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Cover Story

Smart Diagnostics

Smart Diagnostics with Wearable Devices: Principles and Applications

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Life expectancy has increased in the past few decades especially in developing countries, but quality of life of older population can be severely impacted by conditions such as neurodegenerative diseases (dementia, Alzheimer's, Parkinson's, etc.). Early detection and treatment of such conditions is key to increasing quality of life for patients and families. Smart diagnostic methods and tools based on wearable devices and artificial intelligence offer potential for better management and treatment.

Key Points

- Life expectancy is increasing especially in developing and low-income countries.
- Quality of life does not always increase as rapidly because of different factors, not least neurodegenerative diseases.
- Healthcare and social costs of neurodegenerative diseases are increasing, and new methods to improve treatments and quality of life are necessary.
- Wearable devices and AI can act on large quantities of different types of data and allow early detection, remote diagnostics and personalised treatments
- A case study on automated Parkinson's disease detection and treatment analysis has been highlighted.

21st Century Problem

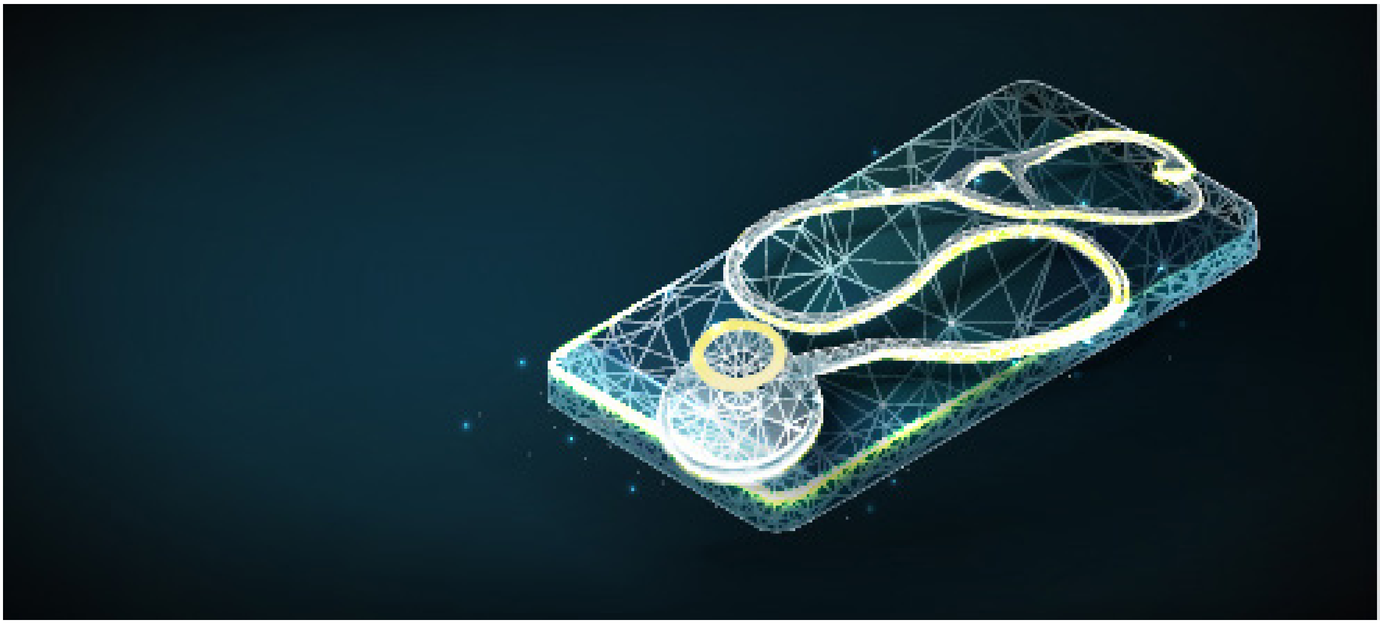
According to the World report on ageing and health (WHO 2015), expectancy of life has dramatically increased in the last decades. As reported, "a child born in Brazil or Myanmar in 2015 can expect to live 20 years longer than one born in those countries just 50 years ago."

However, despite the strong evidence that older people are living longer, particularly in high-income countries, the quality of life during these extra years is quite unclear (Crimmins and Beltrán-Sánchez 2011).

Among the most common consequences of ageing population, neurodegenerative diseases are rapidly growing and represent one of the major causes of disability and dependency among older people worldwide.

The total number of people with dementia is projected to reach 82 million in 2030 and 152 million in 2050. Dementia is a broad category of neurodegenerative diseases, which impact the ability to perform normal activities, think and remember, with a devastating impact not only on the affected people, but also their family and society at large.

