Architecture of a Hybrid Clinical Decision Support System

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Abstract. Precise risk assessment and individualized preventive strategies are essential areas in healthcare, as cardiovascular diseases (CVD) are the leading cause of death in the world. Our prototype Clinical Decision Support System (CDSS) for predicting and preventing cardiovascular risks is based on a hybrid architecture that integrates machine learning models and knowledge bases, utilizing a microservice architecture with a Cloud-Edge approach and implementing the principles of explainable artificial intelligence (XAI) due to their importance for the success of CDSS and its acceptance by healthcare providers. The system incorporates risk assessment tools (SCORE, SCORE 2, GRACE, EuroSCORE II, Diamond-Forrester, etc.) and proprietary machine learning models for predicting in-hospital mortality, development of postoperative atrial fibrillation, and the probability of obstructive coronary artery disease. These models contribute to informed clinical decision-making for the diagnosis, prevention, and treatment of CVD. The prototype system was implemented at the Medical Center of the Far Eastern Federal University and integrated with the healthcare information system "1C". The implementation experience demonstrated the high potential of hybrid CDSS based on microservice architecture for clinical practice use.

Keywords: Clinical Decision Support System, Hybrid Technology, Microservice Architecture, Machine Learning, Knowledge Base, Explainable Artificial Intelligence, Prognostic Models

1 Introduction

To reduce the risk of medical errors and expand diagnostic capabilities in medicine, healthcare process management systems are employed, which include medical information systems (MIS) and clinical decision support systems (CDSS) [18]. The development of CDSS is associated with the history of AI, trends in healthcare, and architectural solutions for corporate information systems. Several CDSS architectures are distinguished: autonomous, MIS-integrated, standardized, and service-oriented models [20]. Contemporary autonomous systems are scale calculators with a service architecture (SaaS), where data is manually entered by physicians, but integration with a physician's workplace is complex. MIS-integrated systems do not require repeated input but are demanding in terms of developer competencies, limiting their scalability potential [8]. An attempt was made to standardize CDSS content for simplified embedding in MIS from different manufacturers [2]. Over the last two decades, CDSS have interacted with MIS through application programming interfaces (APIs) [15]. Virtual medical records are used to standardize medical terminology across multiple MIS for a single concept. It is now the turn of web service-based CDSS [11]. Such a system requires electronic medical records (EMR) transmission from MIS, increasing demands on MIS providers and expenses for medical organizations. Formalized knowledge from individual clinical medicine domains is stored in CDSS and matched with patients' clinical-functional and laboratory indicators to support clinical decision-making [13]. Machine learning (ML) is used for diagnosing and predicting disease development and complications [4]. Data-based ML models expand CDSS capabilities [12].

The goal of the study is to develop a hybrid CDSS architecture based on the integration of knowledge and machine learning models into a single set of services that provide diagnosis and prediction of diseases and their complications, as well as treatment prescription.

2 Publication analysis

The CDSS are classified as either knowledge-based or data-based. The former includes knowledge bases and the ability to combine these rules with patient data, applying inference and reasoning mechanisms [3]. The CDSS evolve by providing physicians with up-to-date knowledge from clinical guidelines [14]. The advantage is explanations based on formalized rules [19]. The second type of CDSS uses machine learning for decision-making [17]. Despite successes, few machine learning models have been implemented in clinical practice [6]. The success of machine learning-based systems is associated with the development of methods to explain the decisions made [10]. However, CDSS often do not yet include explainable AI [1].

Contemporary projects propose a hybrid architecture; for example, the ITMO CDSS combines machine learning models and knowledge bases [12]. Supporting explanation tools, updating models and knowledge, enhance trust in the system [7].

The use of service-oriented architecture is attractive for CDSS design [7]. The integration of CDSS into HIS through the FHIR interface is relevant against the backdrop of microservice architecture [16].

For image processing, it is proposed to combine cloud-edge computing, where part of the processing is performed in the cloud, and part at the physician's workstation [5]. Authors of CDSS projects based on microservice architecture point to increased system complexity, longer transaction times, and more complicated logging of multiple services..

