# Principles of creating a Decision-Making System for a Radiologist-Mammologist

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***Abstract —*** For the main method of breast cancer prevention-screening, there is currently no CAD system that can work on the "white box" principle. False positives also reduce the confidence of doctors with the CAD system. Also, there are no systems for monitoring the laying of the breast for an X-ray technician. The development of CAD systems in mammology is mainly carried out using computer vision technologies, while the proposed solution uses not only computer vision but also a knowledge base for verifying the output of neural networks and production output, taking into account the probabilities of the appearance of signs of the disease. This approach is quite flexible and scalable – knowledge can be both accumulated and obtained, and recognition modules can be added or retrained. Changing the knowledge base allows you to show the doctor based on which knowledge the pathological formation was determined. But most importantly, knowledge base agents in the future can connect to the hospital information system (HIS) and independently request the data necessary for the preparation of the study report. This approach allows you to fully simulate the activities of a diagnostic doctor.

***Keywords —*** breast, cancer, CAD system, knowledge base, radiologist-mammologist, OSTIS, neuron networks, white box, nosological form, agents.

## I. INTRODUCTION

Breast neoplasms continue to lead to the structure of the incidence of diseases of the female reproductive system. Only in the United States, more than 268,600 cases of breast cancer were detected in 2019, and 41,760 cases led to death [1].

The detection rate of breast neoplasms during prophylactic checkups is one of the highest [2]. Timely detection of symptoms of such diseases strongly depends on the qualifications of restricted specialists. The main method for recognizing signs of breast cancer is digital X-ray mammography – a low-dose radiological procedure for visualizing the internal structure of the breast. Therefore, mass prophylactic checkups in combination with digital mammography are the most effective method of early detection of breast neoplasms.

During the screening, the scope and quality of the study and its interpretation are critical. The effectiveness of screening will determine not only the number of detected diseases but also the number of false-positive and false-negative results. About 20% of cases of detected malignancies already had X-ray signs in the images of previous studies [3]. A typically recommended breast screening procedure is to obtain and interpret images of two lateralities (left and right) in two projections: the cranio-caudal (CC) and the mediolateral oblique (MLO). X-ray examination is usually carried out by two specialists: an X-ray laboratory assistant and a radiologist. The X-ray lab technician performs breast placement and image acquisition, and the doctor interprets the images obtained.

During screening studies, the obtaining and interpretation of images are almost always separated in time. In this case, the X-ray laboratory technician may make a mistake and make an incorrect set-up or perform a study with incorrect exposure parameters, which will make the study unsuitable for further interpretation.

Mammograms are monitored and interpreted by radiologists. The analysis of X-ray images requires a highly qualified doctor. Therefore, the development of methods and algorithms for intellectual support of the doctor's decision-making and the work of the X-ray laboratory assistant will improve the quality of early diagnosis of breast diseases, reduce the number of repeated X-ray studies and biopsies, which is a pressing scientific and engineering task.

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## II. LITERATURE ANALYSIS

Computer-aided detection and diagnosis (CAD) [4] systems for mammography have existed since the 90s of the last century. Almost all vendors of digital mammography offer their CAD system as a universal solution for the radiologist-mammologist. Such systems solve the problems of segmentation and classification of masses, classification of images by the category of risk of breast cancer (BiRads) [5]. On average, the area under the curve (AUC) of CAD systems based on artificial intelligence was higher than that of the corresponding systems based on mathematical methods: 89% vs 87% [6]. Except for the CAD systems of the radiologist, there are systems for controlling the quality of the resulting image. The input to such systems is an image of a special phantom that simulates strange masses, and the system interprets whether the image quality allows you to detect all of them.

If the goal of CAD systems is clear - to increase the probability of detecting breast neoplasms, then the tasks of such systems in the literature are formulated equivocally.

To support the screening of breast neoplasms, two CAD systems are needed: the X-ray technician support system and the radiologist support system.

The X-ray laboratory assistant support system performs the following tasks:

1. Automatic detection of foreign objects in the image and defects in the breast placement according to the PGMI system (Perfect, Good, Moderate, Inadequate);
2. Determination and correction of the levels of the picture.

