CT, MRI, and X-ray images (Microsoft, 2023). The program itself started years earlier as part of Microsoft's extensive AI and machine learning research initiative in collaboration with Cambridge Hospitals NHS Foundation Trust (Suresh et al., 2020). The initial focus of the project was on developing machine learning algorithms for three-dimensional radiological imaging to discern between normal and malignant cells. The technology behind the toolkit is Python-based and uses the well-known PyTorch deep learning frameworks and thus, 3D fully convolutional networks for segmentation tasks (Oktay et al., 2020). The training models themselves have been scaled via Microsoft Azure Learning and generic models were developed using anonymized data from eight diverse clinical centers throughout Australia, Europe, New Zealand, North America, and South America. After several successful test phases, the core machine learning model was presented as an end-to-end deployment solution to be seamlessly incorporated into hospital operations.

Today, the Toolkit has been extensively integrated into Addenbrook Hospital Cambridge as an AI system under the name OSAIRIS (Rizi-Shorvon, 2023). Initially implemented for the detection of prostate head and neck cancers, the AI system is developing into a multi-use system for the detection of different types of cancer. Most notably, OSAIRIS diminishes the labor-heavy task of manually demarcating healthy organs in scans before radiotherapy, known as "segmentation". The accuracy of this segmentation is crucial in safeguarding the healthy tissue surrounding the cancer from radiation exposure (Rizi-Shorvon, 2023). Generally, this task would demand between 20 minutes to three hours of a physician's time for each patient. OSAIRIS simplifies this procedure by handling the segmentation allowing oncologists to devote more time to treatment planning (Rizi-Shorvon, 2023). Importantly, the oncologist maintains control throughout the process by carefully examining each scan to ensure precision. In blind evaluations, commonly referred to as "Turing tests," physicians were unable to distinguish between the work done by OSAIRIS and that of a fellow doctor (Rizi-Shorvon, 2023). Consequently, integrating the technology can achieve more precise differentiation of healthy and diseased cells. This significantly reduces both personnel costs and stress for patients due to long waiting times (Ballamudi, 2016).

3.3 Fraud Detection Using Machine Learning

Fraudulent practices, such as upcoding in healthcare, where providers overcharge patients or insurers, contribute significantly to inefficiencies in healthcare spending. Estimates suggest that fraudulent activities account for 3% to 10% of total healthcare expenditures in the United States, potentially resulting in losses exceeding $300 billion (The Challenge of Health Care Fraud – NHCAA, n.d.). Existing research has predominantly employed supervised machine learning techniques to identify fraudulent actors, yet this approach faces challenges with rapidly evolving and increasingly sophisticated fraud types (Joudaki et al., 2014), risking an overemphasis on outdated patterns and diminished predictive capability as new records are assessed over time (Massi et al., 2020). In contrast, unsupervised learning holds theoretical promise for detecting novel forms of fraud by comparing claims and evaluating their relational or differential aspects. This methodology enables the identification of sequence and association rules, facilitating the separate categorization of potentially fraudulent and regular applications (Joudaki et al., 2014).

The subsequent section elucidates an exemplary unsupervised machine learning approach proposed by Lin et al. (2008) for fraud detection. The authors employ a two-stage unsupervised learning paradigm to unveil general practitioner (GP) practice patterns and provide managerial guidance. Utilizing knowledge discovery in database (KDD) procedures, Lin et al. (2008) initiate the process with a two-level self-organizing map (SOM) neural network, identifying patterns in high-dimensional GP practice profiles and organizing them into 10 clusters. These profiles, characterized by 10 input attributes, undergo analysis for maximum value locations, determining cluster centroids. Simultaneously, the maximum value centroids of the 10 attributes identify outlier clusters. Lin et al. (2008) employ data principal component analysis (PCA) to reduce dimensions, consolidating attributes into factors, resulting in 5 factors cross-matched to the 5 clusters with maximum value centroids. To apply this data practically, expert interviews utilizing the Analytic Hierarchy Process (AHP) are conducted, yielding weighted clusters indicative of potential issues (e.g., billing for unperformed services) and managerial advice based on expert insights.

