AI Approaches in Processing and Using Data in Personalized Medicine

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Abstract. Nowadays, more and more people suffer from serious diseases and doctors and patients need sophisticated medical and health support. Accordingly, prominent health stakeholders have recognized the importance of development of such services to make patients' life easier. Such support requires the collection of patients' complex data. Holistic patient's data must be properly aggregated, processed, analyzed, and presented to the doctors/caregivers to recommend adequate treatment and actions to improve patient's health related parameters. Advanced artificial intelligence techniques offer the opportunity to analyze such big data, consume them, and derive new knowledge to support (personalized) medical decisions. New approaches like those based on advanced machine/deep learning, federated learning, transfer learning, explainable artificial intelligence open new paths for more quality use of health and medical data in future. In this paper, we will present some crucial aspects and examples of application of artificial intelligence approaches in (personalized) medical decisions.

Keywords: Artificial intelligence · Machine learning · Personalised medicine · Cancer treatment · Quality of life parameters

1 Introduction

We are witnesses of more and more sick population and it is necessary to take care of development of sophisticated multi-disciplinary approaches for medical diagnoses and treatments [7, 21]. Consequently, development of helpful medical services is getting crucial traction in medical innovation. The importance of improvements of patients' health related quality of life (QoL) parameters are also widely recognized in therapies and follow-ups of serious diseases survivors. Cancer patients experience a serious disruption of QoL parameters (fatigue, pain, psychological difficulties, appetite loss, sexual problems and so on). Additionally, they experience also "usual" problems like the majority of the population (anxiety, stress, sleep disorders, and so on) during active oncological treatment period.

S. Chiusano et al. (Eds.): ADBIS 2022, LNCS 13389, pp. 11–24, 2022.
https://doi.org/10.1007/978-3-031-15740-0_2

To support the development of sophisticated software services that can help patients to successfully cope with everyday activities it is necessary to find ways to collect and properly integrate wide spectra of complex patient data (apart from traditional clinical data also data collected from smart wearable devices, nutritional data, and so on). Health-related data should be aggregated in such forms that obtain adequate, useful, and reliable conclusions after processing. Results achieved after data processing should be presented to the doctors/clinicians in understandable and friendly form [7].

Modern, emergent approaches in collecting, processing, and analyzing patient's data support more appropriate interventions, and usually more tailored and personalized treatments [4, 10]. In this paper we will present the current state-of the-art in developing medical and clinical platforms, discuss crucial aspects and functionalities, and present characteristic examples of applications of artificial intelligence approaches in (personalized) medical decisions [23, 24].

The rest of the paper is organized as follows. In Sect. 2, different sources of patients' medical and health-related big data are briefly discussed. Section 3 considers some emergent artificial intelligence approaches that support quality medical decisions. characteristic medical decision support systems are presented in Sect. 4. Concluding remarks and future trends in processing big medical data are pointed out in the last section.

2 Different Sources of Patients' Medical Big Data - Collection and Processing

Electronic Health Record (EHR) is usually seen as basic source of information for any patient. It keeps data of several important aspects of a patient (like clinical information, diagnoses, medication, …). For more reliable follow-ups of patient's health, it is necessary to consider also other data sources and in modern medical data processing they also can include so called Patient Health Record (PHR). A PHR usually contains the same (or similar) kinds of information as an EHR but it is managed by patient. For better analysis and use of all information collected for a patient it is necessary to combine them but also if possible, to incorporate patient's data from other diverse and multiple sources. For example, the CrowdHEALTH project [5] is oriented to the combination of patient's data from various sources to benefit from community knowledge and form Holistic Health Record (HHR). As a result of this project an integrated holistic platform is developed and it incorporates big data management mechanisms to support the logical pipeline of data management: acquisition, cleaning, integration, modelling, analysis, information extraction and interpretation [13].

