A Proposal to Evolving Towards Digital Twins in Healthcare

Cecilio Angulo[1(✉)], Luis Gonzalez-Abril[2], Cristóbal Raya[1], and Juan Antonio Ortega[2]

[1] IDEAI-UPC, Universitat Politècnica de Catalunya, Barcelona, Spain
{cecilio.angulo,cristobal.raya}@upc.ede
[2] Universidad de Sevilla, Seville, Spain
{luisgon,jortega}@us.es

Abstract. The main objective in this proposal is to orchestrate an ecosystem of manipulation of reliable and safe data, applied to the field of health, specifically lung cancer, by introducing the creation of digital twins for personalised healthcare about the behaviour of this disease on patients. Digital twins is a very popular and novel approach in digitisation units in industry which will be used by both kind of experts: (i) data analysts, who will design expert recommender systems and extract knowledge – explainable Artificial Intelligence (AI); and (ii) professionals in medicine, who will consume that knowledge generated with their research for better diagnosis. This knowledge generation/extraction process will work in the form of a lifelong learning system by iterative and continuous use. The produced software platform will be abstracted so it can be applied like a general purpose service tool in other domains of knowledge, specially health and industry. Furthermore, a rule extraction module will be made available for explainability issues.

Keywords: Digital twin · Healthcare · GAN · Proposal

1 Introduction

Data, data, data... In recent years there has been a huge proliferation of companies and research groups working with different volumes of data. There exist solutions that store and process these data and from them infer knowledge and/or know better about our experience, invading even privacy when manipulating or extracting this information. Thus, mobile phone's geolocation allows knowing about our position, and people we interact with. Furthermore, new technologies in smart wearable sensors [1] allow continuous monitoring on people of physiological functions – heart rate, oxygen saturation in blood, temperature, movement, rest periods, etc. –, adding to diagnostic tests and clinical information, a third

This research has been partially supported by the EDITH Research Project (PGC2018-102145-B-C21,C22 (AEI/FEDER, UE)), funded by the Spanish Ministry of Science, Innovation and Universities.

source of continuous information: the patient himself through mobile devices (mHealth) [2].

In order to carry out a study about these topics, the elements to be considered are:

- *Data privacy for ethical issues.* It is appropriate to put some coherence, limitations on data use, data quality, and a long list of factors and aspects on which there is now a broad social and political debate, establishing criteria on this new science that it is created around the data.

  Hence, in particular, sources of medical data in health services are causing important concerns, the main one being privacy and legal issues when sharing and reporting health information of patients. However, an accurate diagnosis will depend on the quantity and quality of the information about a patient, as well as extensive medical knowledge. These data will be treated taking into account that our objective is to generate patterns, this is to perform their analysis and structuring them through mathematical, statistical, mining techniques of data and machine learning. In this context, anonymization arises as a tool to mitigate the risks of obtaining and massively processing personal data [5].

  Statistical methods protecting sensitive information or the identity of the data owner have become critical to ensure privacy of individuals as well as of organizations. In [6], anonymization methods are investigated based on representation learning and deep neural networks. The training procedure aims at learning representations that preserve the relevant part of the information (about regular labels) while dismissing information about the private labels which correspond to the identity of a person.

  We propose an initial GAN-based [7] anonymization phase, so a seedbed would be obtained from the training data that allow not only to capture information from the original data, but to generate new information with a similar behaviour to the original one.

  Generative Adversarial Networks will be designed and developed to anonymize original data for both objectives, privacy-preserving and data synthesis. Privacy is in the origin of the ethical and legal dimension.
- *Knowledge generation (in the health domain).* "To generate information and knowledge that are valid for the user and her/his environment" . This is very important in the field of health since it allows measurement of the immediate advantage it brings to the user and the rest of the actors involved around: family, doctors, administration and society.

  At this point, it is worth to note that during the last few years important advances have been experienced in applying new information analysis technologies and their introduction in different aspects of society, including, of course, medicine and health. Most of these technologies are coming from the social media domain due to the huge volume of information to deal. Medical information from a patient can imply also a large volume of data (not ever), however the nature and purpose of this information seems more aligned with dealing critical industrial processes and devices that social media.

How data should be structured, stored and analyzed the information, with the aim of extracting knowledge form it, is highly correlated with industrial issues about data protection, safety, regulations, expert knowledge, and so on [3].

