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A Swarm Artificial Intelligence Approach for Effective Treatment of Chronic Conditions

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***Abstract*—Long-term conditions or chronic diseases are multifaceted and challenging. Current treatment options, for patients with long-term conditions, are mainly pharmacological, causing numerous adverse drug events and pressing for alternative management strategies such as personalized interventions. Areas of machine learning, such as deep learning, would enable researchers to develop predictive modelling algorithms, using continuous monitoring and allowing assessing the medical risk for long-term conditions and their related complications. In this paper, we claim that harmonization of data, novel machine learning algorithms, swarm-based technologies, and the involvement of the entire healthcare community will lead to acceptable and effective personalized healthcare. Our proposed approach aims to amplify the intelligence of the healthcare community. Based upon the patients' characteristics empowers better decisions, personalised medical risk prediction and recommendations of acceptable and effective interventions. Our future work includes the validation of the SwarmAI framework by actively engaging relevant stakeholders.**

Keywords—swarm intelligence, artificial intelligence, cybersecurity, personalized healthcare, long-term conditions

I. Introduction

Long-term conditions or chronic diseases are multifaceted and challenging [1, 2], while having a crippling effect on the patient, society and healthcare systems [3]. This rapidly growing epidemic is responsible for more than half the global budget for diseases. One in three adults suffers from multiple long-term conditions, because of the growing life expectancy and the aging population [4]. This accounts for 41 million deaths each year, which number is expected to reach 52 million, in total, by 2030 [5]. In Europe a small group of chronic diseases is mostly accountable for 86% of deaths and 77% of the disease burden [6]. Functional healthcare systems are the foundation for societal well-being and thriving economies. This is why common long-term conditions such as diabetes, cardiovascular diseases (CVD), and rheumatic and musculoskeletal diseases (RMDs) ought to be studied, to explore the most effective ways for overall management.

The financial costs of diabetes have increased by 26% from 2012 to 2017 due to this growing prevalence [7]. CVD is responsible for 31% of all global deaths yearly with global cost reaching $1,044 billion in 2030 [8]. RMDs are the main cause of disability in the European Union, and its economic impact exceeds CVD's [9-11]. Current treatment options are mainly pharmacological [12, 2] and there is a pressing need for alternative management strategies while utilizing modern technological approaches.

Personalized care, treating patients individually while allowing them to make choices [13], has been successfully applied to various healthcare systems [14]. The digitalization of a system, meaning utilizing digital devices and systems for collecting, analysing and utilizing data [15], providing personalized interventions could facilitate that. Previous studies using digital health care approaches to long-term conditions have shown promising results. Electronic health (eHealth) interventions, which are interventions distributed through technology, have helped patients with condition management [16-20]. A recent study investigating Artificial Intelligence (AI) methodologies in diabetes [21] suggested that common AI medical applications for diagnosis and therapy have been successful.

Areas of machine learning, such as deep learning, would enable researchers to develop predictive modelling algorithms, using continuous monitoring and allowing assessing the medical risk for long-term conditions and their related complications. The use of descriptive analytics techniques (i.e., clustering discovery) could also provide options for personalized interventions. These strategies could be useful to healthcare professionals and cost-effective. Cybersecurity in healthcare infrastructures and healthcare tools is also of critical importance, as healthcare organizations store a vast amount of sensitive and confidential patient data. The increased digitization of healthcare records, telemedicine, and the use of connected devices has created new opportunities for cyberattacks. Therefore, it is essential to protect against cybersecurity threats to ensure patient safety and privacy. There are various measures which can be implemented in healthcare organizations to reduce the risk of cyberattacks and protect sensitive patient data, such as risk assessment, access controls, encryption, sensitivity awareness training, incident response plan, and vendor management.

The usability of digital healthcare tools, and multidisciplinary teams, are needed to unlock the full potential of AI in health [22]. It should be noted that the success of AI in the clinical sector has fuelled a growing debate for the future role of healthcare professionals. When machine-

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learning models can perform diagnostic tasks autonomously, there is speculation whether the comprehensive diagnostic interpretive skillsets of healthcare professionals can be replicated by these algorithms. In particular, the adoption of AI solutions from healthcare providers to optimize the diagnosis of chronic diseases may result in replacing human resources with systems. However, AI is plagued with several disadvantages such as, biases due to limited training data, lack of cross-population generalizability, and inability of deep-learning models to contextualize, making the collaboration of AI and humans compulsory. Swarm AI was introduced by Beni [23] and is based on the organizational format observed in natural communities including insects and animals where individual members perform very simple actions co-operating with one another. We claim in this paper that the Swarm AI is a promising approach to contribute towards the successful diagnosis, management, and treatment of long-term diseases.