3 Clinical decision support system

Hybrid CDSS, combining knowledge bases and machine learning models, leverage the advantages of both system types. Knowledge bases provide interpretation of results, while machine learning models offer up-to-date risk assessments and forecasts. Explainable AI methods are required for further research to interpret machine learning results, which can then be integrated into knowledge bases.

Service-oriented architecture, especially microservices, is beneficial for long-term application, refinement, and maintenance of complex multi-module systems requiring integration with HIS, laboratory information systems, and patient monitoring devices.

3.1 Key Requirements

A physician's activity involves solving several tasks: disease diagnosis, including differential diagnosis; assessment of disease development prognosis and complications; treatment prescription, including invasive procedures; treatment outcomes prediction; patient health monitoring; communication with patients; administrative tasks related to medical care.

Physicians' activities are regulated by protocols and clinical guidelines, requiring validation of new tools and explanations of decisions made. These conditions define the functions of CDSS:

1. Patient health monitoring: a) verification of criteria values and selection of recommendations; b) identification of risk factors and prognoses.
2. Disease diagnosis according to the international classification and intelligent data analysis.
3. Treatment prescription considering patient-specific features.
4. Prediction of disease development dynamics and treatment.

The CDSS employs a hybrid architecture, combining intelligent systems and machine learning models to support regulated rules and prognostic scales. Decision explanations can be facilitated using both concepts. Convenience and integration with HIS are ensured by a built-in user interface, providing information to physicians at their workplace in a familiar environment.

3.2 The Concept

To support decision-making, CDSS utilize artificial intelligence methods based on data and knowledge. Knowledge is extracted from datasets using mathematical statistics and machine learning methods, and formalized rules are applied to medical data for diagnosis and treatment recommendations. Explanations can be based on protocols and recommendations or on explainable AI methods. Thus, the informational components of CDSS include:

1. Ontologies – templates for formalizing knowledge in the form of conceptual schemas, knowledge bases.

2. Knowledge – formally represented dependencies and cause-effect relationships between data. They can be formalized, semi-formalized, and non-formalized.
3. Data – facts of the subject area, organized according to the conceptual schema.

Formalized data, such as electronic medical records, are organized according to ontology and include named fields with characteristics describing modality, synonymy, multilingualism, etc. Synonymy ensures compatibility with different HIS and the use of different terms for identical concepts. Non-formalized (or semi-formalized) data, such as images, texts, graphs, diagrams, audio information, etc., require additional specialized formalization procedures.

Formalized knowledge contains domain-specific rules and is applied to data or the results of their processing to make decisions. They describe diagnostic protocols, treatment, and clinical recommendations.

Using formalized rules, CDSS describe prognostic scales, interpretation of results, and application of knowledge to data. Semi-formalized knowledge contains descriptions of machine learning prognostic models, while non-formalized knowledge includes textual, graphical, and audio information. Prognostic machine learning models, such as linear and logistic regression, random forest, stochastic gradient boosting, and artificial neural networks, are used for diagnosing and predicting the development of diseases and their complications.

Primary medical data (EHR) are used to provide information to physicians and form datasets for scientific research and model training. CDSS obtains data through integration with HIS, import from external sources, or via the user interface.

Data from HIS are used for processing physician requests and further research. Imported data are intended for analysis, model training, and rule verification, as well as for searching for clinical case analogs. Inputting data through the user interface allows for testing the operation of models, algorithms, and simulating prognostic and diagnostic decisions when changing patient risk factors and in the absence of HIS.

Microservices and software solvers apply knowledge to data. Microservices implement calculations using machine learning models, while software solvers verify the fulfillment of conditions and implement actions through the ontological tree of the knowledge base. System-forming services provide message routing, integration, and user interface generation. Integration with HIS can be optimal (the doctor receives all information while at the workplace in HIS) or alternative (the doctor uses the CDSS user interface), depending on the support of HIS manufacturers.