Hence, the industrial concept of *Digital Twin* as just a digital representation of the actual physical product [8] can be proposed for the health domain. One of the most important advantages of digital twins is to test decision in a simulated "real" environment to check how the simulated environment behaves or obtain some kind of feedback about how good the decision was. Hence a bidirectional (dyadic) communication is established between medical doctors and data analysts in a lifelong learning system.

– *Lifelong learning.* A digital twin is defined as a digital representation of an entity, including attributes and behaviors, sufficient to meet the requirements of a set of use cases, that is, they are virtual representations of physical assets. Differently to physics or mathematical models, as the digital twin model represents more of the object's behaviors, covering more of its life cycle, it becomes a digital twin of the real-world object.

  Digital Twins, a concept from the "industrial internet of things" or IIoT, is the discipline of devising highly capable simulation models, especially those that consume streaming data from sensors to anticipate maintenance issues, impending failure of components and improving performance. Devising a simulation model of clinical behavior in front a disease, such as the classical propensity models, is much more difficult because humans are so unpredictable and engineering approaches obviously don't apply.

  In our case, we are not worried about modelling artificial pancreas for diabetic patients or artificial lungs in the case of lung cancer, but to model the behaviour of these diseases in the patients; how patients' measures drift along the evolution of the disease.

  This approach means a continuous learning and reshape of the behavioural model, as well as continuous bidirectional interaction between data analysts and professionals in medicine.
– *General purpose service.* The complete system should be designed as a general purpose service to be used in multiple domains. As a general purpose approach, it would facilitate the process of abstraction of the knowledge embedded into a bidirectional recommender system [9], being approached by an explainable AI module able to extract rules from the dialogue between professionals in medicine and data scientists, avoiding lack of accountability [4].

2 Our Proposal

The goals pursued in this proposal are multiple. We can summarise them by observing the diagram in the Fig. 1.

Hence, the complete system depicted in Fig. 1 is designed as a general purpose service to be used in multiple domains, from health to industry. As a general purpose approach, it will facilitate the process of abstraction of the knowledge embedded into the bidirectional recommender system, hence could being

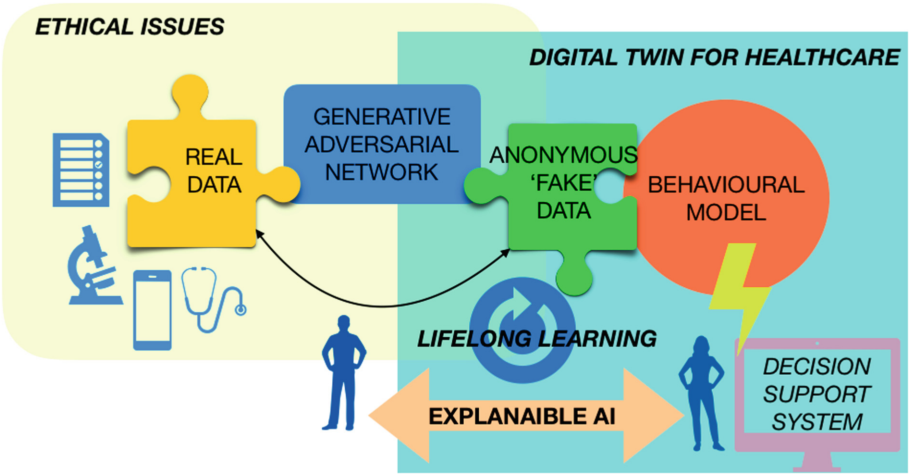

Fig. 1. Diagram of the elements of the proposal for a healthcare digital twin

approached by an explainable AI system able to extract rules from the dyadic dialogue between professionals in medicine and data scientists.

The overall aim of this project is to research in the following three meta-hypotheses and associated general objectives:

- Hypothesis 1: The use of Generative Adversarial Networks on sensitive health data information will allow:
  - anonymizing data in the form of a 'fake' dataset;
  - to generate a seedbed along with the GAN machine for generating fake patients that health professionals can use to perform a deeper study on the disease.

  Let us indicate that in our context 'fake' is not negative aspect since we sought this dataset in order to improve the capacity of the doctor in your work.
- Hypothesis 2: The use of the digital twins approach, extrapolated from the industrial domain, will lead to a behavioural model of the disease (lung cancer) that allows:
  - experimenting new health treatments with simulated 'real' patients before to be applied in hospitals;
  - extracting knowledge from regular data science research to be implemented in the form of a decision support system.
- Hypothesis 3: A decision support system developed in a bidirectional form will allow:
  - a dyadic dialogue between health professionals and data scientists in order to work in a lifelong learning paradigm, that means an iterative and adaptive process;
  - this dialogue will eventually drive to an AI explainable system able to generate decision rules.