In this paper we claim that harmonisation of data, novel machine learning algorithms, swarm-based technologies, and the involvement and collaboration of different teams of the entire healthcare community (e.g., patients, physicians, nurses, carers, analysts) will lead to acceptable and effective personalized healthcare. Our proposed approach amplifies the intelligence of the entire healthcare community and based upon the patients' characteristics (e.g., medical, psychological, behavioural) empowers better decisions, personalised medical risk prediction and recommendations of acceptable and effective interventions. Three chronic diseases, diabetes, CVD and RMDs have been selected to demonstrate this approach since these diseases are mainly responsible for disease burden worldwide as reported by the World Health Organization.

II. Swarm AI framework

Our long-term vision is to fuse the knowledge, experience and expertise residing in the minds of individual healthcare professionals, in order to further elevate, through AI and machine and deep learning-facilitated guidance, the diagnosis, care, and treatment of patients. To this end, we propose an advanced, configurable, re-adaptable, iterative and incremental framework, the SwarmAI Framework (Figure 1), for enhancing and augmenting the intelligence of healthcare professionals, and aid them to move towards more personalized diagnosis, risk prediction, and treatment. The main goal of the proposed approach is to improve, intensify and coordinate the overall efforts for efficient diagnosis, management and treatment of three chronic diseases, namely diabetes, CVD and RMDs.

The proposed SwarmAI framework (Figure 1), comprises three main parts that are broad, dynamic, and thoroughly interconnected: (i) Swarm intelligence; (ii) Autonomous Coordination protocol; and (iii) Augmented Personalized AI Model.

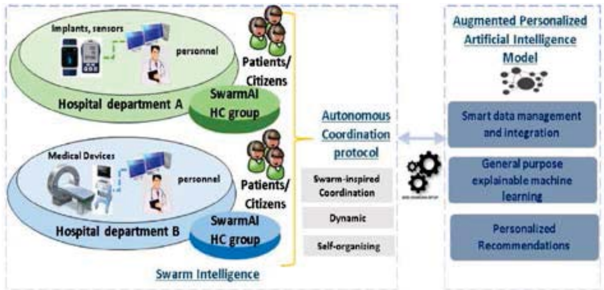

Fig. 1. Main Aspects and Principles of the SwarmAI framework

Specifically, the SwarmAI framework will introduce a pioneer community-driven approach that will enable the healthcare community to optimally use the potential and intellectual resources of its members to infer the state and predict the progression of diseases providing more accurate diagnosis and prognosis. In order to fulfil this, we propose to transfer the emerging idea of Swarm Intelligence (SI), to the healthcare community enabling them to cooperate in a way they have never done before i.e. the individual physicians and the independent groups of healthcare professionals will be enabled to act in a swarm-based manner, each requested to provide diagnosis and prognosis and determine treatment options.

In addition, we propose to implement this new type of collaboration based on SI through an Autonomous Coordination protocol that provides autonomic deployment, cluster formulation and hierarchical communication in the healthcare community. This protocol will be designed to amplify the accuracy and manage the effective coordination of the networked groups of healthcare professionals, named SwarmAI Healthcare (HC) groups, by applying biological principles (i.e., Bio-inspired computing) on their design. This includes the decentralized exchange of knowledge, the design of advanced self-organized networks/systems and the support of self-functionalities in the network (e.g., self-organization, self-awareness). In this way, the proposed protocol will be able to harvest the full collective intelligence of different groups of healthcare professionals (SwarmAI HC groups) defining and leveraging their actions towards a more personalized approach in the disease progression, intervention recommendation and future risk prediction.

This approach leads to a new type of swarm- inspired, self-organizing and dynamic collaboration of the SwarmAI HC groups, which provides the potential for an unprecedented merging of human and AI for the benefit of the patients. In order to meet its objectives, the protocol encompasses a set of SI algorithms and models [24-29] that will monitor the actions of the SwarmAI HC groups and their effects and "learn" the capabilities of each group.

Finally, the SwarmAI framework includes an Augmented Personalized AI Model aiming at enhancing the intelligence of the SwarmAI HC groups by analysing massive amounts of medical data sources of heterogeneous nature and providing personalized recommendations and interpretations to patients and healthcare professionals. The proposed model will augment the intelligence of SwarmAI HC groups in diagnosis, prognosis, early-detection, and personalized treatment decisions by medical practitioners. More concretely, the Augmented Personalized AI Model will rely on the following big data analytics and machine learning technologies:

• Smart data management and integration: A set of big data pre-processing, management, and integration methods will be used for managing the data sources that will be generated and used by SwarmAI HC groups.