Further improvement steps are oriented towards advanced approaches based on the integration of HHR and Social HHR (SHR). HHR as an extension of EHR usually contains data like physical activity, nutrition, environmental conditions, information collected from variety of sensors, social care information, and so on. SHR covers patient's aspects of social life and usually contains information about different social aspects and activities like: relationships, particular events, experiences, etc..

After identifying and considering different patient's data sources the next step in medical systems/platforms/frameworks is to find adequate ways and techniques to better acquire, manage, model, and process this data in order to achieve as much as possible, high-quality outcomes and results. Such result, based on huge amounts of data, should be exploited and presented in a user friendly way to doctors/clinicians, caregivers, or even to patients. The main intention in such systems is to try to achieve satisfactory level of tailored decisions to achieving better patient's QoL parameters.

Another interesting approach oriented towards use of complex patient's data and processing it by application of modern AI/ML approaches is developing under BD4QoL project [2]. The focus in the project is on implementation of a personalized management of head and neck cancer survivorship by providing doctors and survivors with an unobtrusive, privacy compliant, real-time monitoring. Such complex supportive environment should offer personalized interventions based on integration of Big Data-driven AI algorithms and models. Patient's traditional health data will be integrated with data collected from mobile and wearable devices for real-time assessment of patient's QoL.

Measuring cancer patient's QoL is about understanding the impact of cancer and how well people are living after their diagnosis and treatment. This includes a wide range of concerns, such as people's emotional or social wellbeing, finances, and ongoing physical problems, such as tiredness, sleep disorders, and pain.

We can conclude that there is trend in medical decision support systems to integrate "traditional" medical and health data sources with novel ones that include data from smart and wearable devices, IoT and sensors generated data, open data, environmental data, etc. Integration of multiscale/multimodal big health data is a challenging task in intelligent big data processing. Heterogeneous data should be aggregated in such a way to enable to generate meaningful conclusions to be presented to doctors in user friendly way.

The rapid development of information communication technologies, applications of IoT and pervasive smart environments in our everyday life promotes the frequent use of different smart wearable devices for monitoring and measuring some health parameters [8]. Constant improvements and development of such devices impose that they should satisfy specific requirements. So, for standard healthcare intervention 5 main features of wearable devices are detected in [16] to ease data collection: "(1) wireless mobility; (2) interactivity and intelligence; (3) sustainability and durability; (4) simple operation and miniaturization; and (5) wearability and portability."

If we concentrate on cancer patients, then it is evident that in several last decades the number of cancer survivors are increasing. Thus, there is a need to develop medical systems with tailored, personalized services that will help in improving patients' QoL parameters. So, it is important to include in patient's medical records their personal experiences. So, in contemporary medical decision support systems a number of questionnaires/tools to measure cancer patient's individual views of his/her health status should be considered. PROMs (Patient Reported Outcome Measures) and PREMs (Patient Reported Experience Measures) are widely used to check patient's perceptions from two aspects: health and experiences after receiving treatment/care. The QoL parameters are getting very important for cancer survivors. Therefore, the research activities should be oriented towards obtaining reliable and early predictors and QoL parameters over time, and improve treatment decisions and follow-up strategies. Medical systems/platforms/frameworks should support the utilization of big HHR and datasets, powerful AI/ML approaches that facilitate the integration of QoL instruments (like

PROMs and PREMs), implementation of a user-centered communication interface, and personalized support.

Modern societies are getting more and more “smart”. Smart environments equipped with sensors, mobile and wearable intelligent device have a potential to positively influence patient’s QoL. Especially, wearable devices play an important primary role to establish and maintain a connection between patients and doctors which offers a great potential to support the quality of medical treatment and recommendations. Additionally acquired complex data generated in smart environments and with wearable devices offers numerous opportunities in medicine and healthcare for the development of more powerful mobile health applications [18] or the development of complex IoT sensing-based health monitoring systems [6, 14].