Endowed with this information, doctors may decide whether a specific treatment would be likely to help and at what dosage it should be given, based on the digital model.

The overall approach of this proposal implies research in three meta-hypotheses as displayed in the following sections.

3 Generative Adversarial Networks on Sensitive Health Data

The progress in information and communication technologies (ICT) allows us to promote a new model where data is the core, the most precious asset, the support on which it must pivot and orienting the solution of information systems.

Sources of medical data are very heterogeneous, so technological barriers exist in the communication of the data of the same patient between health services causing important difficulties when it comes to collecting and harmonising patient data. Several reasons can be adduced, the main one being privacy and legal concerns when sharing and reporting health information of patients. However, an accurate diagnosis will depend on the quantity and quality of the information about a patient, as well as extensive medical knowledge.

In this context, anonymization arises as a tool to mitigate the risks of obtaining and massively processing personal data, consisting of a process that allows identifying and hiding the sensitive information contained in the documents, allowing its disclosure without imply to violate the rights to the protection of data of the people and organisations that can be referenced in them[1].

Anonymisation of information, as a method protecting sensitive information or the identity of the data owner, for legal or ethical issues, is usually seen as a major problem in data analytic because it could lead to reduce the explainability of the dataset. However, new training procedures, like Generative Adversarial Networks (GANs), aim at learning representations that preserve the relevant part of the information (about regular labels) while dismissing information about the private labels which correspond to the identity of a person. The success of this approach has been demonstrated, in [10] for instance. A diagram to the architect to GAN can be seen in Fig. 2.

As a result of this GAN-based anonymization phase, a seedbed is obtained from the training data that allows not only to capture information from the original data, but to generate new information with a similar behaviour to the original one. This result is currently being applied in generative applications on speech, vision or natural language, but we want to demonstrate that it can be also applied in the health domain.

Medical knowledge implies an experience acquired through learning, detecting signs, looking for symptoms, assessing risks, until reaching a diagnosis and being able to propose a treatment indicated for each patient. However, often,

[1] https://www.aepd.es/media/guias/guia-orientaciones-procedimientos-anonimizacion.pdf.

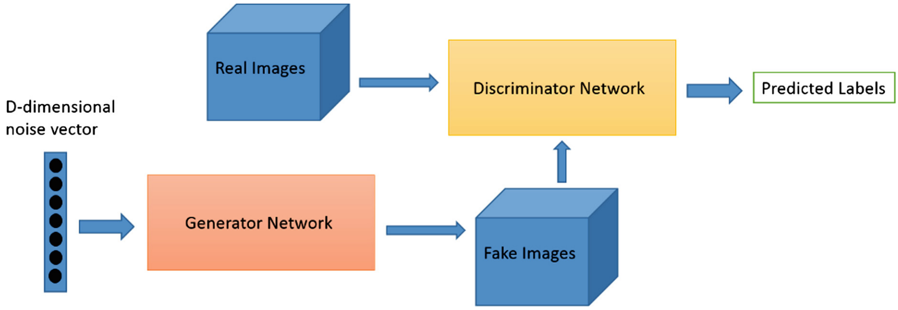

Fig. 2. Overview of a Generative Adversarial Network structured. Source: towardsdatascience.com/generative-adversarial-networks-gans-a-beginners-guide-5b38eceece24

physicians are unable to fully consider the large amount of data obtained from a patient and use it to make diagnostic decisions. If we consider the total set of patients, even for a single disease, and generate 'fake' experiences from a seedbed emerged from real patients, we expect that they can benefit from this valuable information better than buried within huge amounts of data.

On the other hand, this volume of data is obviously interesting for the data science community. Many approaches can be considered in this point that will not be discused here because we have a limited space. From our perspective, the nature and purpose of medical information from a patient seems more aligned with dealing critical industrial processes and devices than social media. How data should be structured, stored and analyzed, with the aim of extracting knowledge form it, is highly correlated with industrial issues about data protection, safety, regulations, expert knowledge, and so on.

In order to see as the GAN can provide some help, the Fig. 3 is shown as an illustration.

