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Leveraging Clinical Data Treasures: Integration of an AI Platform into Clinical IT

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Abstract. In recent years, there has been a rapid growth in the use of AI in the clinical domain. In order to keep pace with this development, a framework should be created in which clinical AI models can be easily trained, managed and applied. In our study, we propose a clinical AI platform that supports the development cycle and application of clinical AI models. We consider not only the development of an isolated clinical AI platform, but also its integration into clinical IT. This includes the consideration of so-called medical data integration centers. We evaluate our approach with the aid of a clinical AI use case to demonstrate the functionality of our clinical AI platform.

Keywords. clinical AI platform, Medical Data Integration Center, machine learning, clinical IT, artificial intelligence, healthcare

1. Introduction

The ongoing digitalization of healthcare has led to an immense increase in data production in clinical environments [1]. Hospitals collect vast amounts of patient data on a daily basis, including diagnostic information, laboratory results and imaging data. These extensive data sets represent a valuable resource that has the potential to deepen the understanding of diseases, develop personalized therapeutic approaches and improve the quality of patient care [2].

In order to make the data available for secondary use, German University Hospitals are currently implementing and rolling out so-called (medical) data integration centers (MeDICs/DIZ) within the German Medical Informatics Initiative. The primary objective of these MeDICs is to incorporate clinical routine data derived from the electronic medical record (EMR) systems of the respective University Hospitals. This involves the harmonization, standardization, and rendering of the data accessible and usable for research purposes, particularly for general secondary use [3]. At the same time, the use of artificial intelligence (AI) in the clinical environment is becoming increasingly relevant [4]. An ongoing issue is that clinical applications of AI often exist as isolated solutions. Efforts are already being made to establish clinical AI platforms that centralize

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and provide clinical AI applications in hospitals. However, these AI platforms focus on certain aspects and only handle certain types of data, such as imaging data or alphanumeric data [5-7].

In this study, we focus on the integration of an AI platform within clinical IT. We evaluate our Clinical AI Platform based on a clinical use case.

2. Methods

2.1. Setting

This research was performed at the University Hospital Schleswig-Holstein (UKSH). A distinction can be made between two IT system landscapes at the UKSH: 1) the primary systems, such as the EMR or PACS, 2) the research IT systems, such as the medical data integration center (MeDIC), which integrates, harmonizes and annotates data from the primary systems and makes it available for secondary use [8].

The KI-SIGS project aims to improve the healthcare ecosystem in northern Germany. The project consists of four platform projects and nine clinical use cases [9]. This research was carried out as part of the Technical AI Platform project.

2.2. Clinical AI Platform

First, a requirements analysis was carried out to identify and categorize functional and non-functional aspects of the Clinical AI Platform. Based on this, we developed BPMN diagrams that depict the clinical AI development cycle from data selection, data annotation, training/testing up to inference [10]. The BPMN diagrams facilitate the translation of the requirements into the architecture. Based on the BPMN diagrams, the architecture of the Clinical AI Platform was developed.

The architecture of the Clinical AI platform consists of the components DataLake API, Storage for Temporary Data, AI Model Registry, AI Container Manager, AI Algorithm Registry, AI Processing Unit and User Access Management (cf. Figure 1). The DataLake API ensures the exchange of data and all communication between the MeDIC and the AI platform. The Storage for Temporary Data stores the predefined cohort data sets [11] that come from the MeDIC Mart. Training and inference are carried out in the AI Processing Unit. The AI Model Registry's tasks are to store the models and make them available for inference. Within our platform, we implemented the open-source Model Registry from MLflow [12]. The AI Container Manager has the task of controlling the processes of data retrieval, training and inference. The AI Algorithm Registry contains all AI algorithms that are developed in a Local AI Development environment and are supposed to run in the AI platform. A HTTP(S) client can be used to send requests to the Clinical AI platform, if no front-end is available. Every communication request is verified by the User Access Management.

A proof-of-concept was then developed, which contains the basic functionalities of the Clinical AI platform. This includes the data acquisition and preparation of the data cohort from the MeDIC's data mart, the storage of the data in the Clinical AI Platform, the training and monitoring of the AI model, storage of the model and the inference.