• General purpose explainable machine learning: General purpose machine learning methods will be supported that are powerful enough in terms of predictive performance while being trustworthy to healthcare practitioners and patients by providing explanations for their predictions. The main goal is to enhance these methods with explainability capabilities at three levels: (1) data level, (2) model level, and (3) prediction level.

• Personalized recommendations: We will build and employ a set of unsupervised learning algorithms that will be used to generate patient profiles. These profiles will be calibrated and integrated using collaborative filtering for providing personalized treatment recommendations to healthcare practitioners and patients..

III. OPERATIONAL ASPECTS OF THE SWARM AI FRAMEWORK

The proposed model, illustrated in Figure 2, operates by first defining the Augmented Personalized AI Model (step 1) which is then shared with all the participating entities (healthcare professionals) holding data. The networked groups of healthcare professionals modelled after biological swarms (SwarmAI HC groups) feed the Augmented Personalized AI Model (step 2) with the necessary patients' data. The latter produces an output (step 3) providing insight into the presence and evolution of a disease in a short period of time.

The Autonomous Coordination protocol will identify the SwarmAI HC groups (step 4) that are able to validate and compare the output with a desired one in order to create a combined better decision on the input; also, the selected groups will readjust the information based on the difference (step 5). The Augmented Personalized AI Model takes the inputs, the desired outputs and the adjustments and updates its internal state accordingly (step 6), so the calculated output get as close as possible to a personalized output based on the updated patients' characteristics, risk factors and treatment response as well as taking into consideration the clinical evolution over time.

The proposed model takes the above as inputs and then generates personalized recommendations (step 7) according to its past "training experience". In this context, the Augmented Personalized AI Model fits into a process (SwarmAI framework) where recommendations are discussed, rethought, validated and multiplied among the SwarmAI HC groups rather than simply rejected.

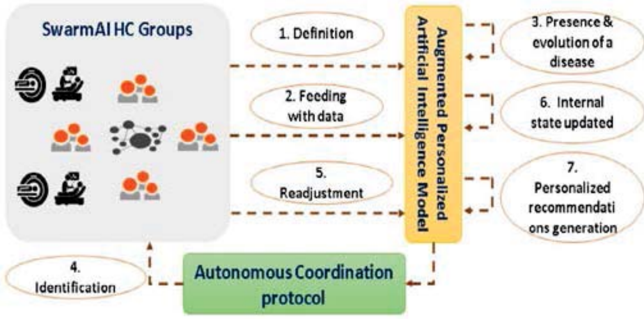

Fig. 2. Operation of SwarmAI framework

The SwarmAI framework realization (Figure 3) consists of three main phases:

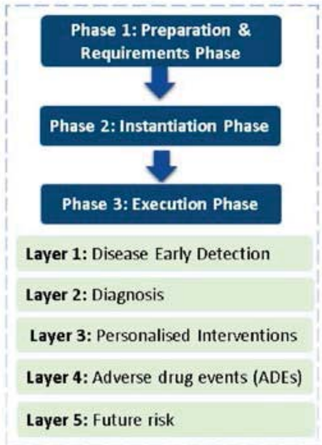

Fig. 3. SwarmAI framework

Phase 1: Preparation & Requirements Phase

The purpose of this phase is to identify and build the health care community that can provide the patients' primary data (which are described in Phase 3).

Phase 2: Instantiation Phase

This activity includes the instantiation of the intelligence model. The primary patients' data and their dependencies are required in this phase. The dependences will be created by the healthcare community, and they will fall under the following categorisation: Physical Dependencies; Behavioural Dependencies and; Confounding interactions of physical and behavioural dependencies.

Phase 3: Execution Phase

This phase implements the full steps of the SwarmAI framework including procedures for diagnosis, risk prediction, and treatment. It consists of 5 conceptual layers (described below), which are the conceptual pillars of building and implementing the SwarmAI approach that will support the prediction, diagnosis, and treatment of various diseases.

Layer 1: Disease Early Detection

Layer 1 targets on the early detection of a disease to eliminate the burden and its associated risk factors. This layer will assess the risk for a potential disease diagnosis. Attention will be given to the collection of the primary data from the categories shown in Table 1. This Layer will adopt an automated process for activating early alerts, warning systems, updating the healthcare professionals about the risk level of a patient's diagnosis, and providing personalised recommendations in a collaborative manner with the patient. The latter allows patients to get acquainted with underlying health information, proposed healthy lifestyles and treatment options that lead to an increasing health literacy.