4 Digital Twins in Healthcare

The concept of *Digital Twin* in industry exists since 2003: it should be just a digital representation of the actual physical product [11]. According to [12], digital twins play three distinct roles when extrapolated to healthcare: hospital design, hospital management and patient care. Digital twins for hospital design and management exists and are selled by GE Healthcare Camed Group. For patient care, Dassault Systèmes claims to have one of the first realistic model of a human heart, including the electricity, mechanics and blood flow of the heart. Also, Philips sees the potential of digital twins in healthcare, especially a digital twin of devices and humans. Philips breaks down a digital twin of a device into four components. Firstly, you need real device data and secondly there must be some kind of artificial intelligence (AI) or data analytics. Those two components could be described as the basic components. To understand the outcome of the AI or the data analytics you need human knowledge. The last component is about physics-based device modelling, therefore no special AI has to be used here.

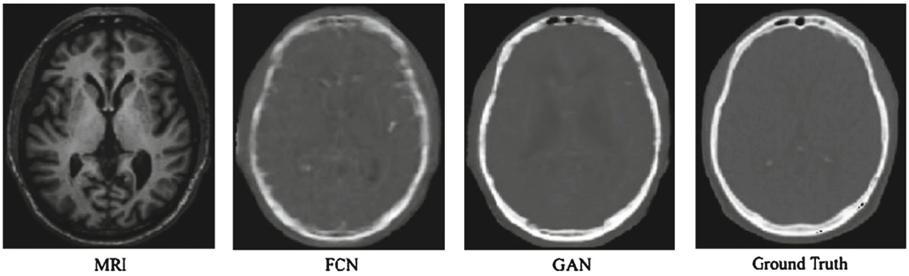

Fig. 3. Generated CT images from an MRI scan. Second image has been generated with a Fully Connected Network (FCN) and third by a GAN. Last image is the original CT image of the patient. Source: https://www.researchgate.net/figure/Conversion-of-MRI-to-CT-using-GAN-38-Adapted-with-permission-Fig-5-Example-of-a_fig3_322657913

One of the most important advantages of digital twins is to test decision in a simulated "real" environment [2]. Then it is possible to see how the simulated environment behaves, also the digital twin could give some kind of feedback of how good the decision was. Maybe it can also tell how to change the initial decision to make the outcome even better. Especially the last aspect can be in healthcare very useful. An ideal example would be, if a doctor wants to treat a patient, but the doctor tests the treatment on the patient's digital twin first. The digital twin will then return a feedback of how effective the treatment was and optimally returns an alternative treatment with a better outcome result. Hence a bidirectional (dyadic) communication is established between medical doctors and data analysts in a lifelong learning system.

Therefore, the Digital Twins approach will lead to behavioural models that allows both, experimenting new health treatments with simulated 'real' patients before to be applied in hospitals and extracting knowledge from regular data science research to be implemented in the form of a decision support system. Figure 4 shows a pictured of the Digital Twins.

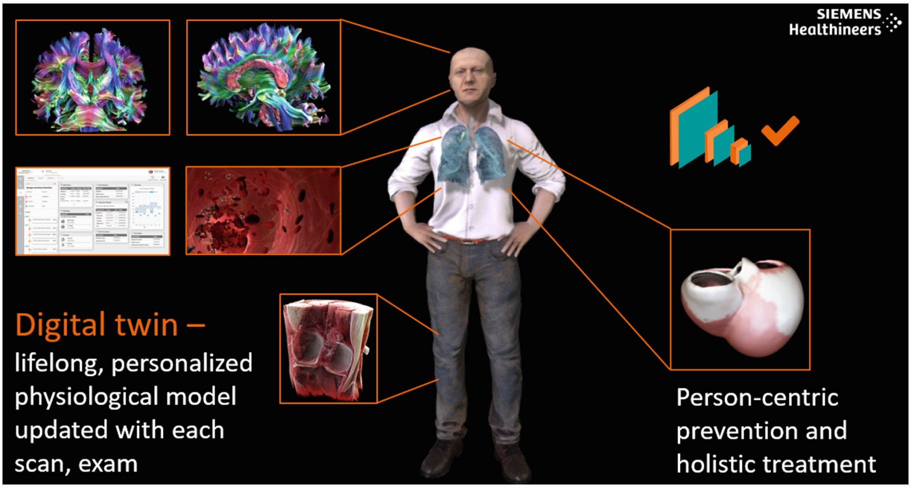

Fig. 4. Digital twins for a patient. From European society of radiology

5 Decision Support System

The anonymized GAN-generated information will allow creating repositories from the seedbed from which the digital twins will generate a behavioural model of the disease, and, from here, provide the data as needed by both kind of analysts: develop a decision support system for data analysts, and generate fake patients' data for clinic professionals, in a lifelong learning system that integrates a dyadic iterative interaction between both kind of professionals, health professionals and data scientists.