3 Emergent Artificial Intelligence Approaches for Supporting Quality Medical Decisions

With appropriate medical treatment and support more and more people suffering from different critical diseases are living and normally go about their everyday routine activities. Also, more than ever people are living with and beyond cancer. Receiving adequate treatment tailored to their needs patients can keep and even increase their positive experience and QoL.

Different personalized services that support humans in their numerous activities are a modern approach in software development. Personalization is the process of tailoring specific service to reach the needs of individuals or groups with similar attitudes. Such an approach is also crucial in medical and healthcare domains. Personalized medical services for patients with similar needs are adequate therapies, decisions, interventions, and recommendations adjusted to their specific health status [1, 7]. Therapeutic strategy for “the right person at the right time” can support improvement and efficiency of the treatment, reduce possible side effects and increase the QoL.

QoL parameters are getting essential for cancer survivors. They influence the development of adequate services for person-centered monitoring and follow-up planning. Complex patient’s data collected from multiple sources (EHR, PHR, data from wearable, smart devices, patient’s reported outcomes, etc.) should be processed to be used in improving personalized treatment. Powerful AI/ML approaches are essential instruments for quality data processing that lead to better predictions, interventions and good health status. However, before applying AI/ML techniques diverse data must be prepared in an adequate way (i.e. aggregated, processed, analyzed). Contemporary AI approaches: (deep) ML [7], explainable AI (XAI), image processing (IP), natural language processing (NLP), agent technologies [10], robots, and so on, immensely influence the development of medical systems/platforms/frameworks. Contemporary AI approaches as federated learning (closely related to cloud/edge concepts), high possibilities of neural network architectures combined with transfer learning (e.g., repurposing features of established models explored to address data heterogeneity) offer great capability for developing powerful medical applications. Existing but also newly developing medical systems should utilize patients’ big datasets integrated with QoL instruments, make more power and reliable AI/ML engines, support more friendly user-centered communication, visualize results of AI predictive models and make them more understandable to doctors (employing different XAI techniques), improve personalized support, and so on. Such holistic systems should: improve post-treatment patients' health status and QoL; follow-up the patients to meet their needs and make their everyday life bearable; but also help in predicting the status of new patients.

Many large projects focus on cancer patients and better QoL parameters based on their available complex data. Considering some of them (e.g. https://oncorelief.eu/, https://www.gatekeeper-project.eu/, http://www.bd2decide.eu/, https://ascape-project.eu/, etc.), we outline a "typical Health AI system". Such a system is composed of several subsystems each containing various components devoted to specific task. Three groups of such subsystems can be distinguished.

1) Data Management subsystem that is responsible for secured patients' data collection from multiple sources usually taking care of anonymization [22]. They are also focused on the aggregation of heterogeneous data, their transformation in some of widely used clinical data standards which address different aspects [21] (like SNOMED Clinical Terms, openEHR archetype, FAIR) but also to prepare them in formats appropriate for AI/ML processing. The essential tasks of this subsystem are focused on multiple sources data collection and its preparation for AI/ML processing. During these activities privacy preservation of patients' data must be guaranteed, and its preprocessing, harmonization, and semantical alignment is needed based on variety of services: Data Collection service, Privacy preserving Service, Data Curation/Filtering services, Data Harmonization services, and some others.

2) AI/ML subsystem is tightly related to the Data Management subsystem. This subsystem, for which depending on the nature of the data suitable AI/ML methods are selected to be applied, is responsible for comprehensive data processing and analyses of computed results. Based on a wide variety of techniques after data processing important and influential features/parameters are discovered, characteristic patterns of behaviors are noticed, powerful predictive models are generated. Predictive models, based on available patients' datasets, produce quality predictions, interventions, treatment recommendations that should be presented to doctors/caregivers/patients.

This subsystem usually includes Big Data analytics and modelling, and it is the central in a medical system and represents the logical link between the data management part and interface part. The AI/ML subsystem uses a variety of ML algorithms (for feature selection, outlier detection, classification, regression, and so on) based on available modern ML frameworks (like TensorFlow, Mahout, etc.). Depending on the application domain of a platform and particular disease, ML approaches can also include Medical Imaging Analytics using Recurrent (RNN) and Convolutional Neural Network (CNN) architectures, communication supported by virtual companions [10].

