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ORIGINAL ARTICLE

Composition of a Service-Oriented Clinical Decision Support System using Machine Learning

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ABSTRACT

Introduction: Digital health applications have gained popularity in the healthcare industry. Clinicians are inundated with new types of data to promptly synthesize to make a qualified clinical decision about patient care. This study presents an overview of the architectural specifications to construct an innovative service-oriented software suite, which can be used to support evidence-based healthcare decisions in a variety of clinical settings and procedures. **Methods:** The designed system will use data from repositories and clinical systems to produce a multidimensional view of a patient, infer possible outcomes, and propose actions. Predefined pathways, as well as paths developed by artificial intelligence, machine learning, and process mining algorithms, will be used to construct inferential models, and use them to suggest further actions, which adapt to changing patient circumstances. **Results:** The intended system's adoption depends on numerous requirements, including the need for cooperation, the development of protocols for legal purposes, and clinical decision-making and procedure assistance. As a basis, electronic clinical information is used to evaluate human decisions against predefined protocols or statistically known evolution patterns. **Conclusion:** The system will enhance strategic decision-making in the diagnosis of heart disease using the large quantity of accessible data in the healthcare system and providing full and transparent assistance for patient treatment and clinician workflows.

Keywords: Pathways, Path Diagnostic Therapeutic Care, Computer Interpretable Guideline, Clinical Guideline, Artificial Intelligence

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INTRODUCTION

Despite limited time and resources, clinicians seek to care for and treat patients to the best of their abilities. However, globally, many people suffer from the incorrect prescription of medications and other medical errors from healthcare professionals. The indiscriminate data display influences decision-making, which leads to a challenging and complex process in patient treatment and care. According to recent research in the field of health-associated errors, medical errors may account for up to 251,000 fatalities each year in the United States, making them the third-largest cause of death (1).

Additionally, approximately 1.7 million individuals in the US get health-associated infections annually, wherein approximately 98,000 results in fatality (2, p. 2321-2333). Over the last decade, the nation has focused on decreasing adverse occurrences and showed the need for advanced clinical decision support systems, CDSS (3). Conducting research that helps improve the general lives of humans and makes things simpler and sustainable in the long-term fulfills with great passion. The use of information technology to reduce the impact of human errors in decision-making is a promising concept. Developing and integrating approaches based on artificial intelligence, AI, in this field is essential to improve and support decision-making. The support of clinical decision-making would pursuit the provision of better healthcare solutions. Few software solutions currently exist in healthcare system domain (4).

For the thematic classification of the present work, the state-of-the-art research, related methods, and concepts of relevant scientific papers are briefly introduced and differentiated. Designing and developing Decision Support Systems, DSSs, or advanced analytics systems in medicine is difficult and complex. Despite constantly growing fields, they are frequently restricted to the research level. The use of AI in CDSS began in the early 1970s, and several experimental systems were developed. The early AI program or expert system MYCIN, a computer-based advisory system that supports clinicians in the detection and treatment of bacterial infections in patients, is one of them. The system diagnoses patients based on their symptoms and medical test results. Additionally, it suggests laboratory tests and results to a diagnosis with a recommendation (5). Another system is HELP, a hospital information system that is among the most well-known and long-running clinical information systems (6). In clinical DSSs, numerous AI methods have been applied (7).

To gain a global overview of the different approaches reflecting on the standardization use of guideline-basedpatient-specificdecisionsupportinthehealthcaredomainthe (8) is used. The guideline-modeling methodologies are being compared (8, Tbl. 1-3) including EON, a task-based approach (9), GLIF, medical object-oriented data model (10), GUIDE, graphical authoring tool for create a guideline flowchart (11), PRODIGY (12), or PRO-forma, combines logic programming and object-oriented modeling (13).

Dongxiao Gu, Changyong Lianga, and Huimin Zhaob addressed the issue of AI application in clinical decision-making in their study (14). They provide proof of contempt for a case-based reasoning system to diagnose breast cancer. Through the retrieval of similar cases of decision support systems in the area of breast cancer, oncologists can get powerful knowledge and information that can be used to complement their skills and knowledge in medical decision-making.

