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AIHEAL: AN ARTIFICIAL INTELLIGENCE HEALTHCARE SYSTEM

Abstract: AIHeal healthcare system is a new solution creating explainable and causal artificial intelligence (AI) infrastructure by combining the benefits of the accuracy of deep-learning algorithms with visibility on the factors that are important to the algorithm's conclusion in a way that is accessible to physicians, solution in which they can trust, which open new routes to delivering better, faster, and more cost-effective medical care. The proposed AIHeal system defines a new structure of Electronic Health Record (EHR) that can connect longitudinal data providing insights across episodes of treatment and settings of care, and incorporating new types of data from wearables, sensors and genomics and other omics data. Another innovative contribution of this project is an extensible big data architecture which makes it possible to collect huge volumes and wide spectrum of data.

Key words: *Artificial Intelligence in Healthcare, Electronic Health Record, AI Clinical Decision Support*

INTRODUCTION

Advances in medicine, supported by innovation in technology, are accelerated dramatically in recent years. By the 1950s, medical knowledge had doubled in about 50 years. In 2020, the volume of medical knowledge will double in 73 days [1]. This evolution has significantly risen average life over the past century from less than 50 years to 78.9 years for the USA and to

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80.9 years for EU [2]. By 2050, 1 in 6 people will be over the age of 65, in Europe and North America, this will be 1 in 4. This demographic shift, combined with rapid urbanization, modernization, globalization and accompanying changes in risk factors and lifestyles, means chronic conditions will be more common, and an increasingly comorbid population's demand for healthcare will increase [3].

Managing patients with complex needs is typically more expensive, especially in conditions when health systems are already stretched. It also adds complexity to information flows, as large volumes of healthcare data no longer sit primarily in hospital. It also requires a different set of skills and a strong culture of collaboration between physicians across specialties. In this context, financial sustainability is a core challenge for European, and Montenegro also, healthcare systems. In 2018, healthcare expenditure ranged between 8.8 and 11.2 percent of the GDP (Italy 8.8%, Spain 8.9%, UK 9.8%, France 11.2%, Germany 11.2%) and are expected to continue rising [4]. Healthcare spending as a share of GDP has been growing since 1990, outpacing average wage growth and the growth of GDP itself [5].

Without major structural and transformational change, healthcare systems will struggle to find the funding needed to address growing demand, whilst maintaining or improving standards of care, access, and patient experience. Also, according to the World Health Organization, projected staff shortages of 9.9 million physicians and inevitable skill gaps will be limiting healthcare systems' ability to satisfy this increasing demands.

In recent decades, we are witnessing increased usage of artificial intelligence (AI) in various domains of science and technology. Healthcare systems are not an exception. With artificial intelligence in healthcare, a medical institution can significantly improve self-care, prevention, overall wellness, triage and diagnosis, clinical decision support, care delivery and management, etc.

In Montenegro, these challenges are even more serious. How many people, especially in rural areas, are far from satisfying standards of medical care? Medical staff shortages and skill are already not tolerable, with the trend to become worse.

The proposed AIHeal system has the potential to transform healthcare organizations and healthcare services and meet the current and future society needs not only in Montenegro.

Following chapters present the problem definition, existing healthcare systems and technologies, proposed solution, a new AIHeal healthcare system, analysis of the proposed AIHeal system, and conclusion. This work is described using the proposed method for presenting research results [6].

EXISTING HEALTHCARE SYSTEMS AND TECHNOLOGIES

Computers are utilized in healthcare for decades, ranging from relational database systems [7], over hardware acceleration of most commonly used operations [8] to complex simmulations of fluid dynamics [9]. Many efforts have been tried to exploit potentials of Artificial Intelligence to transform how care is delivered. Some of them are related to using robots for communication purposes and stimulating patients for activity [10, 11]. Others use sensors to extract data that will undergo the automated reasoning process [12, 13]. Effort has been made to exploit AI for advising medical personel [14].