3) Intelligent/Smart Interface subsystem usually is the connection between patient's data and results achieved by AI/ML subsystem. Depending on the main aim of a medical system this subsystem can generate different forms of interfaces for doctors, caregivers, but also for patients. To extract and represent insights of the patient's health status and conditions the interface is usually implemented using powerful AI techniques (like XAI, data visualization, agent technologies and so on). Interface uses generated AI/ML models and suggests adequate, personalised treatments, interventions, various actions, activities, nutrition and so on. In some advanced medical systems AI/ML models can also be downloaded to patients' devices, locally analyze patients' data and recommend appropriate actions for improving their QoL.

In typical medical systems various predictive models are generated to support personalized medical decisions. To make results of predictive models more understandable to doctors and other end-users recently XAI methods are using (like Shapley Additive exPlanations, LIME, Anchors, Textual Explanations of Visual Models, Integrated Gradients) [9], and different ways of data visualization adjusted to different dashboards, smartphones and similar devices are applied. Additionally, the devices that end-users use in communication with a platform should allow for full access to relevant health-related data, support regular updates and obtain information about the patient's QoL parameters and effects of suggested interventions.

Depending on general organization and use of specific medical systems/platform/frameworks, it can incorporate and consider patients' datasets from arbitrary number of hospitals, train and lately use AI/ML predictive models considering common knowledge gained from all available datasets. Such types of systems adopt federate style of data processing, models training and using achieved powerful AI/ML predictive models. Federated learning (FL) as rather new ML approach creates an ML pipeline which significantly reduces the risk of data privacy being compromised. Federated ML is based on existence of multiple clients (edge nodes), that work together to train a single model organised and stored on single server i.e. cloud. In case of medical systems edge nodes usually represent hospitals.

An FL system has two actors: multiple edge nodes and the server. The server coordinates the training process between all edge nodes that participate in the construction of a global model. Each edge node receives a copy of the global model to be trained and updates it based on available local data. When training phase is finished all edge nodes are participating in the training send their updated model's weights back to the server to synchronize them and produce unique global model.

In such an approach sensitive patient's data remains decentralized and FL keeps the data at its local edge nodes (hospitals) and transfers only models' updates to the main server. Predictive models created and trained on local nodes'/edges' data are participating in creating global/centralized federated models. This is succeeded by distributing the model architecture and initial weights to all edge nodes participating in producing a global/federated model. Furthermore, edge nodes train their copy of the global model on local data. When training is finished achieving satisfactory results of the training, updated weights are sent back to the FL server (cloud) to contribute to creating new or updating existing common global/central model.

The central AI/ML component in a medical system is the main source of predictive models trained on a number of datasets from local edge nodes/hospitals, and the models are constantly updating when new data appears and getting more and more reliable and with higher prediction power.

4 Medical Decision Support Systems

In this section we will briefly present two characteristic medical systems based on contemporary technological achievements that incorporate abovementioned concepts and approaches.

4.1 Smart Ambient Intelligent Living Environments

Development of 4G and upcoming 5G and 6G networks have significant influences on development medical services and decision support systems/platforms/frameworks. Accordingly, a range of more and more sophisticated smart, intelligent devices support monitoring patients' daily activities and follow changes of their health related parameters. In such a way more and more patients are living in technologically interconnected worlds. Technological advancements and innovations can significantly support patients to efficiently cope with everyday activities [10].

Ambient Assisted Living (AAL) and Ambient intelligent (AmI) environments facilitate patients in their living space. They incorporate intelligent and flexible services to patients acting in their living space like: Sensors, Networks, Pervasive Ubiquitous Computing and AI, Unobtrusive Human-Computer Interfaces [20].