Steven Walczak also identifies the important role that AI plays in CDS systems (15, p. 31). In his article, different systems that utilize AI are being evaluated and applied to medical systems to improve decision-making. The study (4) addresses issues related to AI in CDS systems, including the evaluation and the practical design implications and challenges. The authors conclude that the complexity of the evaluation is essential in the integration of AI in the complex field of medicine as a socio-technical setting and further recommended that specific enhancements are needed for the new generation types of CDSS founded on AI, which can be achieved through practical applications.

Sloane and Silva (16) are elaborated on the use of AI in medicine by analyzing the differences between rule-based and machine learning-orientated systems. The authors begin by addressing the historical aspects of AI in medicine and clinical support systems, as well as the current state and future of the field. They demonstrated the necessity of CDSS by providing watchdog and advisory roles and helping the patients, clinicians, and other stakeholders in the healthcare industry.

Thus, integrating AI into CDSS would result in better healthcare. According to Sloane and Silva, AI would serve as a significant factor that surrounds the issue of big data since the healthcare system has massive data, which is hard to manage. The challenge that clinicians face regarding big data has often led to medical errors that AI seeks to eliminate. Overall, the authors concluded that the integration of AI in CDSS would assist in dealing with big data and thus lead to better healthcare provision through reduced medical errors that result from poor decision-making (16, p. 557–567).

Unfortunately, a large portion of patient health records is still represented by written documents in natural language, with a serious lack of structured, machine-actionable, information. The study of G. Litjens et al. (17) demonstrated various approaches to analyze those medical images and extract the information with Natural Language Processing, NLP, using Convolutional Neural Networks, CNNs.

The Path Diagnostic Therapeutic Care, PDTA, are essential in developing CDSS, which need to be formulated and designed. Studies by M. Peleg and S.W. Tu (18) and M. Ramos-Merino et al. (19) addressed this issue of using a design pattern to tackle the bottleneck of formulating computer-interpretable PDTAs. BPMN and structure screening guideline templates are described. Those approaches show weakness regarding the accommodation of resilience and exceptions or unexpected outcomes. The current scientific consensus shows that clinical decision systems that combine the use of AI for, among others, applied NLP for unstructured data and PDTA matchmaking in an industrial environment is a new approach.

A system that utilizes machine learning in clinical pathways to make the procedure of patient wellbeing invaluable could have a significant impact in providing correct medications and recommending related procedures. Designing the software architecture and the potential pathways of patients is essential in effectively providing a diagnosis and thus correct medication. Such a prospect could disrupt the healthcare market; the software to support the CDSS would lead to an advancement in healthcare delivery, which help doctors to flag problems and make more informed choices that would lead to improved diagnosis. This study aimed to develop an applied intelligent clinical information wizard (ICIW), which shows a multidimensional view of a patient and implements a way to increase clinical decision-making with AI.

MATERIALS AND METHODS

The context of the research will focus on the implementation of an intelligent component, which will be integrated into a complex clinical product solution and monitor every useful information, which is accessible via the Fast Healthcare Interoperability Resources (FHIR) Standard. The solution can obtain two important results:

- A real-time match of patient conditions against

configured pathway models to recommend (and synchronize) actions that introduce a different perspective in the application machine-to-machine (M2M) and machine-to-human (M2H) collaboration.
- Fluent and continuous enrichment of statistical and knowledge models through AI-based techniques to identify clinical conditions and propose advice, such as recommending protocols and clinical actions, computing outcome probabilities, or identifying relevant adverse events.

Key objectives to be realized are the following:
- Introduce new and more specific ways to represent the patient's condition as the result of selected information.
- Introduce new way store present multidimensional evolving protocols to manage clinical conditions.
- Integrate AI-based tools to support medical decisions.
- Develop an effective human-computer interface to allow the easy use of the above-mentioned functions.

This approach relies on the efficacious combination of AI and business process management techniques. The application of these techniques into the healthcare sector is of great interest due to the peculiarities of the domain, characterized by the following:
- The high availability of clinical data about the patient and similar cases, which can be utilized to understand previous experiences to modify constraints and sequence future actions.
- The requirement is to leave each decision to the doctor, who must have all patients' information to read and interpret.

Dealing with and solving these problems in a complex domain can advance progression in the state-of-the-art in research field of combining data mining with machine/deep learning, logical reasoning, and process representation and execution. Finally, the implementation of this approach in a component designed to be used in everyday practices can pave the way for these techniques to be used in real clinical settings, thus providing substantial feedback to academic research.