While deep learning techniques produce state-of-the-art performance on a variety of tasks, one of its main criticisms is that the resulting models are difficult to naturally interpret. In this regard, many deep learning frameworks are often referred to as „black boxes“, where only the input and output predictions convey meaning to a human observer. Since correct clinical decision-making can be the difference between life and death, many practitioners must be able to understand and trust the predictions and recommendations made by deep learning systems. There are authors attempts and approaches [15] to make clinical deep learning more interpretable include: Maximum Activation: A popular tactic in the image processing community is to examine the types of inputs that result in the maximum activation of each of a model's hidden units. This represents an attempt to examine what exactly the model has learned, and can be used to assign importance to the raw input features; Constraints: Others have imposed training constraints specifically aimed at increasing the interpretability of deep models. For example, Choi et al.'s Med2Vec framework [16] for learning concept and patient visit representations uses a non-negativity constraint enforced upon the learned code representations; Qualitative Clustering: In the case of EHR concept representation and phenotype studies, some studies point to a more indirect notion of interpretability by examining natural clusters of the resulting vectorized representations. This is most commonly performed using a visualization technique known as t-Distributed Stochastic Neighbor Embedding (t-SNE), a method for plotting pairwise similarities between high-dimensional data points in two dimensions [17]; Mimic Learning: Che et al. [18], [19] first train a deep neural network on raw patient data with associated class labels, which produces a vector of class probabilities for each sample. They train an additional gradient boosting tree (GBT) model on the raw patient data, but instead use the deep network's probability prediction as the target label. Since GBTs are interpretable linear models, they are able to assign feature importance to the raw input features while harnessing the power of deep networks. The approaches given and known from the open references cannot be recognized as full naturally interpretable, and are not widely accepted.

Companies around the world implemented numerous products where AI is having an impact in healthcare. Some of the prominent applications available today grouped around use cases in healthcare are [20]:

— Cronic Care Management: Sensely –virtual nurse, Karantis360–automated personal monitoring and alerting system, AICure–treatment adherence, Pill Pack–personalised presorted meds for repeat prescriptions.

— Care Delivery: Moxi–nurse assistant robot, Amelia–virtual health assistant, Bionic Pancreas–insulin/glucagon administration for Type-1 diabetes patients, EarlySense–contact-free patient monitoring.

— Clinical Decision Support: IBM Watson For Oncology, DeepMind–prediction of acute kidney injury.

— Improving population-health management: Mount Sinai Health Systems–risk prediction for emergency admissions, Sheba Medical Cancer–prediction of complications.

— Improving operations: Qventus–optimisation of operating room flow.

— Self-care/Prevention/Wellness: AliveCor CardiaMobile–personal ECG, Activity and sleep trackers.

— Triage and Diagnosis: Symptom checkers: Babylon, Mediktor, Ping An Good Doctor, Ada Health, K Health.

— Diagnostics: Sight Diagnostics–point of care blood testing, Arterys–medical image analysis, Idx –detection of diabetic retinopathy, Detection of eye diseases: DeepMind, UCL and Moorfields.

PROBLEM DEFINITION

Even available applications have many patients who uses its, why do they not widely accepted from patients and specially from physicians? What are common disadvantages for these applications? We would stress some of the problems which are important from the technological point of view and where technology could help:

— Applications are designed to cover only specific use cases.

— Applications focusing on areas that simplify routine processes are better accepted because they are more understandable for patients and physicians, and obviously free up physician time.

— Applications focusing on use cases such as Clinical Decision Support, Triage and Diagnosis, Diagnostics and other more complex segments of healthcare are less straightforward and are not understandable enough for physicians. Physicians cast doubt on the readiness of the technology and have not confidence to apply them in practice.

— The major challenge is data. Data can be incomplete or of poor quality and consequently AI applications cannot be better than the data used. Data are often poorly suited to AI due to quality issues, inconsistent formats, or the challenges of linking data and obtaining the necessary consent to use in different use cases.