Moreover, this dyadic interaction should help to develop explainable reasoning from the behavioural model of the disease, leading to explainable AI in the form of generated decision rules.

6 Discussion and Conclusion

The proposed architecture aims to provide a clinical information integration model in the form of a digital twin of the behavior of the lung cancer in patients under treatment. Thus, there is research, in the medical field, on the adequacy of treatments to patients, based mainly on clinical data. However, in order to achieve improvements in the diagnosis as well as in the treatments, the combination of the clinical data and the diagnostic tests seems appropriate, eventually with other data coming from the outpatient setting of the patient and obtained from intelligent sensors.

The generation of digital twins will allow the use of data in a manner adapted to the needs of each researcher or scientist in particular, and also incorporate tools from the field of ICTs to analysis, study, validation, visualization, etc. of these data. These virtual patients will become a powerful ICT tool that allows the proposal of new biomarkers of diseases, made up of the aggregation of data, and in addition, the visualization and interpretation of the results by doctors and researchers.

Data from patients will be approached from a novel perspective, the GAN machines, that allows a complete anonymization of health records, hence this technique will impact on the EU data protection laws. Nonetheless, flexible and interpretable models will be obtained that will lead to the generation of 'fake' patients serving as both, training patients for novel doctors and a source of new insights about the disease for expert doctors.

Finally, on a different matter, the possibility of generating an infinite number of samples through a GAN is also very coveted. This virtue could allow the continuous simulation of certain variables from a patient for research purposes. This could help as well in the training process of other types of models by augmenting the number of samples, which are usually scarce in private datasets. It could also be convenient in educational areas to avoid misconceptions in the subject because of a scarcity in examples.

References

1. Soria, L.M., Gonzalez-Abril, L., Ortega-Ramirez, J.A., Alvarez, M.A.: Low energy physical activity recognition system on smartphones. Sensors **15**, 5163–5196 (2015)
2. Bruynseels, K., Santoni de Sio, F., van den Hoven, J.: Digital twins in health care: ethical implications of an emerging engineering paradigm. Front. Genet. **9**, 31 (2018)
3. Raghupathi, W., Raghupathi, V.: Big data analytics in healthcare: promise and potential. Health Inf. Sci. Syst. **2**, 3 (2014)
4. Ford, R.A., Price II, W.N.: Privacy and accountability in black-box medicine. Mich. Telecommun. Technol. Law Rev. **23**(1) (2017)
5. El Emam, K., Arbuckle, L.: Anonymizing Health Data: Case Studies and Methods to Get You Started. O'Reilly Media, Inc., Cambridge (2013)
6. Feutry, C., Piantanida, P., Bengio, Y., Duhamel, P.: Learning anonymized representations with adversarial neural networks. https://arxiv.org/abs/1802.09386. Accessed 12 Dec 2019
7. Goodfellow, I., et al.: Generative adversarial nets. Adv. Neural Inf. Process. Syst. **27**, 2672–2680 (2014)
8. Kharat, R., Bavane, V., Jadhao, S., Marode, R.: Digital twin: manufacturing excellence through virtual factory replication. Glob. J. Eng. Sci. Res. [**NC–Rase 18**], 6–15 (2018)
9. Nguyen, J., Sanchez-Hernandez, G., Armisen, A., Agell, N., Rovira, X., Angulo, C.: A linguistic multi-criteria decision-aiding system to support university career services. Appl. Soft Comput. **67**, 933–940 (2018)
10. Feutry, C., Piantanida, P., Bengio, Y., Duhamel, P.: Learning anonymized representations with adversarial neural networks. https://arxiv.org/pdf/1802.09386.pdf (2018)
11. Grieves, M.: Digital twin: manufacturing excellence through virtual factory replication (2014). http://www.apriso.com
12. Hempel: Digital Twins in healthcare. https://www.dr-hempel-network.com/digital-health-technolgy/digital-twins-in-healthcare/