The development and creation of such a new software solution entailing the construction of a big data pool that would support doctors in decision-making in a more efficient and precise manner. As the system focuses on the transparency of information and case studies, the medical errors due to wrong decision-making would be reduced and further improved. Through assuring patients of high-quality care, the system would be advantageous and preferred once tested and available in the market.

RESULTS

In the proposed system, machine learning is used in two ways;

1. To analyze past treatments with unstructured data, with a deep learning CNN model based on text classification and structures data by accessing the Fast Healthcare Interoperability Resources, FHIR, database.
2. To match the current patient conditions against a pathway repository provided by the industrial system that is predefined to introduce and recommend the alternative perspectives in making medical decisions and utilizing rule/case-based reasoning.

The Block diagram presented in Figure 1 shows the overview of the necessary components. The process engine executes the process at every decision point, the machine learning engine analyses the available data and show the current status of the patient, the PDTA repository hosts the clinical guidelines, and the patient health data contains access to the relevant databases and provides functionality to extract information based on NLP.

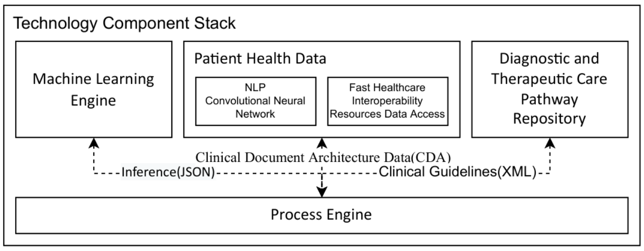

Figure 1: Block components

Based on the neural network or case/rule-based reasoning and clinical guidelines, the machine learning component will make an elaborated clinical decision that utilizes the clinical meta information. Results are visualized in an engineered ICIW, which provides a new multimedia environment for fast and reliable access to patients' health records and supports clinical decision-making. A clear concept and design are essential to implement such a proposed system and show an overview of the architecture of the proposed components.

The system is divided into Frontend, Backend, and Data management. First, the Angular framework is used in the Frontend to structure the logical functionality and design the user interface. Compliancy is important when developing the user interface; therefore, the foundation is based on the Material Design guidelines and the CSS Bootstrap framework. A customized version is included to match the corporate design of the industrial partner (22, p. 92).

For the Backend, a Java Hibernate Backend is used to develop the required API endpoints. The application is deployed using a J2EE Wildfly server that utilizes a PostgreSQL Database to store configurations and user information.

The authentication of the system is implemented with the Security Assertion Markup Language protocol and the open-source identity provider KeyCloak. This technology provides methods for single sign-on and cross-system compatibility (20, p. 86-90). Additionally, authentication methods can simply be integrated.

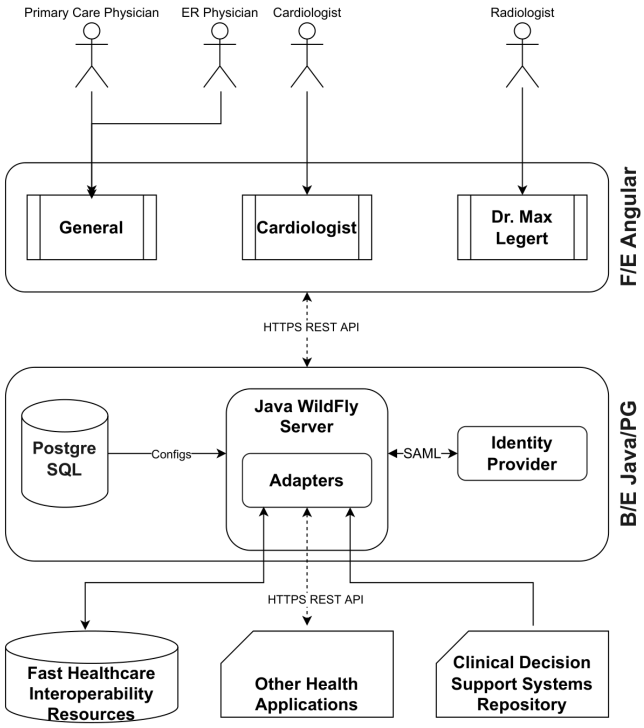

Figure 2: Software technology stack architecture

The FHIR is used to access health care information and records and is a source that allows a third-party application to simply be integrated into existing systems (21).