The AIHeal healthcare system has an ambition to solve above mentioned disadvantages:

— The AIHeal can cover all medical use cases offering EHRs which may include structured (demographics, medications, diagnoses, laboratory tests, doctor's note, radiology documents, clinical information), semistructured (from various medical devices, wearables,...) and unstructured data (text, voice, biomedical images,..).

— The extensible big data architecture for such kind of data is proposed, capable of batch and stream processing.

— The most important aspect is that we also propose interpretable system, understandable for physicians. The decision making process can be based on deduction and known facts. Our goal is to create a solution which will be adopted from physicians recognizing that it will make or break the success of AI in healthcare

PROPOSED SOLUTION

The proposed AIHeal system (Figure1) offers three innovative contributions to the field of AI Healthcare systems.

Data

The major challenge is data. How does it possible to manage such quantity of data and reach the necessary quality and interchangeability. One of the most serious obstacles for AI in healthcare is that while enough data are available from pharmacy companies and healthcare institutions, they are not connected or interoperable. Two innovative contributions in a relationship with data are proposed.

The first innovative contribution is the new structure of Electronic Health Record (EHR). The proposed EHRs are medical records for patients with any information relating to the past, present, or future physical/mental health or condition of an individual and connect longitudinal data and new types of data from wearables, mobiles, NL data, sensors and

