Applications of Artificial Intelligence for Palliative Care

Subjects: Medical Informatics

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Artificial intelligence (AI) model development for synthetic data generation to improve Machine Learning (ML) methodologies is an integral part of research in Computer Science and is currently being transferred to related medical fields, such as Systems Medicine and Medical Informatics. Palliative care (PC) uses a team-oriented approach to improve the quality of life of patients and their families who are facing problems associated with a life-threatening illness.

Keywords: palliative care ; screening ; personalized medicine ; artificial intelligence

1. Introduction and Definition of Palliative Care

Patients with advanced, incurable cancer suffer from changing psychological and physical symptoms in terms of type and severity. In addition, there are social burdens for both the patient and for the informal caregivers. As per the definition of the World Health Organization (WHO) (https://www.who.int/news-room/fact-sheets/detail/palliative-care (accessed on 27 July 2022)) and extended via Radbruch et al. [1], Palliative care (PC) uses a team-oriented approach to improve the quality of life of patients and their families who are facing problems associated with a life-threatening illness. It prevents and relieves suffering through the early identification, correct assessment, and treatment of pain and other problems, whether physical, psychosocial, or spiritual. Thus, it offers a support system to help patients live as actively as possible until death [1]. Furthermore, PC values patients' needs to receive adequate, personally, and culturally sensitive information on their health status to make independent decisions about a treatment [2]. Palliative care is applicable throughout all health care settings (place of residence and institutions) and in all levels (primary to tertiary care) [3]. Primary care is performed by general practitioners, oncologists, and in outpatient structures, as well as in hospitals [4][5]. Secondary palliative care involves palliative-care specialists acting as consultants and is offered to all patients with a symptomatic advanced, progressive life-threatening disease and limited therapeutic options [6]. Furthermore, most guidelines refer to this collective [3]. Over the past five decades, PC has evolved from serving patients at the end of life into a highly specialized discipline focused on delivering supportive care to patients with life-limiting illnesses throughout the disease trajectory [4]. Still, there are different perceptions about the timing of palliative care in the course of disease, including the difficulty of a reliable and timely screening [7].

2. Existing and Prospective Applications of AI for Palliative Care

So far, research in artificial intelligence (AI) and machine learning (ML) dealing with PC have focused on survival prediction and mortality rates. To obtain an overview about these current developments, the researchers briefly highlight and discuss the most prominent studies in the field. Random forests, feature selection, and logistic regression were applied to general patient electronic health records (EHR) [8]. In addition, a long short-term memory (LSTM) model was able to effectively predict mortality by using a combination of EHR data and administrative claims data [9]. A rapid review showed that ML approaches are powerful in predicting mortality in older and/or hospitalized adults [10]. Patients' outcome is dependent on the right timing of specialized PC referral. Palliative patients go through different phases of their disease (stable, unstable, deteriorating, terminal/dying, deceased) [11]. Data-driven ML and network analysis were expected to identify these phases through symptoms reported on IPOS [12]. ML was moderately successful to predict cases within phases. Precision-recall curves (PRCs) were calculated in addition to ROC area under curve (AUC). PRC figures decreased from stable to terminal, leading to reduced relevance of the model for the later stages due to greater proportions of patients being in earlier palliative stages [13]. Deep learning (DL), an area of ML that uses mathematical and statistical models, has also tried to predict mortality and beneficence from PC by using a combination of clinical features including disease diagnosis and patient demographics. A Deep Neural Network model was trained on the EHR data of patients from previous years, to predict the mortality of patients within the next 3–12 month period [14]. Another study used the information on symptom burden of free-text notes in the EHR [15]. Here, natural language processing (NLP) was able to identify hospitalized cancer patients with uncontrolled symptoms (pain, dyspnea, or nausea/vomiting) in the EHR. The accuracy was between 61% and 80% with low sensitivity for nausea/vomiting (21%) and dyspnea (22%). For this reason, this model also has to be further developed before it can be used to trigger early access to PC [15]. However, despite these existing success stories, specific screening tools or CDSS of patients in need for palliative care in early, intermediate, and late stages are missing because time-specific screening parameters and a reasonable amount of underlying data are not yet available to build such tools.

