Medical Data Understanding

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Abstract

1. Healthcare's Digital Future

Currently, the patient care is conducted in functionally and geographically isolated medical facilities. It causes fragmentation of medical processes leading to media and technology gaps in the information flow. Missing interoperability of devices and data transfer interfaces is only an exemplary reason for this. A digital and patient-centred care consequently defined along all its steps would improve its medical quality and economic efficiency.

Considering the current degree of digitalisation over the healthcare stages depicted in Figure 1, the digitalisation has mainly been established in the diagnostics. Especially the modern medical imaging modalities and molecular approaches demonstrate the huge amount of digital data generated in today's healthcare systems for diagnostics. In the remaining healthcare steps, such as prevention or therapy, the degree of digitalisation in the treatment procedures has recently gradually increased. The demographic change leading to society ageing along with the shortage of medical staff (especially in rural areas) critically challenges healthcare systems in industrialised countries in their conventional form. For this reason, less cost intensive forms of data-driven algorithmically supported treatments will experience an extremely high scientific, societal and economic priority in the near future. Luckily, the digitalisation of our society progresses with a tremendous speed, so that more and more health-related data are available in digital form. For instance, people wear intelligent glasses or/and smartwatches, provide digital data with standardised medical devices (e.g., blood pressure and blood sugar meters following the standard ISO/IEEE 11073) or/and deliver personal behavioural data by their smartphones.

This huge amount of personal data generated everyday significantly improves the accuracy of machine learning and pattern recognition algorithms aiming at holistic assessment of the human health. Better understanding of human physical, mental and cognitive condition makes personalised and preventive interventions possible. However, the ethical, legal and social implications (short ELSI) of this trend must be analysed very carefully. For instance, data-driven precise medical profiles of patients may lead to ethically and legally completely unacceptable pricing models in the health insurance.

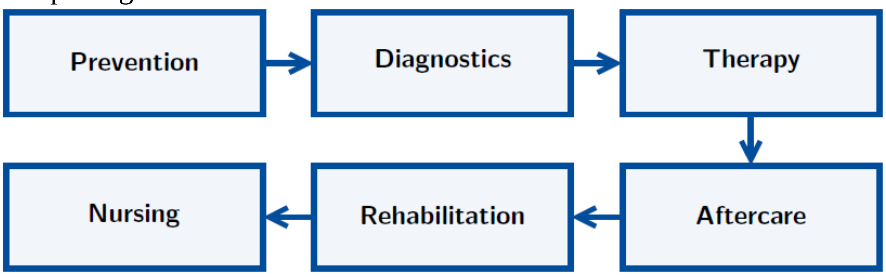

Figure 1: Healthcare Stages

2. Machine Learning for Data Understanding

The health-related digital data voluntarily generated by patients on a daily basis (Section 1) can be automatically processed, analysed, classified and medically interpreted with support of semiautomatic machine learning and pattern recognition algorithms. However, abstraction of the data towards their medical understanding using fully automated algorithms is a very challenging scientific problem. The so called semantic gap, the lack of coincidence between automatically extractable data features and human-perceivable semantic meanings [6], must get bridged for this. A person’s everyday life requires an immense amount of knowledge about the world. Much of this knowledge is subjective and intuitive, and therefore difficult to articulate in a formal way. Computers need to capture the same knowledge in order to behave in an intelligent way. One of the key challenges in artificial intelligence is how to get this informal knowledge into a computer [3]. In contrast to human experts from a certain application area (e.g., medical doctors), computers do not possess the context knowledge required to interpret low-level digital data on a high-level of semantic abstraction (e.g., early diagnosis in medicine).

One of the approaches towards closing the semantic gap aims at integrating knowledge bases called ontologies into the process of low-level data analysis [7]. However, the ontology generation process has been automated up to a certain limited level only which makes this strategy very time consuming. In addition, the integration of the high-level ontology-based reasoning techniques into the low-level data analysis algorithms usually requires the pattern recognition algorithms to be customised towards the context model (application ontology) currently used [1]. This hinders the portability of such solutions across application domains.

Currently, the most widely investigated family of approaches aiming to reach high-level interpretations from low-level digital data is called deep learning [2, 3]. Generally, deep learning algorithms allow computers to learn from experience and understand the world in terms of a hierarchy of concepts, with each concept defined in terms of its relation to simpler concepts. By gathering knowledge from experience, this approach avoids the need for human operators to formally specify all of the knowledge that the computer needs. The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones.

3. Exemplary R&D Projects

Currently, we participate in several interdisciplinary applied research projects with the objective of data-driven automatic holistic health assessment for prevention and personalised intervention. In the following two of them are shortly summarised.

In the project Cognitive Village [5] funded by the German Federal Ministry of Education and Research, technological, economic and social innovations as well as the participatory design approach are integrated into technical assistance systems enabling long-term independent living of elderly and diseased people in their own homes, and even in rural areas where well-developed infrastructure is often missing. Under careful consideration of ethical, legal and social implications as well as the users’ real needs, the technical system is collecting digital data about the elderly’s daily life provided by sensors voluntarily distributed in their homes as well as by wearables such as smartwatches, intelligent glasses and smartphones. These sensory data is then automatically processed, analysed, classified and interpreted by adaptive machine learning algorithms. The objective is to automatically achieve high-level semantic interpretation of activities as well as physical and cognitive states of elderly for the detection of emergency situations with different criticality grades. Equipping the algorithms with adaptive properties (different users, behaviour changes over time) belongs to the most prominent scientific contributions of Cognitive Village from the machine learning and pattern recognition point of view. In addition, the system is required to cope with the dynamically reconfigurable sensor system delivering the data. The semantic gap in automatic data processing is reduced here by applying probabilistic methods for sensory data fusion, introducing adaptive learning mechanisms, integrating ontological background knowledge as well as probabilistic modelling and automatic detection of extreme events in the data. Deep learning strategies (see Section 2) are also used in the Cognitive Village system.

My-AHA (My Active and Healthy Ageing) is an EU-funded project (Horizon 2020) [4] which aims at preventing cognitive and functional decline of older adults, through early risk detection and tailored intervention. A multinational and multidisciplinary consortium is developing an innovative ICT-based platform to detect subtle changes in physical, cognitive, psychological and social domains of older adults that indicate an increased risk of subsequent vicious cycle of disability and diseases, including dementia, depression, frailty and falls. For this, we develop, apply and investigate machine learning approaches for multimodal data understanding in the context of healthy ageing. Our activities follow the increasing level of semantic abstraction. On the low-level data classification level we apply and extend multiple existing approaches targeting concrete tasks such as sleep quality estimation, speech emotion analysis, gait analysis, indoor/outdoor localisation, etc. The outcomes of these low-level classifiers are then fused on the middle data analysis level to assess the cognitive, social and physical states of elderly. Coming onto the high-level of semantic interpretation, the outcomes of the middle layer are fused and jointly analysed towards general multimodal state description of elderly in context of healthy ageing. These multidimensional elderly description profiles deal subsequently as inputs for a generic intervention model that, using concrete parameter values of a particular profile, provides a specific intervention programme optimised for a particular individual.

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