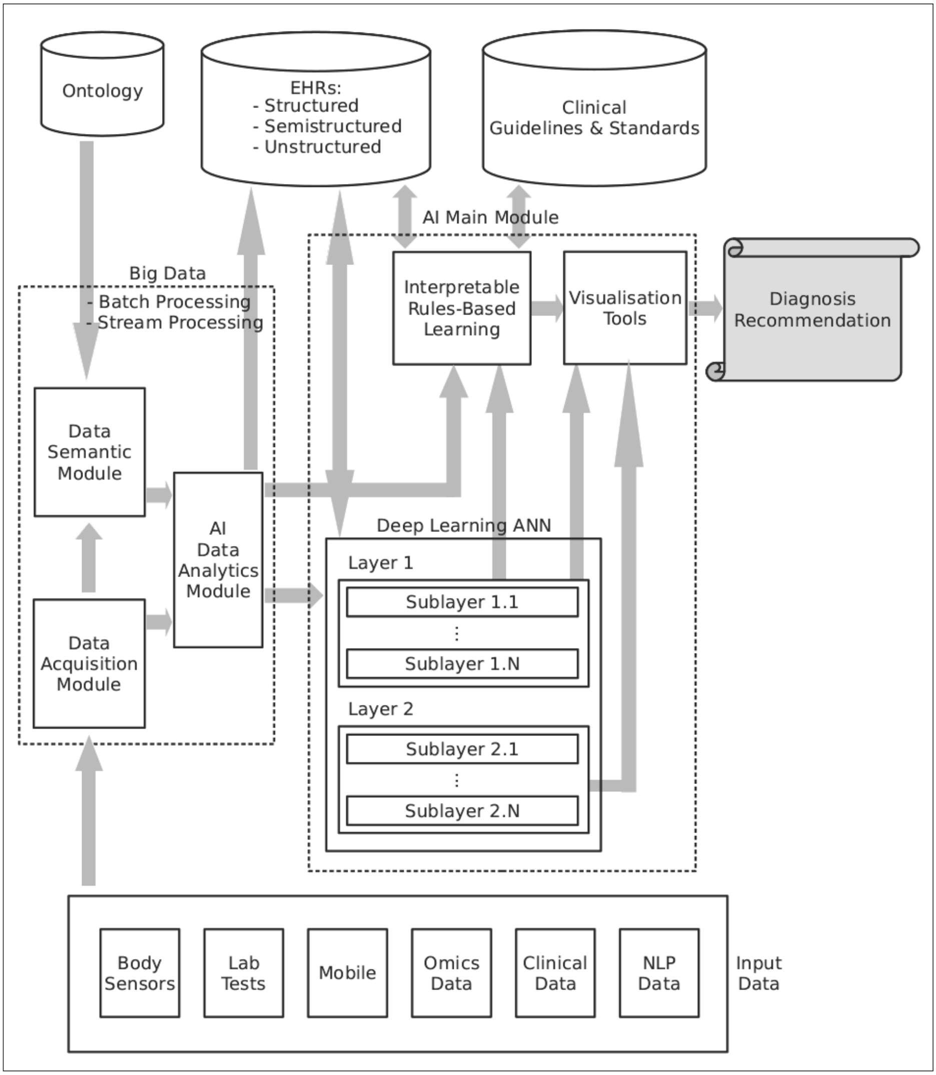

Figure 1. The structure of the proposed AIHeal system

genomics and other omics data. Genomics data are becoming more accessible as the costs of sequencing and bioinformatics techniques have significantly reduced. Healthcare data are typical big data which combine volume (high amounts of data), velocity (data is generated at a rapid pace), variety (data comes under different formats), veracity (data originates from trustable sources), and variability (variations in the data flow rates). Improvements in data, processing power and algorithms are rapidly changing what is feasible. The scope and quality of healthcare data produced and the potential to link datasets are opening new possibilities. Both the quality and consistency of data are improving as more data are machine generated. Focus is on developing consistent interconnected data infrastructure capable for data exchange and semantic interoperability of different medical fields and use cases. The proposed EHRs, unlike the traditional ones, may include structured (demographics, medications, diagnoses, laboratory tests, doctor's note, radiology documents, clinical information), semistructured (from various medical devices, wearables...) and unstructured data (text, voice, biomedical images,..). This data integration allows us to develop the „digital twin" of the patient and makes a prerequisite to design modular and flexible AI infrastructure capable to cover different use cases. This is multidisciplinary approach for medical and software development experts. The ambition of the project is not to cover every medical field, but the cardiology topic as a prototype and a proof of data infrastructure concept. The future multidisciplinary projects, based on this infrastructure, are expected to complete the puzzle.

Extensible big data architecture

The process of extracting from big data can be broken down into five stages [21]. These five stages form the two main sub-processes: data management and data analytics. Data management involves processes and supporting technologies to acquire and store data and to prepare and retrieve it for analysis: Acquisition and Recording; Extraction, Cleaning and Annotation; and Integration, Aggregation and Representation. Analytics, on the other hand, refers to techniques used to analyze and acquire intelligence from big data. The proposed extensible big data architecture consists of Data Acquisition, Data Semantic and AI Data Analytics modules (Figure 1). The Data Acquisition module is responsible to collect data from various sources. This component may be combination of HDFS, NoSQL such as MongoDB and SQL database. The Data Semantic module is mapping heterogeneous databases into common structure and semantics. The Web Ontology Language with XML syntax can be used as standard interchange format regarding ontology. The thorough analysis through the design and development of these modules is expecting to suggest the most suitable solution. The AI Data Analytics module is responsible for Extraction, Cleaning and Annotation, Integration, Aggregation and Representation, and is based on AI mechanisms proposed through the Main AI module proposal. The AI Data Analytics module compares every processed data to predefined user's threshold. If the value of a particular data exceeds alarming threshold value, it will be stored while an emergency alert is generated to the Main AI module. The Main AI module decides if it is value of data for final emergency alert, or regular storage in EHRs. The proposed extensible big data architecture is capable of batch and stream processing and be based on available frameworks. Various available frameworks will be analyzed. For batch processing mode Hadoop allows distributed big data on a cluster of machines but may not be appropriate for stream processing. When stream processing is required, Storm, S4, Apache Spark, Apache Flink may be a suitable choice. Apache Spark may be serious candidate. It is open source unified engine for distributed data processing that includes higher-level libraries for supporting SQL queries (Spark SQL) that restore data from many sources and manipulate them using SQL, streaming data (Spark Streaming), iterative machine learning algorithms through library mechanism (MLlib), provides efficient algorithms with high speed, structured data analysis using Hive, and graph processing based on GraphX. Further information extraction and processing from EHRs requires specialized toolsets for Natural Language Processing, Image Analytics (Visualization Toolkit, GIMIAS, Elastix, MITK), Machine Learning (Tensorflow, Keras, Theano, Torch, Caffe...) and analytics for „Omics“ data (SparkSeq, SAMQA, Distmap, Hydra...).