This method enhances the segmentation of GP practice patterns, enabling auditors to more effectively detect fraud on a broader scale. The outcome is a reduction in costs for patients and insurers and the establishment of a mechanism incentivizing healthcare providers to adhere to cost containment strategies (Lin et al., 2008). Although implemented in the Republic of China, limitations persist concerning the skewed attributes of GP practice profiles, deviating from the assumption of normal distribution, and potentially leading to biased and inaccurate results (Lin et al., 2008).

4 Impact on Organizational Performance and Efficiency

The three examples have shown that unsupervised learning offers a wide range of use cases in healthcare, leading to better precision medicine, more accurate diagnoses, shorter waiting times for patients and better bed utilization. To build on this foundation, the following section explores the broader impact it has had and will have on organizational performance. Overall, this will enable an accurate assessment of the general opportunities and challenges of unsupervised learning in healthcare.

Unsupervised learning presents significant opportunities for the healthcare sector. Primarily, the ability to explore extensive datasets unveils novel patterns, segments, and possibilities that traditional research methods might overlook (Desai, 2023). This data exploration prowess not only enhances the understanding of complex medical phenomena but also facilitates informed decision-making (Eckhardt et al., 2023). Anomaly detection provides the healthcare sector with a robust mechanism for identifying irregularities, such as fraud, equipment malfunctions, or rare diseases (Arihant Information Systems, 2023). Unsupervised algorithms process vast datasets swiftly, alleviating the resource-intensive burden associated with collecting labeled data (Desai, 2023). This scalability enhances organizational efficiency by facilitating the rapid analysis of massive datasets. Furthermore, by simplifying high-dimensional datasets, unsupervised learning enables faster processing and efficient storage, streamlining data analysis and visualization processes (Awotunde et al., 2022).

However, these advantages are juxtaposed with notable challenges. The interpretability of unsupervised learning results poses a formidable obstacle, especially for non-technical stakeholders (Miller, 2023). The complexity of patterns and correlations generated by unsupervised algorithms may hinder the acceptance and trust in these solutions (Eckhardt et al., 2023). Sensitivity to initial conditions, especially observable in methods such as k-means clustering, introduces an element of unpredictability. This sensitivity may lead to convergence towards inefficient or inconsistent outcomes, thereby compromising the quality and reliability of the findings (Arihant Information Systems, 2023). Additionally, the absence of objective evaluation metrics, a characteristic feature distinguishing unsupervised learning from its supervised counterpart, complicates the assessment of model performance (Desai, 2023). This absence poses challenges in comparing and selecting appropriate unsupervised learning solutions, impeding the validation process (Miller, 2023).

5 Conclusion

In conclusion, the transformative power of AI and ML might change the foundation of how the healthcare sector is understood, governed, and prescribed, yet the unique set of accompanying opportunities, challenges, as well as complexities and limitations are evident. The ability of unsupervised learning to leverage unclassified and unlabeled data provides a multitude of opportunities as shown in the examples. While opportunities such as these are considerable, the challenges inherent in interpretability, sensitivity to initial conditions, and the absence of objective evaluation metrics necessitate careful consideration (Eckhardt et al., 2023). Striking a balance between leveraging the transformative potential of unsupervised learning and mitigating these challenges is imperative for realizing its full impact on organizational performance, efficiency, and the overall advancement of healthcare practices (Desai, 2023). Ongoing research efforts and strategic integration initiatives will be pivotal in navigating this intricate landscape and optimizing the integration of unsupervised learning methodologies within healthcare systems. In the future, the capabilities of unsupervised learning are only expected to increase as the permeation of AI and ML technology has become increasingly prominent and efficient, yet a successful implementation is not inherently guaranteed (Eckhardt et al., 2023). Alongside the specific considerations of unsupervised learning in healthcare, a broader societal debate has gathered significant momentum, discussing fundamental issues surrounding the use of AI, such as ethical considerations, bias, and regulatory compliance (Milmo, 2023). Therefore, the implementation of unsupervised learning in healthcare is a development that should be closely scrutinized.

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