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Case Report

Machine Learning and Big Data in Remote Health Care

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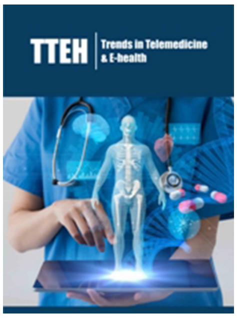

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Abbreviations:

ML: Machine Learning; QoL: Quality of Life; HRQOL: Health-Related Quality of Life; ePRO: Patient Reported Outcome and Experience Measures; AI: Artificial Intelligence; WB: Well-Being; PROMs: Patient Reported Outcome and Measures; PREMs: Patient Reported and Experience Measures; IoT: Internet of Thinks; IoMT: Internet of Medical Thinks

Introduction

In the recent decades, have been developed several solutions that support medicine inside the hospital. Recently, the Internet of Thinks (IoT) and the wide use of wearables are the most prominent trends in telemedicine. Also, it is known that the healthcare providers invest in software that connects physicians and patients through such devices and applications. Thus, we are moving to the Internet of Medical Thinks (IoMT) applications that can help both, the clinicians and the patients. The clinicians can monitor the patients remotely at home, while the patients can interact with their physicians.

The Challenge in Health Care

In the present era, Machine Learning (ML) has been extensively used for many applications to real world problems. ML techniques are very suitable for Big Data Mining, to extract new knowledge and build predictive models that given a new input can provide in the output a reliable estimate. On the other hand, healthcare is one of the fastest growing data segments of the digital world [1,2], with healthcare data increasing at a rate of about 50% per year. There are three primary sources of big data in healthcare: providers and payers (including EMR, imaging, insurance claims and pharmacy data), -omic data (including genomic, epigenomic, proteomic, and metabolomic data) [3], and patients and non-providers (including data from smart phone and Internet activities sensors and monitoring tools). The growth of big data in oncology [2], as well as other severe diseases (such as Alzheimer's Disease, etc.) can provide unprecedented opportunities to explore the biopsychosocial characteristics of these diseases and for descriptive observation, hypothesis generation, and prediction for clinical, research and business issues. The results of big data analysis can be incorporated into standards and guidelines and will directly impact clinical decision making [4]. Oncologists and professionals from related medical fields can increasingly evaluate the results from research studies and commercial analytical products that are based on big data, using ML techniques. Furthermore, all these applications can be Web-based, so are very useful for the post treatment of the patients [5]. In addition to these opportunities, multiple challenges remain related to data quality, acquisition and processing, analytical methodology and interpretation. Considering all the above, the key questions to be answered are:

I. What are the main factors or variables underlying the assessment of Quality of Life (QoL) and Well-Being (WB) in cancer patients, after-treatment, and how could these be better assessed?

II. How can we develop efficient and effective assessments of patients' QoL and WB in order to select timely candidates for interventions before these patients increase their side-effect burden, emotional distress, or bio-behavioral factors that promote cancer progression?

III. How should information and education about cancer care be provided to patients since these are the support services most frequently requested by the patients?

IV. How should cancer patients be supported (e.g., stress management interventions via internet, nutritional coaching for appetite loss) in order to improve their physical, mental and social dimensions and therefore extend and improve their QoL and WB?

V. What can health care institutions and health professionals do to provide high-quality care for the psychological and social effects of cancer, maximizing the health and healthcare of cancer patients?

In addition, hearing the patient voice at greater volume is a constantly increasing need. The power of Patient Reported Outcome and Experience Measures (PROMs and PREMs), lies in their ability to turn subjective experiences into numerical scores that can easily be utilized for quantifying how effective health care interventions are, both on an individual and a larger population level. This allows the data to also be used for strategic and analytical purposes, including health policy decisions, quality improvement and comparison of clinical practices, even across different countries. The scientific evidence in support of using PROMs and PREMs in routine clinical care is robust [5]. A large part of the benefits can be traced back to improvements in patient-clinician communication caused by the increase in timely, automated and systematically collected patient-reported information. For patients, key benefits include improved quality of life, symptom management and satisfaction with care. For health care professionals, the main advantage is gaining a better awareness of the patient's experience on care outcomes. PROM and PREMs data help the clinician to focus on symptoms that need attention, both during and between clinic visits and without prolonging consultation time or interfering with workflows [6,7].