Main AI module

Until the last few years, most of the techniques for analyzing rich EHRs data were based on traditional machine learning and statistical techniques such as logistic regression, support vector machines (SVM), and random forests. Recently, deep learning techniques have achieved great success in many domains through deep hierarchical feature construction and capturing long-range dependencies in data in an effective manner. Machine learning approaches can be broadly divided into two major categories: supervised and unsupervised learning. Supervised learning techniques involve inferring a mapping function $y = f(x)$ from inputs x to outputs y. In contrast, the goal of unsupervised machine learning techniques is to learn interesting properties about the distribution of x itself. The representation of inputs is a fundamental issue spanning all types of machine learning frameworks. For each data point, sets of attributes known as features are extracted to be used as input to machine learning techniques. In traditional machine learning, these features are hand-crafted based on domain knowledge. One of the core principles of deep learning is the automatic data-oriented feature extraction. The vast majority of deep learning algorithms and architectures are built upon the framework of the artificial neural network (ANN). ANNs are composed of a number of interconnected nodes (neurons), arranged in layers. The most common deep learning architectures for analyzing EHR data differ in terms of their node types and the connection structure (e. g. fully connected versus locally connected). Several open source tools exist for working with deep learning algorithms in a variety of programming languages, including TensorFlow, Theano, Keras, Torch, PyTorch, Caffe, CNTK.

While deep learning techniques produce state-of-the-art performance on a variety of tasks, one of its main criticisms is that the resulting models are difficult to naturally interpret. In this regard, many deep learning frameworks are often referred to as „black boxes", where only the input and output predictions convey meaning to a human observer. Since correct clinical decision-making can be the difference between life and death, many practitioners must be able to understand and trust the predictions and recommendations made by deep learning systems. There are authors attempts and approaches to make clinical deep learning more interpretable include: Maximum Activation: A popular tactic in the image processing community is to examine the types of inputs that result in the maximum activation of each of a model's hidden units. This represents an attempt to examine what exactly the model has learned and can be used to assign importance to the raw input features; Constraints: Others have imposed training constraints specifically aimed at increasing the interpretability of deep models. For example, Choi et al.'s Med2Vec framework for learning concept and patient visit representations uses a non-negativity constraint enforced upon the learned code representations; Qualitative Clustering: In the case of EHR concept representation and phenotype studies, some studies point to a more indirect notion of interpretability by examining natural clusters of the resulting vectorized representations. This is most commonly performed using a visualization technique known as t-Distributed Stochastic Neighbor Embedding (t-SNE), a method for plotting pairwise similarities between high-dimensional data points in two dimensions; Mimic Learning: first train a deep neural network on raw patient data with associated class labels, which produces a vector of class probabilities for each sample. They train an additional gradient boosting tree (GBT) model on the raw patient data, but instead use the deep network's probability prediction as the target label. Since GBTs are interpretable linear models, they are able to assign feature importance to the raw input features while harnessing the power of deep networks. The approaches given and known from the open references cannot be recognized as full naturally interpretable and are not widely accepted.

Our approach to reach naturally interpretable AI is synergistic AI concept. The main idea is to reach explainable and causal AI by combining the benefits of the accuracy of deep-learning algorithms with visibility on the factors that are important to the algorithm's conclusion, in a way that is accessible to physicians and other practitioners, as in rules-based systems, enabled by richer data and improved computing. Therefore, we propose AI in healthcare as a synergy of two concepts, where encoding clinical guidelines and/or existing clinical protocols provides a starting point, which then can be augmented by models that learn from data and demonstrate the distinctive properties of AI, the ability to perform tasks in complex environments without constant user guidance and improving performance by learning from experience. The proposed concept is realized through Main AI module (Figure 1) with two threads: supervised and unsupervised thread. Supervised thread is based on interpretable rules-based systems upgraded with visualization techniques. Unsupervised thread is deep learning ANN with two layers.