Explanations of CDSS decisions are implemented through mechanisms including traversing the knowledge base tree, formalized clinical interpretation of results, risk factors (corresponding to the analyzed case and serving as predictors), relative importance of predictors, and risk factor phenotypes. These mechanisms facilitate physicians' understanding of the proposed decisions and recommendations obtained from CDSS. Thus, the system ensures the explainability of artificial intelligence's operation and enhances the interaction between physicians and technologies.

3.3 System Architecture

The developed CDSS is based on hybrid technology with a distributed microservice architecture (see Fig. 1). The system's functionality is implemented through computational agents and knowledge bases with solvers. Expansion of CDSS functionality occurs by developing new microservices or updating the knowledge base. The distributed architecture and integration of knowledge bases, ontological solvers, and machine learning models ensure the flexibility of the CDSS. The main components of the CDSS include:

1. System services: integration with HIS, request routing, including access to computational agents and the intelligent solver.
2. Clinical medicine knowledge bases: formalized protocols, recommendations, reference materials, interpretation of prognostic models, and their application results.
3. Computational agents (microservices): implementation of prognostic and diagnostic machine learning models, algorithms for calculating event development probabilities.
4. Intelligent solver: verification of condition fulfillment and action implementation in accordance with the ontological tree of the knowledge base.
5. Healthcare information system with EHR database.
6. Electronic health records databases, including data for training and testing prognostic models and research results.

Machine learning models in the CDSS are developed based on intelligent data analysis and are grouped by tasks: classification for diagnosis and prediction; regression for clinical process modeling; clustering and phenotyping for associating patients with groups having similar disease progression characteristics.

Model development includes statistical analysis, predictor selection and validation, training, cross-validation, and model testing, risk factor identification, phenotype formation, assessment of the relative contribution of predictors and their combinations to endpoint realization, and more. Models are developed based on data from HIS or external datasets. The connection between data and models is maintained for validation and retraining. As new data accumulate, validation, retraining, and implementation of new model versions occur. This process is applicable to machine learning models and formalized rules, as well as for verifying the effectiveness of clinical protocols and recommendations formalized in CDSS knowledge bases. Continuous validation and updating of models and knowledge is a recurring process, initiated when new labeled datasets accumulate.

Explanation and interpretation of decisions made by the CDSS are essential conditions for the system's effectiveness in clinical practice. To implement these approaches in the CDSS, two tasks must be addressed:

1. Using explainable AI methods and interpretable machine learning for each prognostic and diagnostic model in the CDSS, calculate threshold values of indicators with the highest predictive potential, form risk factor phenotypes that explain the development of adverse events, assess the contribution of each phenotype and individual risk factors to their realization, and explain deviations from phenotypes, among other things.