To support the development of the framework and validate our approach, a building a draft of a prototype for the domain of diagnosis. This prototype will be constantly improved to address the inclusion of the proposed components in our approach. In the following section the design of the functionality of the components of the prototype is being introduced. As indicated in the Figure 1 an authentication via SAML is required to support a plug and play system for different regional and national wide hospital system support. Therefore, the ICIW starts with a login, username and password, default accepts SSO with SAML token passing. After the authentication process, the user is redirected to the patient search. With the selected patient it is possible to proceed to the dashboard. Allowing a view of the patient including the clinical history with care taking event. A summary of diagnosis, suggested prescriptions including medications, patient's personal data, and the PDTAs, for the prediction of future events. To gain a more detailed view of a time period the clinician can access the whiteboard. Here the user can select the contents of interest, which are represented on a time-ordered comparison panel (horizontal timeline) that offers the possibility to scroll through time (keeping sight of one's position in events and history). An alternative hierarchical view can be archived via the explorer view. The table view allows you to navigate through the tree both the events and the contents. If the user selects a desired information it is display with the appropriate visualization: images, pdf, or CDA.

DISCUSSION

The proposed system seeks to address well-known problems in the cost-effective diagnosis and treatment of complex conditions, especially in the presence of a huge amount of information, where identifying significant data is challenging for clinicians. Clinical users of the solution are potentially; professional caregivers, PCP (Primary Care Physicians), ER doctor (emergency physician), Cardiologists, Radiologists, and Nurses. Extension to patients and informal caregivers, like social workers or associated patient transport personal, is currently secondary but possible in the future. Every actor or simply every user can create his own dashboard. In our latest approach ER doctors and the Radiologists are the focus of the application. Especially the ER doctors are a promising use case in the adoption of the technology because of the need of a time critical and efficient representation of patient records. They can access the quantitative information in a precise and comparative form e.g. graphical trend of laboratory values in relation to drug consumption as reported by pharmacies or inpatient administrations through the outlined dashboard or whiteboard introduced. The second focus group are Radiologists. Those users can analyze the qualitative information in contextualized form e.g., access to radiological images belonging to a clinical pathway, diagnosis, or other aggregations.

Traditionally access to the amount of clinical data of healthcare organizations, which is needed to train the system, is generally difficult. However, considering the collaboration with the industrial partner a considerable number of cardiologic patient management systems that are installed in several healthcare organizations in Italy and abroad, this task is greatly facilitated, especially if hashing and anonymization techniques complaint with the EU General Data Protection Regulation are used.

CONCLUSION

The application of AI in healthcare is of significant interest since healthcare execution determination is flexible. Clinicians seek to care for and treat patients to the best of their abilities. However, due to limited time and resources, many people globally suffer from receiving incorrect medication and other medical errors from healthcare professionals. The CDSS is computer-based and is designed to improve the quality of healthcare decision-making. Using AI in CDSS allows the utilization of high-quality, as well as unstructured data, to improve the decision-making of the relevant healthcare practitioners.

Few software solutions currently exist in the market that supports clinicians and other healthcare professionals with medical decision-making. In this proposed system, machine learning technology would be used in the analysis of past treatments to match current patient conditions against pathways that are predefined and introduce and recommend the alternative perspectives in medical decision-making. The implementation of software in the research ordinated prototype would illuminate situations in which the proposed model can be validated in real clinical settings.