The first ANN layer, composed of more sub layers, analyses data to provide a mapping of types and features of disease, feeds Interpretable Rules-Based thread (IRB) allowing professionals to reach a clinical decision „independently" by supervised IRB thread. The second ANN layer, composed of more sub layers, analyses this map to present clinicians with a potential diagnosis and recommendation.

The solution proposed in this manuscript is based on the one previously described in a book chapter [22]. On top of the previous work, we've modeled a wrapper classes for parsing the data from various resources in an uniform manner, accompanied by a function that periodically adapts the artificial intelligence knowledge based on new data streamed over sensors and is received by medical profesionals. Implementation guidelines described in [22,23] are extended by modelling a process that automatically feeds data into the artificial intelligence model from various sources. The model is extendable and supports adding new types of input data to be combined with existing ones.

Actually, our approach is an attempt to follow the physicians thinking through the clinical decision procedure. Physicians first follow some rules and knowledge, then „call" experience (data) and make a decision. If we offer rules and knowledge in human understandable way physicians will believe and can check with their experience, but the deep learning ANN will extend that experience improving accuracy.

This transition from rules drawn up by experts to systems that learn from data would be exemplified and proven by applications to triage patients, applications to support clinical decision making in Cardiology Domain. Data from the WHO shows that cardiovascular diseases (CVDs) are a leading cause of deaths worldwide for both sexes and all ages. More deaths worldwide were caused by CVDs than all communicable, maternal, neonatal, and nutritional disorders combined, which is twice more than those caused by cancer.

The AIHeal system, as software that is potentially also a medical device, should be designed, implemented, tested, and documented using generally recognized quality assurance methods for software development used in the medical domain. The methodology is based on reference model for Clinical Decision Support Systems (CDSS) given in Figure 2.

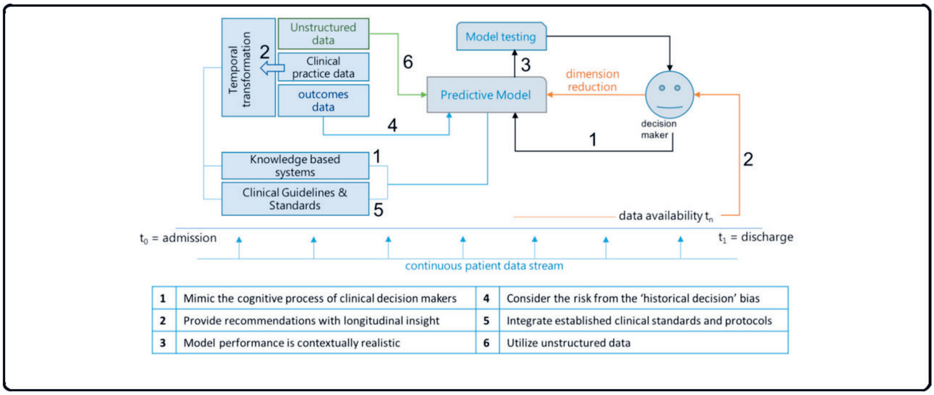

Figure 2. The reference model for Clinical Decision Support Systems (CDSS) [24]

The six elements/considerations of the reference model are: (1) Do CDSS mimic the cognitive process of clinical decision makers? (2) Do CDSS provide recommendations with longitudinal insight? (3) Is the model performance contextually realistic? (4) Is the 'Historical Decision' bias taken into consideration in CDSS design? (5) Do CDSS integrate established clinical standards and protocols? (6) Do CDSS utilize unstructured data?

Methodological steps to develop the AIHeal system are:

— Selection:

— Choose most appropriate data model for the new EHR to cover various medical use cases and clinical workflows.