The decision support system of the radiologist is entrusted with more complex tasks:

1. Defining the structure of the breast by types A-D and defining the breast prosthesis;
2. The detection of volumetric masses and the determination of their shape, margins, and density;
3. Finding calcinates, their classification into benign, suspicious belonging to breast cancer, the nature of distribution;
4. Determination of asymmetries, disturbances of the breast architectonics;
5. Drawing up a machine-readable structured report based on the data obtained;
6. Classification of the study by the category of BiRads.

Unfortunately, modern CAD systems for the laboratory assistant perform only the definition and correction of the image levels, and for the radiologist, they mainly find volumetric masses and classify them by class: suspicious/benign. Such capabilities are not enough, and CAD systems have the following disadvantages that prevent their widespread implementation:

1. False responses (often false positives) of such systems is undermining the doctors ' trust;
2. The doctor still makes a description of the study. The radiologist does not make a diagnosis, he describes in detail all the pathological findings in the image and based on this data assumes the disease;
3. The CAD system knows nothing about anything but the image. The system usually receives only one image as input, the anamnesis, and other important data are not available for it;
4. The system works on the principle of” black box " (magic box), it can not explain to the doctor why it segmented a particular area of the image and classified it as a cancerous tumor with a probability of 70%.

All these disadvantages make CAD systems useless for radiologists.

## III. OBJECT, SUBJECT, AND METHODS OF RESEARCH

An AI system capable of automatically creating a mammography protocol must match the following criteria:

1. The entire study should be provided to the system for input: several projections (images) for each laterality, their metadata, patient metadata (age, information about the hormonal background);
2. Communication with the system should be carried out in a language based on bi-rads;
3. The system must have knowledge of radiation diagnostics in mammology.

The schematic diagram of such a system is shown in Figure 1.

The study is fed to the input of the handler, which sends images to the algorithms for detecting diagnostic criteria. Based on the found criteria, the handler generates a request to the knowledge processing machine for verification and completion of the search results. The knowledge processing machine can request additional data (from the user or another data source) to perform differential diagnostics. The knowledge processing machine's response is translated by the study processor into a machine-and human-readable report in a domain-specific language based on BiRads.

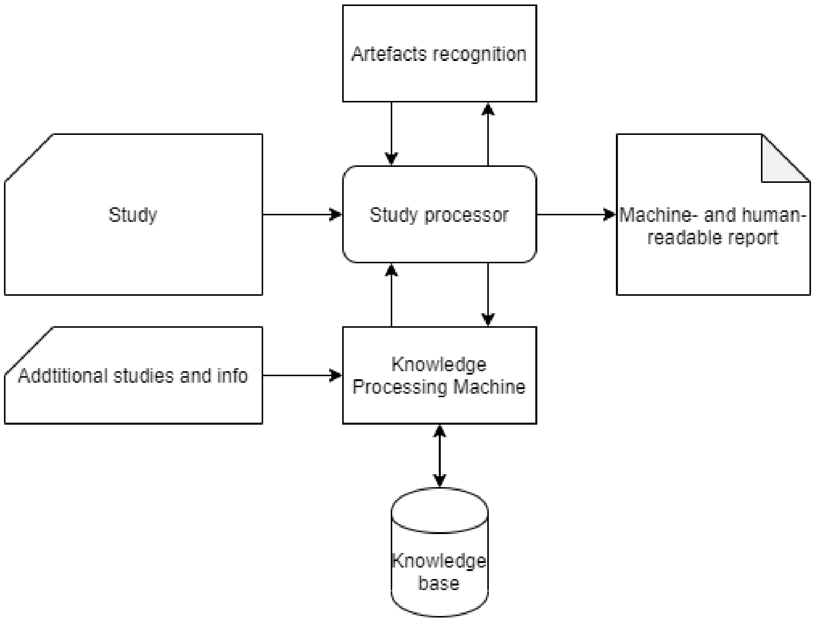


Fig. 1. Schematic diagram of the AI system in radiation mammology.

The research handler consists of a research loader, a set of modules for recognizing diagnostic criteria, a knowledge base with a knowledge processing machine, and a module for generating a machine-and human-readable report.

Diagnostic criteria recognition modules can accept a single image, two projections of the same laterality, or the entire image of the study. The modules must process the study in parallel. The recognition result at the output of the module is presented in the language of the study description. While saving to the knowledge base, the result is translated into the language of the knowledge base.