AAL and AmI encompass monitoring services that supports patients in their everyday activities and living habits, also suggesting them possible actions that can improve their QoL and wellbeing. Main functionalities of a comprehensive ALL environment are described in [3, 17] for a patients' residence or house. Numerous sensors are located at different places, such as sensors for light control, home automation control, presence sensor, medication control, and others to collect patients' data and monitor their daily activities and behaviors (see Fig. 1).

To propose patients' personalized predictions, treatments, recommendations or even possibility of prevention some serious diseases a wide variety of data are collected from such smart environments (like nutrients, physical activities, the microbiome, toxin exposure) and processed using advanced AI/ML methods.

The availability of the smart devices and wearable sensor technology [25] are prominent in a fast accumulation of patient's sensitive and complex health data. Emergent AI/ML techniques are promising in processes of mapping such big data into adequate, personalized health predictions.

4.2 Intelligent System for Supporting Cancer Patients

There are multiple challenges to be addressed by an AI system that aims to enhance clinical practice. A good AI engine with excellent analytical performance characteristics is not sufficient. Matters such as user experience, integration, security, privacy, etc. must also be addressed. The EU-funded research and innovation project ASCAPE (https://ascape-project.eu/) presents an interesting proposition covering all aforementioned aspects of a system that aims to be in a position to enhance clinical practice.

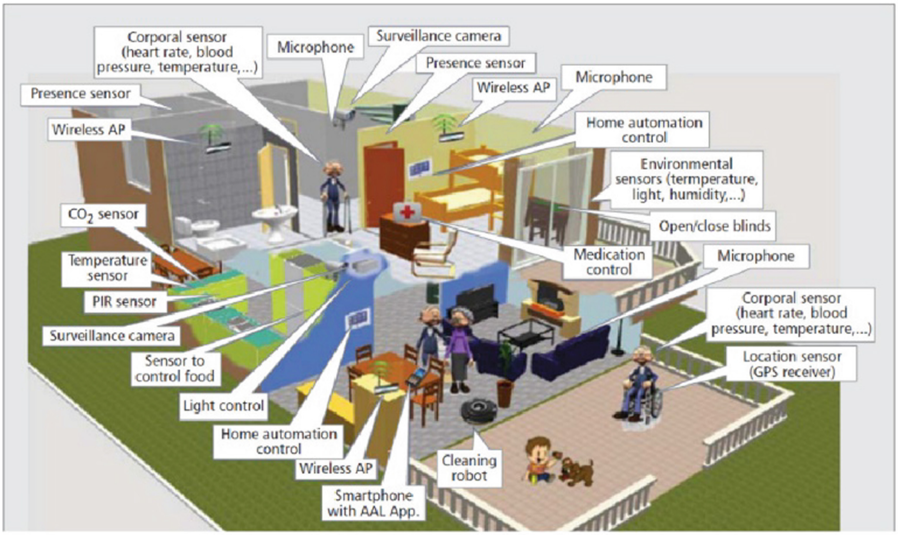

Fig. 1. AAL for elderly people's residence or house (from [17]).

Specifically, ASCAPE aims to provide doctors with an AI-powered tool that monitors and predicts the progression of QoL metrics corresponding to overall QoL and specific issues for a specific patient and offers suggestions for interventions that could improve outcomes. The ASCAPE personalized visualisations widget presents the patient's overall QoL timeline, various QoL issues timelines, a spider chart depicting the latest recorded and the predicted values for the various QoL issues and a list of interventions ASCAPE deems relevant, allowing the doctor to get an overview of the patient QoL and the history of interventions without a litany of interactions. The default view provides both recorded data and predictions for the case that any currently active interventions remain so. Doctors can see how different choices of interventions affect the predictions for the patient's overall QoL and all QoL issues simply by clicking on it. This is a simple interaction producing a predictable response from the system. The system also offers shortcuts, including one where the "ASCAPE-Proposed interventions" are selected.