Alzheimer's disease (AD), Parkinson's disease (PD) and



amyotrophic lateral sclerosis (ALS) are among the most common neurodegenerative diseases together affecting over 50 million people worldwide, with almost 10 million new cases every year according to the World Health Organization (2019). Several studies have attempted to estimate the extent of the issue in different parts of the world (Kowal et al. 2013, Mehta et al. 2014, Alzheimer's Association 2013).

How Can We Address the Problem?

To respond to the continuous population increase and ageing, to the effects and consequences of neurodegenerative diseases, the global healthcare systems must review their care approaches and look at long-term sustainability of the management of cases and the costs sustained by the hospitals and by the charged families.

Several methodologies have been defined over the years to improve care capability and efficiency and demonstrate high potential to improve diseases prevention, remote monitoring and smart diagnosis for dementia. Wearable devices play a major role in such methodologies and have been proven to be effective in different strategies.

Disease prevention

Studies show that people can reduce their risk of dementia, depression, obesity, non-communicable diseases and improve their quality of life by getting regular exercise, not smoking, avoiding harmful use of alcohol, controlling their weight, adhering to a healthy diet, and maintaining healthy blood pressure, cholesterol and blood sugar levels. In general, preserving a healthy lifestyle is the basis for preventing ageing-related diseases and ensuring higher life quality among adults as well as elderly (Alwan 2011). Plenty of wearables and smartphone-based applications and studies about food consumption (Fuchs et al. 2019), activity performance (Manea and Wac 2018), sleep quality (Ciman and Wac 2019), and stress monitoring (Can et al. 2019) have been developed over the last few years. The pervasiveness of wearables permits to monitor many of the user's parameters and potentially influence their health. Last, improvements on machine learning algorithms implemented in wearable devices enable to support and suggest how to improve healthy behaviours.

Remote monitoring

According to E.J. Topol (2019), wearable sensors have the potential to pre-empt patients being hospitalised in the future reducing the costs of care without sacrificing convenience and comfort for patient and family. Remote monitoring solutions include different applications, such as activity monitoring, falls detection, falls prevention, assisted living, remote hospitalisation and rehabilitation. Activity monitoring and falls detection systems based on machine learning techniques are generally fed by inertial data from wearable devices, such as the accelerometer and the gyroscope. Assistance living and remote rehabilitation use smart technology to share information between wearable devices and home sensors (see Baig et al. 2019 for further details).

Smart diagnosis

Wearable devices are valid instruments for dementia's smart diagnosis. As mentioned above, dementia is a progressive degenerative process. All dementia phases require to be continuously monitored to estimate the disease's decline and gravity and promptly intervene with medical decisions and supports. Wearables can aid and support elderly people without being invasive and, at the same time, are helpful technologies for smart diagnosis. Thus, wearables can monitor changes in behaviour, detect dangerous events, and predict the state of the disease (Mohamedali and Matoorian 2016).

Wearable Technology and Big Data

Over the past decade, considerable progress in hardware and software has modified the habits of individuals, society and business. On one hand, the micro-electro-mechanical systems (MEMS) have reduced sensor size, cost and power needs, while sensor capacity, precision and accuracy have increased. On the other hand, the spread of the Internet of Things (IoT) has enabled and accelerated fast connections between devices, objects and environments.

Modern devices are extremely interconnected, accessible to people and effective in terms of capability to collect, share and analyse large amounts of data. Among them, wearable devices have gained more and more attention in many research fields, not least in healthcare.

Among artificial intelligence (AI) algorithms, machine learning and deep learning methods have seen increasing success for Big Data analysis. Based on data-driven approaches, they are powerful algorithms able to classify and predict clinical outcomes, extract high level information, and identify data patterns.

Nowadays, most wearable devices are equipped with highly performing machine learning algorithms, which allow to monitor our daily lifestyle and healthcare (see Witt et al. 2019 for a comprehensive study).

Case Study: Parkinson's Disease Classification

An estimated 6.1 million individuals globally had a Parkinson's disease diagnosis in 2016, 2.4 times higher than in 1990. This increasing prevalence was attributed to improved methods used to detect and diagnose Parkinson's disease, greater awareness of the disease, ageing populations, longer life expectancy, and possibly increased environmental exposures (e.g. pesticides, solvents, metals) associated with industrialisation (Feigin et al. 2019).