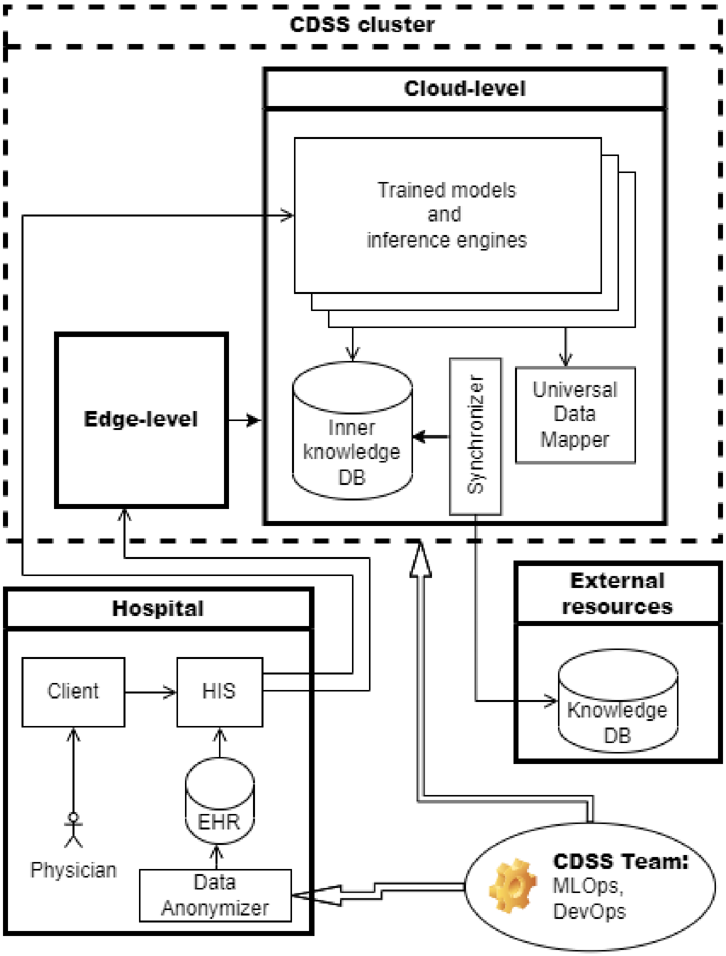

Fig 1. Clinical decision support system high-level architecture.

2. Store explanations and interpretations in a formalized form according to specialized ontology templates.

3.4 Technologies

Considering the above-described concept, the CDSS with a hybrid architecture integrates various components in the IT space, using the Https protocol and JSON format for message and data exchange. The integration of the CDSS with the HIS can be performed in different ways, depending on the HIS's support for functional extensions. The cloud platform IACPaaS [9] is used to manage knowledge bases containing formalized descriptions of models, recommendations, and explanations. Microservice interaction is organized through the Kubernetes (K8S) orchestrator (see Fig. 2).