ASCAPE, unlike the majority of similar clinically-targeted AI-focused research projects, paid particular attention to providing an easy pathway for integration with existing systems. Part of this effort relates to the user interface already discussed. The widget discussed and likewise the widget showing a summary of the current and predicted QoL issues status can easily be embedded into existing Health Information Systems (HIS) doctors are already using. This has the desirable consequence that doctors will not have to log in to yet another IT system and navigate to the patient again. ASCAPE makes integration a priority, point we will return to when discussing the ASCAPE architecture. Another priority for ASCAPE is that hospitals on the one hand maintain control of their patient data and on the other are able to collaborate on building AI models capturing knowledge from multiple hospitals' patients. For this it relies on two different technologies: Federated ML (FL) and ML on homomorphic encrypted (HE) data (Fig. 2, https://ascape-project.eu/marketing-material/ascapeframework-and-technical-innovations).

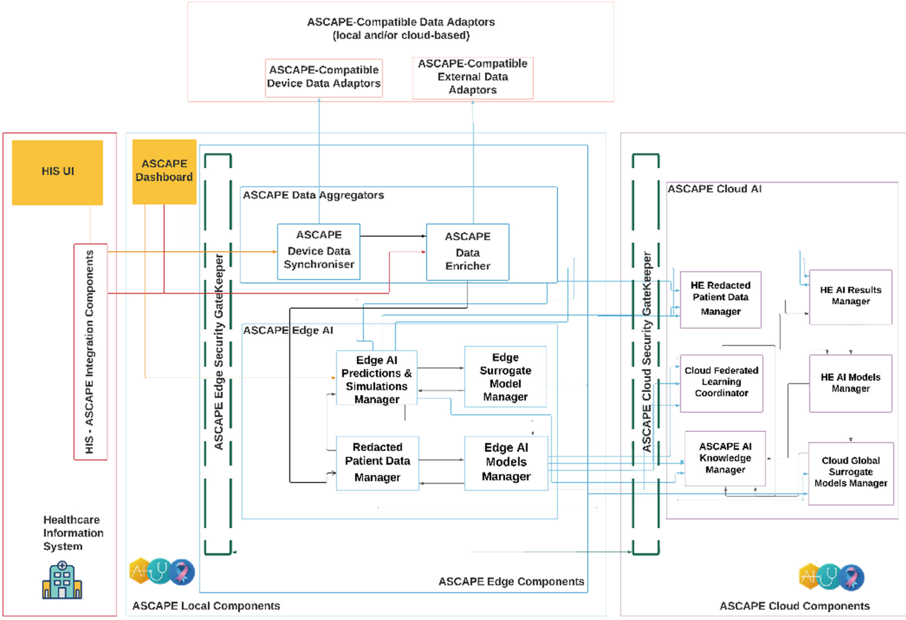

Fig. 2. The ASCAPE framework architecture.

HIS-ASCAPE Integration Components. These components allow an existing HIS to send its data (including both EHR and QoL questionnaire data) to ASCAPE and ideally also integrate the ASCAPE widgets and supporting backend code that provides the HIS with ASCAPE functionality identical to the stand-alone ASCAPE Dashboard's making the latter redundant and offering doctors the benefits of ASCAPE.

The ASCAPE Dashboard. A web application doctors may use, if ASCAPE is not sufficiently integrated into the HIS, in order to access ASCAPE functionality including AI-assisted monitoring of their patients' QoL status and recording information about proposed interventions, registering and de-registering a patient's wearable device.

The ASCAPE Edge Components. Installed locally at each hospital, these components collaborate with the HIS and the Dashboard on one end and, if so configured, with the ASCAPE Cloud which coordinates privacy-compliant collaborative model training with all participating hospitals and provides collaboratively training predictive models to all hospitals. Note that all edge node components that interact with the ASCAPE cloud, any interactions are initiated from the edge node towards the cloud in order to fit as best as possible to firewall settings in place at hospitals IT environments.