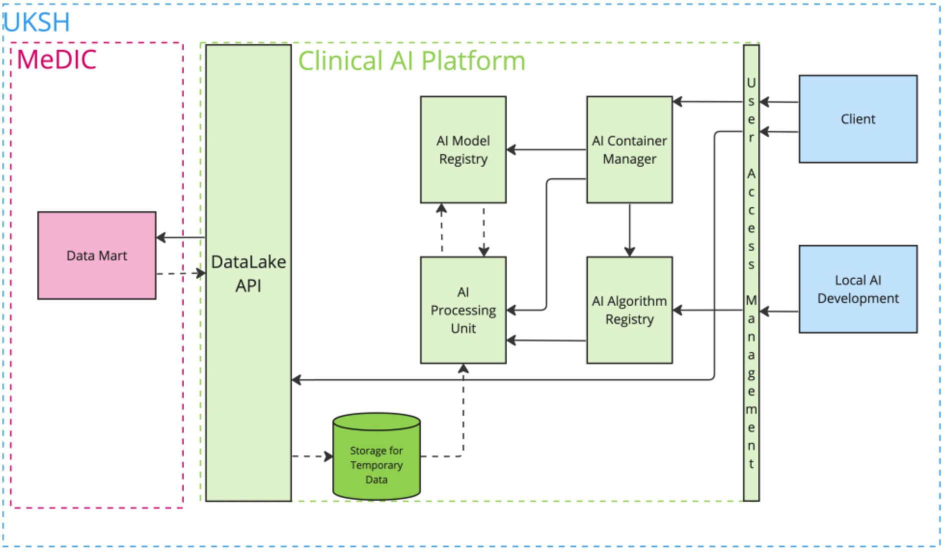

Figure 1. Architecture of the Clinical AI Platform. The solid line represents the control flow, while the dashed line represents the data flow. This figure shows the interaction between the two IT system landscapes of the MeDIC and the Clinical AI Platform within the UKSH.

2.3. Clinical AI Use Case

The use case for evaluation is about the distinction between benign and malignant tumors in breast carcinoma. The Wisconsin Breast Cancer data set, which is publicly available, is used for this purpose [13]. This data set comprises structured pathology reports, consisting of alphanumeric data, which describe the cell nucleus from digitized images of breast tumors. We have opted for an Artificial Neural Network (ANN) that is based on Alshayeji et al. [14]. There are a total of 10 features [15] used as input for the ANN. Additionally, the data are already annotated. Therefore, each data set indicates whether the tumor is benign or malignant. The objective is to train an ANN model that can predict whether new input data represents benign or malignant breast tumors.

3. Results

We deploy our clinical AI platform using Docker-based microservices. We use MLflow for experiment tracking and as a model registry. We use FastAPI to define the routes for the HTTP(S) requests. The AI Algorithm Registry is realized with Harbor. The Storage for Temporary Data is initiated as a volume and mounted in the containers.

In the following, we show the processes of training and inference of an AI model in the clinical AI platform. We evaluate the platform functionality based on the use case of breast tumor detection. First, the ANN algorithm is developed in the local environment. Then, predefined routes are implemented, which are called using HTTP(S) requests. This includes i.e. training initiation. Training tracking is activated in advance using MLflow and the storage of the ANN model in the MLflow Model Registry should be considered.

Once the ANN algorithm has been implemented, it is added as a Docker image to the AI Algorithm Registry by the client. Cohort data sets from the MeDIC Mart can be requested via the DataLake API. For this purpose, the predefined cohort data sets are provided in the MeDIC Mart and authorized users can retrieve them and place them in the Storage for Temporary Data. Once the cohort data set is available in the Storage for Temporary Data and the ANN algorithm is stored in the AI Algorithm Registry, the Docker image of the ANN algorithm can be loaded and executed as a container in the AI Processing Unit. By sending the corresponding request for training to the container, the training is executed and the training is tracked in MLflow. The user can observe the training and evaluate the predefined metrics. In our case, we obtain an F1 score of 97,6 % averaged over 50 training runs. The trained AI model is then stored in the model registry. For the inference, the ANN model can be retrieved from the model registry and executed.

4. Discussion

With this study, we show how an AI Platform can be integrated into clinical IT. Prior research has demonstrated the potential of AI platforms for integration into clinical IT [5-7]. Nevertheless, these studies are either limited to specific data types or medical domains. Leiner et al. [5] and Scherer et al. [6] show the integration of an AI platform using imaging data. Gruendner et al. [7] demonstrate the integration of alphanumeric data limited to FHIR. In contrast, our approach is not limited to a specific clinical data type and can potentially handle a wide range of clinical data types. Moreover, Gruendner et al. [7], Scherer et al. [6] and Leiner et al. [5] do not describe the development of relevant AI processes in hospitals, including medical data integration centers. With our implementation, we demonstrate a novel approach to the integration of an AI platform into clinical IT. We present an approach that considers the medical data integration center and thus describes a broad and sustainable approach to a clinical AI platform.

4.1. Limitations and Future Work

This proof-of-concept Clinical AI Platform shows the potential for further development into a productive AI platform. For a productive platform, methods for user access management would have to be integrated to ensure data protection and data security. Accordingly, security measures should be incorporated to prevent data leakage.

Another aspect of the further development of the clinical AI platform and improving individual AI models is the utilization of data located at different sites. Techniques such as federated learning [16] could enhance model precision by using more data. In addition, the use of different data sources can be helpful to increase the generalizability and robustness of an AI model. This includes the challenge of data heterogeneity. To solve this, the data should be standardized and available in an interoperable format (i.e. FHIR®, DICOM) to prevent data inconsistencies at different locations. In the future, the Clinical AI Platform can be further developed so that the AI models are continuously trained with new data. The degree of automation of the platform would have to be increased for this.

5. Conclusions

The approach of a clinical AI platform integrated into clinical IT offers great potential for improving patient care in hospitals. With the aid of such a platform, it is possible to train AI models for diagnostics and therapy, which can offer significant added value in supporting medical professionals in their daily work.

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