— Choose most appropriate big data architecture to support batch and stream processing. In the case of AIHeal system based on rule based machine learning and deep learning artificial intelligence, an assessment of the quality of the data is necessary. The appropriate processes for anomaly detection, data cleansing, and handling of incomplete or missing data should have been applied to the dataset, and the existence of potential biases assessed and corrected.

— Choose most appropriate supervised thread, based on interpretable rules-based systems upgraded with visualization techniques and unsupervised thread based on deep learning ANN with two layers.

— Definition of acceptance criteria:

— Test that the AIHeal system satisfies security, privacy, and safety requirements applicable to medical devices

— Design:

— Implement the prototype covering workflow for cardiology domain. Design details are given in the concept description.

— Implementation:

— Tailor system to medical professionals expectations. System must offer interpretable results in which medical professionals can trust. The medical knowledge used in the construction of the AIHeal system cannot be proven clinically complete or objectively correct, but it must attempt to capture the current state of professional and scientific opinion. It must be possible to verify formally that the relevant medical knowledge satisfies certain requirements such as being unbiased, consistently interpreted, and reasonably completed.

— Quality assurance:

— Ensure that the quality of the AIHeal remains stable for internal and external updates and upgrades by new medical use cases.

ANALYSIS AND COMPARISON

Comparing to the existing solutions, the proposed one is more general. It not only exploits deep learning techniques for discovering hidden knowledge, but the recommendation to medical professionals are given in a set of directives based on commonly accepted reasoning, and the data feed from various resources including sensors is fed to the artificial intelligence model in a real time.

The additional innovative contribution of the proposed system is a combination of two AI concepts, where encoding clinical guidelines and/or existing clinical protocols, as in rules-based systems, provides a starting point, which then can be augmented by deep learning models that learn from data. The first AI concept makes that the decision explainable and the factors that are important to the algorithm's conclusion are visible which rise the confidence of the physicians and other practitioners. The second AI concept demonstrate the distinctive properties of AI, which also open new routes to delivering better, faster and more cost-effective care, and may have a greater focus on prevention and promoting wellness.

A patient wears specially designed mobile sensor, which is already available as a prototype, or implant. The data are transferred by mobile networks and collected by big data architecture in the proposed EHRs with any information relating to the past, present, or future physical/mental health of an individual. This data integration allows us to develop the „digital twin" of the patient.

The use case planned for implementation is an actual problem, ischemic heart disease, which affect majority of world and Montenegro population, more than 53% of all diseases.

It is intended to identify patients with highest risk and to react in proper time. AI based models can also screen people who are at low risk and do not have symptoms and help predict the progression of chronic coronary disease. The system can enable clinical pathways and protocols to be redesigned towards intervening proactively in the highest risk cases, even if they are asymptomatic. This could force the working patterns of practitioners from reactive care to proactive care.

How many lives could have been saved, if this kind of AI healthcare systems could have been used?

Physicians and other professionals who use AI will replace others who do not use AI. AI needs to serve as a decision-support tool. In the end, it is the decision of a doctor. AI is not going to substitute doctors in the foreseeable future. AI will be able to do some tasks that take a lot of time, need interconnection of many complex data, use mathematical formulas to determine the correct dosage of drugs, use numerous practical cases for data mining and analytics, what can free up physician time for concentration on diagnostic thinking and talking to patients.

Consequently, proposed system has the potential to transform healthcare organizations and healthcare services and meet the current and future society needs not only in Montenegro, but in many other countries.

CONCLUSION

The ground-breaking objective of the AIHeal project is to create explainable and causal AI healthcare system by combining the benefits of the accuracy of deep-learning algorithms with visibility on the factors that are important to the algorithm's conclusion in a way that is accessible to physicians, as in rules-based systems, enabled by richer data and improved computing.

The new EHR concept, big data infrastructure and naturally interpretable AI decision system are proposed.

The proposed AI Healthcare System has the potential to transform healthcare organizations and healthcare services and meet the current and future society needs not only in Montenegro, but in many other countries.

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