A. Edge Gatekeeper - A component that provides TLS/SSL termination, access control and an additional layer of pseudonymization.

B. Data Aggregators - Components that provide support to the task of sending to the ASCAPE Edge Node additional patient-related data not collected by the HIS but rather by ASCAPE-compatible Data Adaptors deployed locally or remotely; currently a FitBit data adapter and a weather service data adapter are included.

C. Redacted Patient Data Manager - The component responsible for storage of all patient data received from the HIS or the data aggregators within the Edge Node. It furthermore includes the extraction of patient specific inference requests and training datasets for the different target variables to train AI/ML models. The inference requests are forwarded to the Edge AI Predictions & Simulations Manager. The training datasets undergo privacy enhancing methods such as outlier detection and differential privacy and are then sent to the Edge AI Models Manager and Edge Surrogate Models Manager as well as after homomorphically encrypted to the ASCAPE cloud. Finally, the component is responsible for providing stored patient-related data to the HIS and/or the Dashboard.

D. Edge AI Models Manager - The component responsible for training local and global models with local data in collaboration with the ASCAPE Cloud, as well as for analytically evaluating models and choosing the ones that best fit local data. For each training dataset received from the Redacted Patient Data Manager several types of models are trained both on local data only as well in federated manner orchestrated by the Cloud Federated Learning Coordinator. For classification tasks, support vector machine classifiers, Naïve Bayes, K-nearest neighbors', Decision Tree, and Random Forest classifiers are trained, and for regression tasks Linear, Ridge, Lasso, Elastic Net, Kernel Ridge, Support Vector Machine, Random Forest, K-nearest neighbors', and AdaBoost regressions are used. All locally trained models are stored in the component as well as any global model obtained from the ASCAPE cloud. The quality of the models is evaluated over the locally available datasets, using appropriate metrics.

E. Edge Surrogate Models Manager - The component responsible for training local surrogate models (linear regression and decision trees) and for training global surrogate models for global predictive models with using the local data in collaboration with the ASCAPE Cloud. Surrogate models are trained to make the same predictions as the primary models (of the Edge AI Models Manager) but due to their nature (e.g. decision tree models) lend themselves to being used for explaining these predictions.

F. Edge AI Predictions & Simulations Manager - The component that uses the locally available models (local models, global models from via federated learning) as well as the Homomorphic Encrypted models at the ASCAPE cloud to produce QoL-related predictions and intervention suggestions to the HIS and/or the Dashboard. The used models are those with the best evaluation over the local data and the predictions from the HE models are obtained by sending encrypted patient-specific inference requests to the ASCAPE cloud and decrypting locally the received encrypted prediction. Furthermore, the component is responsible to compute feature attributions in form of Shapley Values to allow to visualize the impact of the different features on the predicted target values.

In addition to computing predictions and explanations, the component also precomputes intervention suggestion: the goal is use the predictive capabilities of trained models and interventions of any kind for the patient and selected by the medical partners to provide for each patient with suggestions of interventions that have a positive effect on the predicted value. This is performed by simulations estimating the treatment effect of interventions and provide that information for retrieval by the ASCAPE Dashboard to show it to the doctors treating the patients, which can then take a decision.

The ASCAPE Cloud Components. The component allows privacy-preserving ML technologies on the ASCAPE Cloud: (i) the coordination and storage components for FL, (ii) the training, storage components for model training on HE data and encrypted predictions, and (iii) the components used for collaborative surrogate model training.

A. Cloud Gatekeeper - A component that provides TLS/SSL termination and controls which Edge Nodes may collaborate with the ASCAPE Cloud.

B. Cloud Federated Learning Coordinator - This component coordinates the federated training of global predictive models based on the patient data available at each participating edge node. The same type of models as locally are trained in federated manner for classification and regression tasks. The federated training is initiated by the edge nodes. If an edge needs a specific model and no global model is available in Cloud Knowledge Manager, it starts training locally and sends it as a first instance to the Cloud Federated Learning Coordinator. If a global model is available, the edge node updates it with its local training data and submits it again to the cloud (incremental FL mode). If more than one edge node wants to train a model, this component switches to semi-concurrent mode, where training happens in several rounds by collecting the trained or updated model from each edge node, creating an aggregated model.