In a situation where the number of cancer patients is predicted to increase but resources available for treatment and care are not expected to grow, digital solutions such as PROMs and PREMs that have the potential to improve the quality, effectiveness and efficiency of care are welcomed by many healthcare professionals [8]. Nevertheless, the uptake of PROM and PREMs systems in clinical care settings is still faced with implementation barriers, such as planning and designing the system infrastructure, training users, and engaging staff. This is partly because the body of research demonstrating the benefits of using PROMs and PREMs in clinical care has only started growing in recent years. Further research is therefore still warranted. Understanding the patient experience is particularly important within cancer care, as cancer patients go through substantial physical, mental and social consequences of both the disease itself and its treatment. Despite time spent in hospital during active cancer care, much of the treatment side effects and treatment-related symptom burden occur outside the hospital [9].

It has been argued that these consequences may be under-recognized and under-treated in oncology practice, resulting in greater morbidity that is costly to patients and the health care system [10]. Furthermore, compared to clinicians, patients detect subjective symptoms, such as fatigue, earlier and report them with more detail and a higher severity. Health care providers assessing cancer patients' symptoms tend to underestimate symptom intensity; yet are better at unfavorable clinical outcomes. Both perspectives are needed, as both provide clinically meaningful information [11,12]. In this context, PROMs and PREMs provide a patient-focused, clinically relevant, and reliable perspective on the patient symptom experience [13]. The scientific evidence supporting the use of PROMs and PREMs both on an individual and a population level is ever increasing and has revealed a variety of benefits for patients and health care professionals. Importantly, using PROMs and PREMs in everyday practice can improve clinicians' understanding of the effect of disease and treatment on patients' daily lives, and has the potential to narrow the gap between clinical reality and the patient world [14].

Thus a huge, unprecedented opportunity is formed to create intelligent healthcare-patient services and tools to manage the health status and wellbeing of cancer patients at all levels. This is true, especially when considering the following key driving factors:

I. Improved cancer survival rate

II. Proliferation of smart phones.

III. Increased importance of Health-Related Quality Of Life (HRQOL)

IV. Huge volumes of data from clinical, administrative, imaging and omics sources

V. Incoming flood of electronic Patient Reported Outcome And Experience Measures (ePRO), patient internet activities, sensors and monitoring data

VI. Rapid advances in Artificial Intelligence (AI) and Big Data analytics.

To address such a complicated task, one needs to bring together specialists from the scientific areas of Computer & Web Engineering, Data Science, Bioinformatics-Personalized Medicine, clinicians and caregivers. The focus of these experts should be is on current technological advances and challenges about the development of big data-driven algorithms, methods and tools; furthermore, to investigate how ML-aware applications can contribute towards Big Data analysis on post treatment follow up. An ambitious project that leverage, but also skillfully and methodologically overcome technical challenges related to the above 6 drivers, is the ONCORELIEF project (H2020-GA No. 875392): A Smart Digital Guardian Angel Enhancing Cancer Patient Wellbeing and Health Status Improvement Following Treatment. ONCORELIEF aims to deliver a framework that consists of three main sub-systems: 1) a back-end data platform where data are securely collected from heterogeneous sources, anonymized, annotated and stored, etc., 2) an Artificial Intelligence (AI) engine built on top of the back-end platform, which consumes and analyses data, extracts important features, produces meaningful AI models and updates them accordingly, produces correlations, etc.) a downloadable application (ONCORELIEF Guardian Angel) available for portable devices, which will be connected with the ONCORELIEF platform and with patients' sensing devices. It runs locally and uses models produced by the AI engine to extract insights on the patient life and condition and make suggestions. The GA may optionally send data back both for research-related reasons (another source of big data) and for computation offloading reasons (AI engine not powerful enough on the mobile phone). These models are then downloaded to personal, portable devices in order to locally analyze individual data and to generate QoL (Quality of Life) indices, recommendations and warnings for the patients using the application. The application has been implemented and a pilot phase is running. The first results, with real data obtained from cancer patients, were reported and they are very promising.

Conclusion

The ONCORELIEF project proves that combining advanced ML technics, using bio-signals, from wearable devices and smart phones, all the above referred applications can be Web-based, so are very useful for the post treatment of the patients, at home.

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