TABLE I. PATIENTS' CHARACTERISTICS INCLUDED IN LAYER 1

Category	Factors Examples
Determinants of Health	Alcohol consumption
Sociodemographic Characteristics	Age; Ethnicity; Gender
Physical health characteristics	Joint Pain; Medication
Mental Health Characteristics	Depression; Anxiety
Health Related Quality of Life	Physical, and mental health

Layer 2: Diagnosis

Once Layer 1 identifies the risk for a potential disease diagnosis, then Layer 2 will conduct a medical diagnosis. A physical examination by a healthcare professional will be required at this point and the result will be communicated to the patient. The healthcare professional will explore the diagnosis hypothesis, utilizing the results and recommendations from Layer 1. Following the collection of the primary data in Layer 1, in addition to the high risk of diagnosis of a patient, different medical diagnosis will be investigated. This Layer aims to accelerate the diagnostic process by minimizing the different possibilities and providing a valuable tool to the healthcare professionals. The result here will be a specific diagnosis, which in turn will lead to Layer 3 with a combination of personalised interventions.

Layer 3: Personalised Interventions

Layer 3 will suggest a holistic and personalised intervention, or a variety of treatment modalities, which considers patients' needs, responses and preferences to treatment. Based on Layers 1 and 2, additional behavioural characteristics will be collected to determine the personalised interventions in a process that will include mutual engagement of both patients and the healthcare professionals. Behavioural characteristics will be measured according to the Big 5 Personality Traits and estimate the patients' openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. In addition, data of the behavioural factors associated with diagnosis will be collected (i.e., anxiety, depression, pain acceptance). Table 2 presents the categories that will be suggested as personalised interventions according to the patient's needs.

TABLE II. PERSONALIZED INTERVENTIONS CATEGORIES' IN LAYER 3

Interventions Categories	Examples
Lifestyle modifications	Diet; Physical Activity
Behavioural	Mindfulness
Pharmacological	Medication prescription
Combination	Diet & mindfulness

Layer 4: Adverse Drug Events (ADEs)

An ADE is when a medical intervention, related to a drug, causes injury or harm to an individual resulting in human suffering and increased hospital costs. Therefore, it is vital to predict the prevalence of ADEs in order to reduce its associated impacts. Layer 4 will predict an ADE and restrict the suggestion of the drug causing it to the patient. Data from Layers 1-3 will provide input for these predictions. ADEs examples are aplastic anaemia, hypotension, generalized skin eruption, localized skin eruption, anaphylactic shock, and allergy.

Layer 5: Future Risk

Future outcomes of a disease could be either comorbidities, meaning the presence of more than one conditions at the same time, or complications, meaning the development of new symptoms as a direct result of the severity of the disease. Layer 5 aims to predict and mitigate the risk of both the comorbidities and complications based on Layers 1-4 (Table 3).

TABLE III. COMORBIDITIES AND COMPLICATIONS

Disease	Comorbidities Examples	Complications Examples
CVD	cardiovascular impairment	stroke; aneurysm
Diabetes	nonalcoholic fatty liver	Neuropathy; retinopathy
RMDs	hyperlipidaemia; CVD	joint deformities

IV. CONCLUSIONS AND FUTURE WORK

AI systems should be intertwined with the human brain and work as collaborator instead of competitor. In this way, healthcare providers will be able to achieve an optimization of early detection, diagnosis, and management of long-term conditions from the synergy between humans and machines. This Collaborative Intelligence interaction between humans and systems, based on AI techniques, as exemplified by deep-learning technologies, called SwarmAI, amplifies the accuracy of networked human groups and healthcare professionals, by enabling the groups to work together in real-time systems modelled after biological swarms. This Swarm AI achieves superior diagnostic accuracy than the expert systems working independently from human experts.

In this paper we proposed the SwarmAI framework which aims at collecting, compiling, processing, and fusing all patients-related information and data ensuring their integrity and validity. In contrast, from a cognitive point of view, the SwarmAI framework can help healthcare professionals reduce misdiagnosis and missed diagnosis by guiding them in further examination in certain biomarkers or providing second opinions, thus allowing them to stay one step ahead of the diseases and leading to personalized treatment. This newly proposed SwarmAI approach will systematically study all possible combinations in order to provide a risk assessment and prediction model. This model will evaluate the risk levels according to the patients' profile, diagnosis, personalised interventions, and future risk. Overall, this framework will encourage and assist the collaboration of AI and healthcare professionals. Our future work includes the validation of the SwarmAI framework by actively engaging relevant stakeholders.

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