A starting point for important screening features can be obtained from the National Comprehensive Cancer Network (NCCN), which has proposed consensus criteria for screening of patients care needs and subsequent referral to specialized PC: (i) uncontrolled symptoms, (ii) moderate to severe distress related to cancer diagnosis and therapy, serious comorbid physical, psychiatric, and psychosocial conditions, (iii) life expectancy of six months or less, (iv) patient or family concerns about the disease course and decision-making, and/or (v) a specific request for palliative care by the patient or family [16]. Such a systematic screening can be carried out by using checklists [17][18][19]. These included different unspecified criteria like frequent hospital admission or hospital stays due to difficult-to-control symptoms, complex nursing care, or vast deterioration. In addition, there were more specific criteria like admission from a long-term care facility or medical foster home, chronic home oxygen use, current or past hospice program enrollee, limited social support, and a lack of an advance care planning document. Others used a checklist in patients with advanced cancer stage IV, including re-hospitalization in less than 30 days, hospitalization longer than seven days, active symptoms of pain, nausea, vomiting, dyspnea, delirium, psychological distress [20]. Glare et al. [16] examined the use of six NCCN screening and further criteria (metastatic or locally advanced cancer, a limited prognosis, active source of suffering) and later included prolonged length hospital stay as an extra item [21]. Potential parameters for the screening of PC needs can thus be derived from the literature; however, the limited amount of available data across all facets is still missing.

As a supportive addition to sparse real-world data, novel synthetically generated data may serve PC in two different ways: (i) the model is trained using real-world clinical data and once trained, will not require any data in the future (fixed model approach), (ii) the model is constantly fed with data to generate synthetic data (continuous model approaches). There are three different categories of algorithms used in the generation of synthetic data: probabilistic models, machine learning, and deep learning methods. Currently, an implementation towards the field of PC screening is still missing.

3. Potential Impact of Synthetic Data Generation Towards an Improved Identification of Patients in Need of Palliative Care

If only a small amount of data can be made available to the AI model, that oftentimes is not enough for optimizing, training, and testing a precise and robust decision support model at a clinical scale. Synthetic data generation would be a sensible approach to tackle this problem. Here, relevant medical data (pseudonymized, anonymized or actual) is used as an input for an ML-model to learn the underlying data structure, which is utilized in a subsequent step to generate new artificial data that is close to the original. Thus, instead of providing the AI model only with a small amount of data, a larger amount of synthetic data can be provided for the purpose to improve the training of ML-based decision support models, e.g., for patient stratification. Deep generative models, such as Variational Autoencoders (VAE) [22] and Generative Adversarial Networks (GAN) [23][24], play a key role in this. Although VAEs are also widely applied for generative modeling studies, especially with respect to sparse and scarce data in the medical/health domain for images [25][26] and data integration [27], relatively few examples for tabular data exist [28][29][30]. GANs are currently seen as most promising according to the findings of Xu et al. [29]. They see GANs as better suited for privacy preserving data generation in comparison to VAEs, since these are easier to integrate with respect to differential privacy. Several of such models have been developed over the past few years and a current technical review of Hernandez et al. [30] presents the different synthetic data generation methods for tabular healthcare datasets. A comparable work of Georges–Filteau and Cirillo investigates the possibility of synthetic data generation via GANs to ultimately obtain digital twins [31]. However, deep generative models are more popular for synthetic data generation from image datasets and there are only relatively few models relying on tabular patient data yet [32].

4. Conclusions

Palliative care has evolved from serving patients only at the end of life into a highly specialized discipline focused on delivering supportive care to patients with life-limiting illnesses throughout their patient journey. Current AI solutions already provide a well-suited tool set, but are still limited in terms of data availability and, thus, a versatile clinical applicability. A highly promising approach to filling this gap can be attributed to GAN-based synthetic data generation to provide AI classification models with an enriched set of anonymous, heterogeneous patient data to achieve likewise a high degree of data security and an accurate model performance. This novel combination can therefore lead to more precise AI-based models and finally, to improved clinical screening tools in palliative care.

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