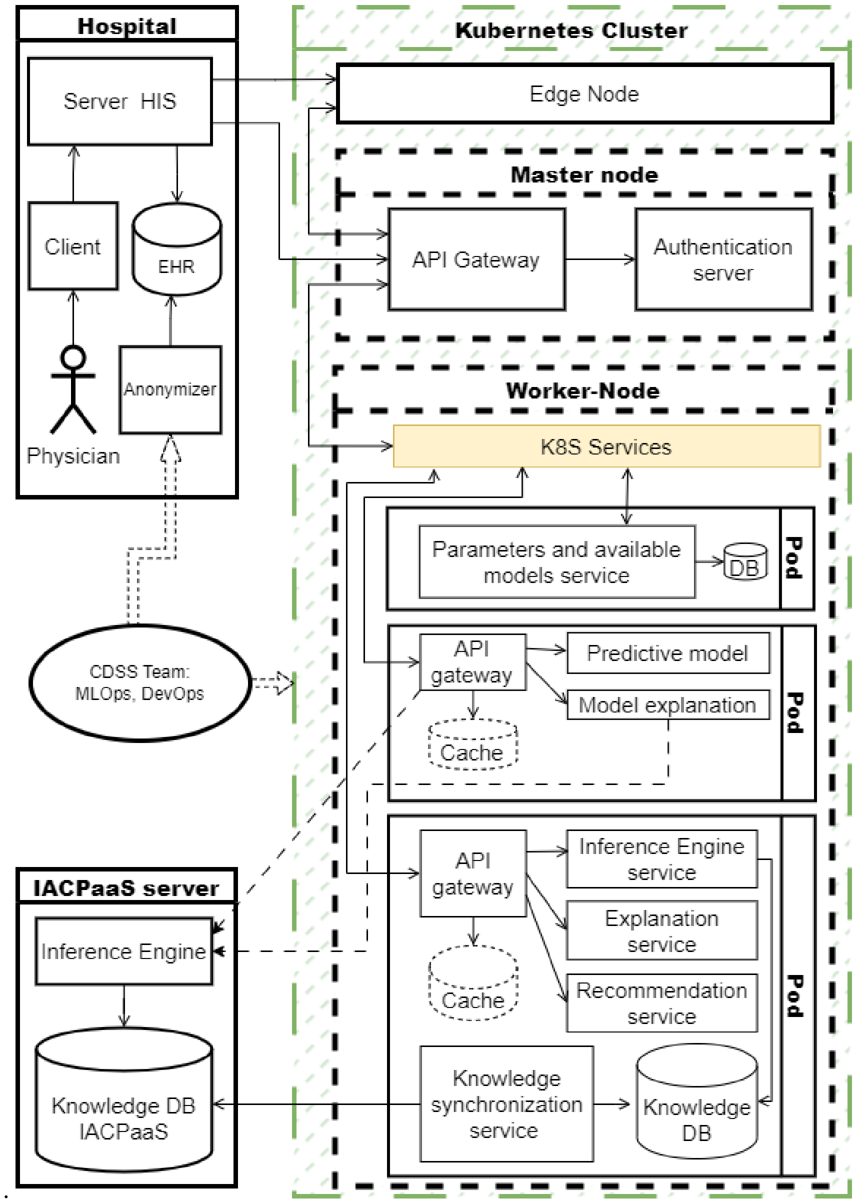

Fig 2. Clinical decision support system low-level architecture.

The system assumes simultaneous interaction with multiple clients using different HISs and located at a considerable distance from each other. The diagram represents edge-node pods in a simplified form (without separating microservices) and worker-node pods in their entirety. The CDSS architecture includes a K8S cluster with three typical nodes: Master (responsible for cluster configuration and providing the API

Gateway), Worker (hosts microservices with machine learning prognostic models), and Edge (a worker node located in the local network of a medical institution). The HIS server and client are implemented in the medical institution, while the IACPaaS server manages knowledge bases and includes a solver for traversing the formalized knowledge base tree. The K8S orchestrator ensures easy deployment and maintenance of containers with microservices. The control plane on the Master node is responsible for various functions, including API server management, pod scaling and management, node management, configuration, access (authentication and authorization), network, monitoring, and logging. To enhance the CDSS performance, the K8S tool – Ingress is used, which provides traffic routing and load balancing in the cluster, allowing the solution to scale as the number of requests increases. Cached computations are stored outside containers in Persistent Volume (PV) to improve performance. PV is an abstraction that allows allocating data storage space outside the pod but makes it accessible within the pod. Thus, the computation cache and updatable knowledge base are independent of the pod's life cycle. The CDSS prognostic models are implemented as microservices on worker nodes, combined into pods for computation execution, value interpretation, recommendation formation, and caching. The K8S orchestrator provides transparent scaling and load balancing between pods and microservices using Ingress. Scaling limitations are determined by available resources.

The CDSS can be deployed in a public cloud or partially within a medical institution's network, where computations occur on the Edge node. A proxy service provides load balancing between instances of microservices. Such a configuration offers advantages: increased data exchange speed, prioritized utilization of computational power, and improved fault tolerance under unstable internet connection conditions. In the CDSS, typical microservice pods are provided: an informative pod – informs about available prognostic models and parameters; a mapping pod – converts HIS data to the predictive model format and vice versa; a prognostic model implementation service – includes computation, explanation, and recommendations; a routing service – distributes computations between Edge nodes and the cloud; and a solver pod – encompasses solver services, explanations, recommendations, and knowledge base synchronization.

3.5 Workflow Scenario

The primary algorithm of the system can be described as follows:

1. The HIS server obtains a list of available prognostic models and parameters through the API Gateway.
2. The physician selects a model and requests a prognosis or diagnosis evaluation.
3. The HIS server retrieves data from the EHR database for model computations.
4. The request is sent to the Edge node (if available) or to the cloud via the CDSS API to the corresponding API Gateway service (the entry point into the model pod) by the model name.
5. The model's API service refers to the Data Mapper service via URL, which converts the EHR data into model input parameters. The model's API service checks for a result in the cache. If the data is present, it returns them, otherwise it obtains

the URL of the required services from the knowledge base and sends requests to the computing service of the predictive model, and after receiving calculations, to the Model Explanation service.
6. The Model Explanation service, according to its configuration file, queries micro-services of explanations known to it (XAI, knowledge-based model on the IASPaaS server, predictor importance calculation services) via URL.
7. The service on the IASPaaS server provides explanations and recommendations from the intellectual knowledge base.
8. The predictive model's API service caches the received data and provides them upon repeated request.
9. The model's response is transformed for the HIS and returned along with additional data.

