AI/Big Data in Healthcare

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Multimorbidity refers to the coexistence of two or more chronic diseases in one person. Therefore, patients with multimorbidity have multiple and special care needs. However, in practice it is difficult to meet these needs because the organizational processes of current healthcare systems tend to be tailored to a single disease. To improve clinical decision making and patient care in multimorbidity, a radical change in the problem-solving approach to medical research and treatment is needed. In addition to the traditional reductionist approach, we propose interactive research supported by artificial intelligence (AI) and advanced big data analytics. Such research approach, when applied to data routinely collected in healthcare settings, provides an integrated platform for research tasks related to multimorbidity. This may include, for example, prediction, correlation, and classification problems based on multiple interaction factors. However, to realize the idea of this paradigm shift in multimorbidity research, the optimization, standardization, and most importantly, the integration of electronic health data into a common national and international research infrastructure is needed. Ultimately, there is a need for the integration and implementation of efficient AI approaches, particularly deep learning, into clinical routine directly within the workflows of the medical professionals.

Keywords: multimorbidity ; artificial intelligence ; machine learning ; population aging ; chronic diseases

1. Introduction

Societies in industrialized countries worldwide are facing an increasing burden of chronic diseases, including type 2 diabetes, cardiovascular and neurodegenerative diseases, and various cancers. This negative trend is the result of an aging population and the prevalence of “modern” lifestyles, such as the consumption of industrially processed foods, predominantly sedentary work, and increasing chronic psychological stress, which are known to accelerate aging and the development of age-related diseases [1][2].

Chronic diseases in the same person rarely appear as a single disease; instead, two or more diseases coexist, which is called multimorbidity [3]. Patients with multimorbidity raise a concern of both policymakers and healthcare providers because of the complex care needs, which requires various healthcare providers and services to deliver care for these patients [4]. The general practitioners (GPs) are faced with the demanding task of integrating different recommendations and prescriptions of these multiple providers [5].

Moreover, current clinical guidelines are disease-oriented, further complicating decision making for these patients [6]. Even recommendations for managing single diseases for these patients may be uncertain because patients with multimorbidity are usually excluded from clinical trials. The delivery of care and the patient self-management may be constrained by complicated medication regimens and information burden [5]. Recommendations that are given to a patient for several single diseases may be mutually conflicting and produce harm rather than good [7].

Multimorbidity has been shown to have a significant negative impact on patient outcomes, and not all patients with multimorbidity have the same risk for adverse outcomes. It has been shown to depend on the number of comorbidities, but also on certain combinations of diseases that a person has [8]. Some disease combinations occur randomly, as some diseases are very common in the population, such as hypertension, while other diseases tend to accumulate [9]. Disease clustering is usually based on common pathophysiology, as evident from the common appearance of cardio-metabolic and vascular disorders, although in some cases, causes are less clear [10]. However, the classical methods of measuring multimorbidity that have been used in epidemiologic surveys and are based on counting diseases are not adequate to capture reliable pre-existing conditions. [11][12].

There is no knowledge base to adequately address multimorbidity problems in terms of patient-centered solutions in predicting specific outcomes and determining personalized treatments [13][14]. This is due to the fact, that no methodological framework has been developed that adequately manages the complexity of multimorbidity.

2. AI/Big Data in Healthcare

Due to the invention of new technologies in medicine and healthcare, in the last decades, such as digital imaging techniques and molecular biology diagnostics, and to the establishment of patient registries and electronic HRs in many countries in Europe and wider, there has been a rapid growth in data quantity and complexity, in both medical research and clinical practice. It made the classical research approach no more sufficient to meet the challenges of the artificial intelligence (AI), Big Data (BD) or machine learning (ML).

A tendency of ML procedures for automatization is likely to diminish the role of a medical expert in the analytic process. However, it is not valid. This role is important because most medical domain problems are challenging and cannot be solved solely by applying the automated process of data analysis and without the medical expert's guidance [15].

Some of the questions that would be of interest for practicing doctors to be provided by the answers, include: which patients with multiple comorbidities are at risk for which specific outcomes, and which ones would benefit from which treatments; which risk factors and pathophysiology disorders refer to which patient groups, and which mechanisms are responsible for patient transition from one trajectory to another?

The most prevalent topics were those related to early diagnosis, personalized treatment, and prediction of outcomes of some chronic diseases, such as cancer, diabetes, and Alzheimer's dementia. These diseases are known for their serious outcomes and are associated with many comorbidities so that by themselves, they are characterized with a high level of complexity. With the recent invention of high throughput (-omics) techniques in the medical domain that were thought to realize personalized patient care, the ML/BD analytical methods have received an additional stimulus for development.

Examples that follow reveal some essential potentials of the ML/BD analytics in the healthcare domain, including the possibility of finding new concepts from routinely collected data to support diagnosis and even improve disease classification, as well as the possibility of using unstructured data, such as the plain text, or images, that otherwise could not be impossible. Automatization, a feature representation without the need for manual efforts and ad hoc input by an expert, is another possibility. Finally, ML/BD analytics is possible in linking eHRs from different platforms and healthcare settings.

The approach based on ML/BD methods has emerged as a real alternative with high potential to address the problems associated with multimorbidity. These problems include, for example, phenotyping of patients and risk stratification based on modeling of multiple interrelated traits that overlap between individuals. Further, identifying patterns of chronic health conditions in the population, as well as tracking progression as health conditions worsen over time in individuals with multiple health conditions. The challenges that need to be addressed to successfully implement this research approach into routine clinical practice mainly relate to the need to establish better coordination between medical experts and data scientists, AI researchers, and IT experts to implement common and validated research protocols tested in real-world conditions and to build a true interdisciplinary knowledge base. From this growing knowledge base, consisting of case studies solving various problems arising from clinical practice, it will be possible in the future to develop new interdisciplinary-based guidelines and recommendations for the management of multimorbidity.

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