C. Cloud Knowledge Manager - This component stores all available final global models on the cloud, from which they can be retrieved by the edge nodes. This way new edge nodes entering the federation can benefit from models previously trained on data from all other edge nodes.

D. HE Redacted Patient Manager - This component receives and stores the HE training datasets from all edge nodes. The training datasets can be identified regarding cancer type and target variables and are combined to a single HE dataset for each cancer type and target variable. These aggregated datasets are then forwarded to the HE AI Models Manager for training global HE predictive models.

E. HE AI Models Manager - This component stores all models trained on the aggregated HE datasets. They can be retrieved by the HE AI Results Manager to provide encrypted predictions on encrypted inference requests submitted from the edge.

F. HE AI Results Manager - The HE AI Results receives all encrypted inference requests for predictions from the different edge nodes. Based on the type, it retrieves the corresponding model from the HE AI Models Manager. If the model is not yet available, it waits until the model is available. The encrypted prediction is stored in the component in order to be retrieved by the edge node that submitted the request. The inference requests can be of different kinds: of course, any inference request in the edge node is also submitted to this component. However, during the computation of SHAPLEY values and the training of surrogate models further requests are created by the edge components and submitted to this component in order to determine these for the HE models.

G. Cloud Global Surrogate Models Manager - This component coordinates all activities to train global surrogate models. The training is initiated as soon as an edge node requests a surrogate model which is not yet trained. The Cloud Global Surrogate Models Manage then initiates the training both for linear regression and decision tree models. Meanwhile, the Edge Surrogate Model Manager creates the local training for the surrogate models by taking the local training dataset used for the global model, but labelling it using the predictions of the global model.

The training of linear regression surrogate models essentially works like the federated learning of normal models. Training of decision tree surrogate models is more involved, as separate training or update of models and aggregating via averaging is not possible. The decision tree with the best overall score across all datasets is used as the resulting surrogate model.

5 Conclusion

Growth of population and rapid technological development offer a variety of possibilities for implementing sophisticated and highly personalized medical services nowadays but in the future as well. Development of more and more powerful AI/ML algorithms, image processing, efficient big data processing, natural language processing, virtual and augmenter reality (VR/AR), IoT, agent technologies and other [11], offer a significant shift in medical and health domains [15].

All these possibilities direct medical research and practice in prominent directions [16]: more reliable and precise health analytics and predictive modeling [7], power data visualization techniques, tailored therapies, recommendations and interventions, personal user-friendly interfaces for communication [9] between different participants and stakeholders.

Avatars, metaverse [16], holographic construction [12] are newest concepts that have a high potential and can influence future development of holistic, sophisticated medical systems. In spite the fact that current achievements in these areas are sporadically used in medical systems it can be expected that they will have great influence and increase quality and functionality of medical systems in the future.

Ongoing and future research in the health domain needs extensive interdisciplinary and multidisciplinary collaborations. Important aspect of future medical systems should take care of patients' cognitive and emotional behavior and support adequate modelling in such systems. In this area agent technologies, holograms, AR/VR and metaverse definitely will play an essential role.

For the future development of complex integrated medical systems, it is also necessary to take care of development of other systems devoted to: **1. Planning and resource management, 2. Data management systems, 3. Decision support systems/knowledge base systems, 4. Remote care/self care systems.**

However, the near future is not so optimistic [19]. There are a lot of problems like diverse, limited, and distributed patients' data sources, satisfactory but not fully reliable AI/ML models, rather slow big data processing mechanisms, integration of wide variety of multiple AI services, personalized medicine limitations and so on.

Acknowledgments. This research was supported by the ASCAPE project. The ASCAPE project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 875351.

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