3.6 Ontologies of Predictive Models

The ontology is used for the description of meta-information of machine learning predictive models in the knowledge base, accessing their implementation via a formalized interface, interpreting the results of forecasts or diagnostics, and offering recommendations. The ontology includes:
1. The name of the service, its general description, and its correspondence to the machine learning predictive model;
2. The service interface, including the URL address, input and output parameters, including risk factors (predictors in categorical form with threshold values);
3. The permissible boundaries for the application of predictive models (restrictions on age, therapy, the presence or absence of a specific medical history, etc.);
4. Reference values of input indicators (if they exist and if they differ from normative values when defined in the knowledge base of physiological indicators);
5. Interpretation of the result (assessment of the likelihood of an adverse event);
6. A set of recommendations for physicians and patients depending on the obtained result.

The knowledge base of predictive models can be used for the selection of the corresponding model service, the formation of a correct request to it taking into account the permissibility of applying the model to the patient, and obtaining a result in the form of the likelihood of an adverse event. The latter is interpreted using the correspondence of probability to the risk scale. For example, a probability from 1 to 3% corresponds to a low risk, from 3 to 5% - moderate, more than 5% - high, and above 10% - to a very high risk according to the SCORE scale and its author's modification. Moreover, the model's predictors are compared with reference values described in the knowledge base, and taking into account the calculated probability, a recommendation for their correction towards reference values is generated. In addition, the system provides for the selection of recommendations corresponding to the calculated probability.

Additional methods of interpreting the result provide for informing the physician about the threshold values of risk factors and their degree of influence on the endpoint (development of adverse events or the presence of a disease), which allows prioritizing the processes of reducing the risk of developing adverse events.

4 Implementation Experience

The development of a CDSS for the Medical Center of the Far Eastern Federal University (FEFU) involves several stages. In the first stage, a Minimum Viable Product (MVP) with a microservices architecture is developed without the use of K8S. The services are hosted on the FEFU server and integrated with the “1C Hospital” HIS. Physicians can select available prognostic models in the Electronic Health Record interface. The patient's history or outpatient card code is used as the primary index for the patient record and must be unique.

Microservices for various prognostic models have been implemented, including those widely used in cardiology and cardiac surgery (SCORE, SCORE 2, GRACE, EuroSCORE II, Diamond-Forrester, etc.), as well as proprietary machine learning models for predicting in-hospital mortality and other cardiological indicators. The use of proprietary models allows for improving the accuracy of prognosis and diagnosis. For example, for the prediction of in-hospital mortality after coronary artery bypass grafting, the proprietary model has a quality metric - the area under the ROC curve (AUC) of 0.88, compared to 0.75 for the classic EuroSCORE II model. The accuracy of the proprietary pre-test evaluation of obstructive coronary artery disease is characterized by an AUC of 0.83, compared to 0.65 for the modified Diamond-Forrester model. Each model service is represented in the knowledge base with a description of input and output parameters, normative values, a URL link to the service, interpretations, and recommendations for physicians and patients, depending on the obtained results.

For the specialists of the FEFU Medical Center, physician workstations and electronic documents have been developed within “1C” HIS. After performing calculations using prognostic models, the CDSS returns the model results, interpretation of the results, and recommendations for reducing the risk of adverse events for the patient..

5 Conclusion

In the present study, the authors proposed a concept and architecture for a hybrid CDSS, integrating machine learning models and intelligent knowledge bases describing methods for assessing cardiovascular risks, their explanation, and recommendations for limitation. The microservices approach provides flexibility, scalability, and independence from hardware resources used. The application of Edge computing allows for optimizing data processing and reducing server loads. The use of cloud technologies and service containerization ensures rapid system adaptation to changing conditions and the needs of medical institutions. Formalized knowledge bases with synonymy mechanisms help address the issue of using different terms in the HIS. The system is being developed using an iterative approach. In the subsequent stages, it is planned to expand the available pool of prognostic models, improve the architecture by using an orchestrator, and integrate with new HIS. The development experience of this system highlights the need for an interdisciplinary approach based on the cooperation of specialists in information technology, machine learning, clinical medicine, and medical institution management. This is a key factor in creating innovative solutions for implementing digital medicine projects..

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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