The quality of life of Parkinson's affected patients may

The pervasiveness of wearables permits to monitor many of the user's parameters and potentially influence their health

Wearable devices encompass all accessories attached to the person's body or clothing incorporating computer technologies, such as smart clothing and ear-worn devices (Godfrey et al. 2018). They are usually fully equipped with many microsensors, such as accelerometer, gyroscope, or GPS, and can be easily integrated with external sensors. Thus, a simple smartphone can capture attributes, such as motion, location, temperature, ECG, blood insulin level and many other parameters from the user. These parameters are precious information for many healthcare applications.

The main characteristic, which makes wearables so attractive, is their pervasiveness. Indeed, wearables such as smartphones and smartwatches are basically designed to provide online almost all services that a person needs to access during their daily activities. For instance, they allow the user to connect with people, read emails and news, play games and watch videos. At the same time, the user can track many other activities, e.g. sports and nutrition, sleep quality, stress level and even disease symptoms. It follows that a simple smartphone becomes a useful, even critical tool for our working and free time as well as for our healthcare monitoring. All the information recorded by wearables generate a considerable amount of data, often characterised as Big Data.

improve with an early, personalised and accurate diagnosis. In these terms, wearable technologies can drastically help clinicians to perform early and personalised diagnosis over time. Plenty of studies have demonstrated the power of wearable devices and machine learning techniques. According to Rovini and colleagues (2017), five critical fields of application cover the entire pathology progression: (1) early diagnosis, (2) tremor, (3) body motion analysis, (4) motor fluctuations and ON–OFF phases, and (5) home and long-term monitoring.

In the following case study description, we will restrict to (4) as it is the focus of the investigations of the authors at the CERN openlab in Geneva. Parkinson's disease patients exhibit motor symptoms such as bradykinesia, tremor and rigidity. Treatments are based on dopaminergic medicine, which leads the patient into two states: the 'on' state where the effect of the medicine is present and the 'off' state where the effect is absent in the patient. Consequently, motor symptoms fluctuate depending on the effect of the medication. Therefore, most clinical and research studies focus on recognising and stabilising fluctuating motor symptoms (Aich et al. 2020).

Data of 15 individuals have been collected in a real scenario for several months using the accelerometer and the gyroscope sensors embedded in a smartwatch and a smartphone. Data have been self-annotated in a range from 0 to 4 (0=on, 4=off) and organised in 20-minute segments. Sampling rate and units of measurement have been normalised. A low-pass filter is used to eliminate instrumental data noises and the effects of body-wide motions (such as walking or moving hands and arms during speech). Data was then subdivided into segments (also called windows) of a given length (for example, 20 minutes of accelerometer data can be split into windows of 1 second), and the windows overlapped to decrease the effect of artefacts at the boundaries. Segmentation permits to decrease the computational time during the feature extraction phase, while at the same increasing the size of the algorithm's input samples.

The major difficulty in achieving sufficient performance encountered in the analysis was indeed related to the relatively small size of the dataset. Another challenge was due to the data acquisition scenario itself. Data collected from real activities are usually very noisy because the use of wearables cannot be precisely controlled. Users are free to wear or not wear the device. The activity that the subject is performing can interfere with the measurements and is often interrupted. Furthermore, the data presents intrinsic variabilities, namely the intra-subject and inter-subject variability. The intra-subject variability means that the same severity level presents different signals for the same subject. The inter-subject variability means that same severity levels have different signals for different subjects. Consequently, the algorithm can struggle to generalise the severity level from data, and estimating a one-to-one signal-severity association becomes rather complex.

In the specific study, machine learning techniques, such as random forest and support vector machines (SVMs), have been preferred over deep learning strategies. It has been shown that ensemble classifier with random forest achieved the best performance. Deep learning algorithms have been also trained, but performance over the limited amount of available data is so far not satisfying.

In the literature, promising results have so far been achieved from SVMs, random forest, k-Nearest Neighbors and Naive Bayesian networks (Aich et al. 2020). Neural networks (MLP) algorithms have been also experimented with (Keijsers et al. 2006) as well as convolutional neural networks (Um et al. 2018).

Although the estimation of 'on' and 'off' state remains challenging due to its strong dependence on the disease stage and on the patient, the current preliminary results show the potential to improve diagnostics and the quality of life of patients by monitoring the effect of treatments and assisting the doctors in defining effective, personalised dosage and intervals.

New technologies have allowed wearable devices to spread in the population. The capability of machine learning algorithms to early detect and monitor neurodegenerative diseases has been drastically improving recently. It is realistic that with the growing use of medical and paramedical devices, increasing amounts of good quality data and improvements in AI algorithms, more flexible, low-cost and high-performing treatments and quality of life conditions will soon become more than a promising idea. ■

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