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REFERENCES

1. Anderson J.G, Abrahamson K. Your Health Care May Kill You: Medical Errors. 2017; 5 p.
2. Haque M, Sartelli M, McKimm J, Abu Bakar M.B. Health care-associated infections an overview – an overview. Infection and Drug Resistance. 2018-11; 11: 2321-2333. http://doi.org/10.2147/IDR.S177247
3. Pham J.C, Aswani M.S, Rosen M, Lee H, Huddle M, Weeks K, et. al. Reducing Medical Errors and Adverse Events. Annual Review of Medicine. 2012-02-18; 63: 447-463. http://doi.org/10.1146/annurev-med-061410-121352
4. Magrabi F, Ammenwerth E, McNair J.B, De Keizer N.F, Hyppцnen H, Nykдnen P, et al. Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications. Yearbook of Medical Informatics. 2019-08; 28: 128-134. https://doi.org/10.1055%2Fs-0039-1677903
5. Copeland B.J, MYCIN artificial intelligence program. 2018; https://www.britannica.com/technology/MYCIN.
6. Gardner R.M, Pryor T.A, Warner H.R. The HELP hospital information system. 3rd rev. International journal of medical informatics. Ireland; 1999-06; 54, 169-182. https://doi.org/10.1016/s1386-5056(99)00013-1
7. Kong G, Xu D.L, Yang J.B. Clinical Decision Support Systems: A Review on Knowledge Representation and Inference Under Uncertainties. 2nd rev. International Journal of Computational Intelligence Systems. 2008-05; 1, 159-167. http://doi.org/10.2991/jnmp.2008.1.2.6
8. Peleg M, Tu S, Bury J, Ciccarese P, Fox J, Greenes R.A, et. al. Comparing Computer-interpretable Guideline Models: A Case-study Approach. Journal of the American Medical Informatics Association. 2003-01-01; 10, 52-68. http://doi.org/10.1197/jamia.M1135
9. Tu S.W. A Flexible Approach to Guideline Modeling. AMIA, Inc. 1999; 5 p.
10. Peleg M. GLIF3: The Evolution of a Guideline Representation Format. AMIA, Inc. 2000; 5 p.
11. Quaglini S, Stefanelli M, Lanzola G, Caporusso V, Panzarasa S. Flexible guideline-based patient careflow systems. Artificial Intelligence in Medicine. 2001; 16. http://doi.org/10.1016/S0933-3657(00)00100-7
12. Johnson P.D, Tu S, Booth N, Sugden B, Purves I.N. Using scenarios in chronic disease management guidelines for primary care. Proceedings. AMIA Symposium. 2000; 389-393 p.
13. Fox J, Johns N, Lyons C, Rahmanzadeh A, Thomson R, Wilson P. PROforma: a general technology for clinical decision support systems. Computer methods and programs in biomedicine. Ireland: 1997-09; 59-67. https://doi.org/10.1016/s0169-2607(97)00034-5
14. Dongxiao C, Zhao H. A case-based reasoning system based on weighted heterogeneous value distance metric for breast cancer diagnosis. Artificial Intelligence in Medicine. 2017; 77: 31-47. https://doi.org/10.1016/j.artmed.2017.02.003
15. Walczak S. The Role of Artificial Intelligence in Clinical Decision Support Systems and a Classification Framework. 2nd rev. International Journal of Computers in Clinical Practice. 2018-07; 3: 31-47. http://doi.org/10.4018/IJCCP.2018070103
16. Sloane E.B, Silva R.J. Artificial intelligence in medical devices and clinical decision support systems. Elsevier; 2020; 556-568. http://doi.org/10.1016/B978-0-12-813467-2.00084-5
17. Litjens G, Kooi T, Bejnordi B.E, Setio A.A.A, Ciompi F, Ghafoorian M, et.al. A survey on deep learning in medical image analysis. Medical Image Analysis. 2017-12; 42: 60-88. https://doi.org/10.1016/j.media.2017.07.005
18. Peleg M, Tu S.W. Design patterns for clinical guidelines. Artificial Intelligence in Medicine. 2009-09; 47: 1-24. https://doi.org/10.1016/j.artmed.2009.05.004
19. Ramos-Merino M, Бlvarez-Sabucedo L.M, Santos-Gago J.M, Sanz-Valero J. A BPMN Based Notation for the Representation of Workflows in Hospital Protocols. 10th rev. Journal of Medical Systems. 2018-10; 42: 181. http://doi.org/10.1007/s10916-018-1034-2
20. Camposo G. Cloud native integration with Apache camel: Building agile and scalable integrations for kubernetes platforms. 1st ed. Berlin, Germany:

APress; 2021. http://doi.org/10.1007/978-1-4842-7211-4

21. Hussain MA, Langer SG, Kohli M. Learning HL7 FHIR using the HAPI FHIR server and its use in medical imaging with the SIIM dataset. J Digit Imaging Internet. 2018;31(3):334–40. Available from: http://doi.org/10.1007/s10278-018-0090-y
22. Walter-Tscharf V, Practical Approach to Monitor Runtime Engine Statistics for Apache Spark and Docker Swarm using Graphite, Grafana, and CollectD in 2021 International Conference on Converging Technology in Electrical and Information Engineering (ICCTEIE). 2021; 91-96. http://doi.org/10.1109/ICCTEIE54047.2021.9650649