Predicting an Optimal Medication/Prescription Regimen Using Multi-Output Models

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The discordant chronic comorbidities care (DC33) model shows how a change in a patient treatment plan can negatively impact symptoms and necessitate revisiting the plan. These interactions make treatment decisions, prioritization, and adherence for DCCs very complex and challenging for patients and their healthcare providers.

complex chronic diseases | discordant chronic conditions | benchmarking

1. Introduction

In the United States alone, one in four patients have multiple chronic conditions [1]. The increasing number of patients with chronic conditions exerts further pressure on an already strained healthcare system. It is difficult for healthcare providers to thoroughly understand the complex care-needs of these people in the limited time allotted in a medical appointment [2]. This problem is even worse for patients with discordant chronic comorbidities (DCCs), a situation where a patient has two or more conditions with conflicting treatment plans. Patients with DCCs often have to juggle multiple complex treatment plans and interacting diseases/symptoms [3][4][5]. The discordant chronic comorbidities care (DC33) model shows how a change in a patient treatment plan can negatively impact symptoms and necessitate revisiting the plan [6]. These interactions make treatment decisions, prioritization, and adherence for DCCs very complex and challenging for patients and their healthcare providers. A treatment plan for DCCs must adapt as the patient's conditions evolves. Machine learning (ML) and artificial intelligence (AI) can support healthcare providers when making these intricate and ever-changing decisions. When deciding on medication, the majority of patients with multiple chronic conditions often are concerned about whether (i) the price of medication is high, (ii) a medication will cause weight gain, (iii) a medication will cause severe side effects, and (iv) a medication will interact/conflict with their other current medications [6]. Thus, it is essential for researchers looking to support the treatment decision-making process for DCCs to consider these concerns when making treatment recommendations. A plethora of research has been conducted for risk prediction [7], disease diagnosis [8], managing treatment plans [9], and medication recommendation targeting a single chronic disease [10].

2. Recommender and Decision Support Systems

Clinical decision support systems (CDSS) and recommender systems are designed to assist physicians, nurses, patients, and other professionals in decision-making related to the patient's clinical condition [11]. For example, Lysaght et al. developed and implemented AI-assisted support systems to support healthcare and clinical-practice decision-making processes [12]. They used large datasets from electronic health records (EHRs) and algorithms in CDSS. A CDSS typically employs computerized, predictive analysis algorithms to filter, organize, and search for patterns in big datasets from multiple sources and provide probability analysis upon which healthcare providers can make fast and informed decisions. This research highlighted some of the ethical issues that may arise with the implementation of these systems and the relevant values that decision-makers can draw on in the design and implementation of AI-assisted CDSS into practice [12]. The decision support was further enhanced with tools that could look for the common attributes and the nearest neighbors of these attributes [13]. These tools could predict the most probable future actions of patients and identify the disease (s) a patient would most likely develop in the near future. With some additional tweaks, these tools could also recommend educational material for such diseases [14]. Many such varieties of these tools were developed to assist patients and healthcare providers.

The majority of patients struggle to find useful resources, strategies, and information when navigating their care and self-management [6][15]. Patients find it hard to identify the most relevant and valuable materials for themselves [15][16]. A system that automatically identifies and recommends appropriate care strategies to patients based on their needs or preferences is needed. There is already research taking that direction, for example, health recommender systems (HRS) are used to provide appropriate educational materials for patients with chronic diseases [17]. Such a recommender system detects the similarities between the patient and text vectors by using keyword extraction. They show how ontology-vector spaces can be used to correlate patient data and educational material. However, such systems do not capture the deep semantic meanings behind sentences or documents.

3. Machine Learning Tools and Algorithms for Healthcare

Several studies are currently exploring/implementing machine learning techniques to support the care and wellness of patients. For example, Woldaregay et al. explored state-of-the-art machine-learning strategies and their hybrid systems focusing on blood glucose (BG) anomaly classification and detection [18]. In addition, ML algorithms such as artificial neural networks, support-vector machines, Bayesian networks, decision trees, and back-propagation algorithms, have been applied to create decision-aid systems for supporting healthcare providers and nurses in their decision-making process [19]. Kavakiotis et al. built predictive models using machine learning algorithms and data mining techniques for diabetes prediction [10]. They used the k-means, application of tree algorithms, decision tree algorithms, neural networks, K-means clustering algorithms, and visualization to predict diabetes among patients. Logistic regression gave the highest accuracy of 96%. This approach could also be applied to chronic comorbidities for prediction and recommendations to manage them. Furthermore, Singh et al. created a multi-output career prediction tool that considers the person's background history (i.e., work and education history) [20].

Apart from implementing ML algorithms, there exists a body of research dedicated to performance of ML algorithms. For example, some studies have investigated and created benchmarks of probabilistic matrix factorization, generative adversarial networks (GAN), and attention-based sequence models. These investigations revealed that the factorization method was relatively simple to interpret [21]. Additionally, they highlighted the remarkable enhancements in medical predictive model performance attributed to deep learning approaches [21]. In a separate study, Kumar et al. evaluated anxiety, depression, and stress using machine learning models [22]. They conducted comprehensive benchmarking, using five (n = 5) distinct algorithms, namely decision tree, random forest tree, naive Bayes, SVM, and KNN. For classification, they employed logistic regression, cat boost, naive Bayes, RFT, and SVM. The outcomes indicated superior performance by the decision tree, followed by the random forest and then naive Bayes algorithms. These studies show the potential for recommending both diseases and corresponding medications. However, it is worth noting that while the insights from this research could benefit individuals with DCCs, the majority of machine learning models still struggle to accurately estimate uncertainty and furnish well-calibrated predictions [23][24]. This deficiency can result in overly confident recommendations in scenarios involving dataset shifts or distributional changes [25][26]. To address this, further endeavors that mitigate uncertainty when recommending medication combinations within real-world clinical settings essential.

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