The output information of the recognition modules is translated into the language of the knowledge base and placed in it as a structure describing the study.

The translator uses the following domain ontologies:

1. Markup Language Ontology;
2. Bi-rads Vocabulary Ontology;
3. Ontology of graphic primitives and images;
4. Ontology of Radiation Mammology;
5. The translator can also use domain-independent ontologies, for example, to describe the probability of occurrence of an attribute.
6. The knowledge base performs 3 main tasks:
7. Verification of the output of each of the recognition modules;
8. Choosing a conclusion on the Bi-rads scale;
9. Conclusion of the disease hypothesis.

So the knowledge base is the main part of the system. It is difficult to imagine a model of such a database based on a relational model. Semantic networks are better suited for this purpose. We chose the OSTIS technology.

OSTIS (Open Semantic Technology for Intelligent Systems) is a technology that allows you to represent knowledge based on semantic networks.

OSTIS [7] technology offers a technology similar in idea to the Semantic Web: the presentation of information takes place in the form of an intelligent portal, i.e. a logical-semantic model that

- does not depend on any options for the technical implementation of the designed system, i.e. it is

platform-independent, up to the possibility of using fundamentally new computers;
- assumes a fairly simple procedure for integration with logical and semantic models of other intelligent systems;
- fully and constructively reflects the semantics (meaning) of the knowledge used and the essence of the methods used to solve problems.

From a formal point of view, the result of designing a logical-semantic model of any intelligent system is a text that includes:
- source text of the knowledge base;
- source code of programs that describe various knowledge processing operations, i.e. the behavior of agents that process a common knowledge base;
- the text of the documentation (the source text of the help knowledge base system that provides extensive information services to users).

The SC-code is used to represent complex structured information. Knowledge is structured in such a way that all the variety of its types is unified (brought to a common form) since this is the fundamental principle of technology that allows the integration of knowledge in the knowledge base and the integration of knowledge bases.

In the technology under discussion, this form is the SCg code - a visual representation of the SC-code.

The advantages of the SC-code are the following features:

- unlimited ability to switch from sc-texts to sc-metatexts containing the characters of the sc-texts described;

- SC-code texts (including those texts whose sc-characters are entered within their respective metatexts) can be hierarchical structures since the sc-element can denote a set consisting of any sc-elements;

- all major semantic relationships between texts in SC-code become set-theoretic.

The SC-code represents the unity of the language and the metalanguage. For example, in the form of sc-constructs, you can describe the syntax, semantics, and ontology of SC-code. It operates only with semantically normalized sets. This makes it possible to clearly distinguish the primary (terminal) sc-elements, which are the designations of external objects (objects that do not sets) from secondary sc-elements, which are notations of sets, all elements of which can be directly included in the composition of sc-structures. After the syntax is formed, a model is built that can describe a fragment of a subject area.

Knowledge Base source Editor is an application that aims to help you create and edit fragments of knowledge bases of intelligent systems, the design of which is based on OSTIS technology. This editor is based on the concept of visualizing the data stored in the knowledge base, which greatly simplifies the process of editing them and speeds up the process of designing knowledge bases.

Advantages of OSTIS:

- the automatic merging of added knowledge and existing knowledge in the system;
- select the presentation format;
- visual presentation.

Disadvantages:

- small amount of documentation;
- low popularity;
- high resource consumption.

The knowledge base was developed using semantic constructs. The patient study description template was developed using KBE.

The description of the study consists of different parts:

- the part of the patient's passport data,
- the image metadata description part;
- the part describing all the artifacts found by the neural network.

The passport data of the patient at the moment consists of the nodes of the hormonal status of the patient and his age. In the future, it will be possible to add information about previous studies and about the studies of relatives, which will affect the calculation of the probability of a particular disease.

The description of the image metadata consists of information about the projection, width and height, laterality, and so on. This information is taken from Dicom files.

Artifacts are divided into laterality artifacts and artifacts that have a specific location in the image. When processing an image, the neural network finds all the artifacts and their attributes and uses tags and values to describe them. The information is then translated into a graph view. Artifacts have properties that are also described in the graph structure. For example, the formation has margins, shape, density, size, distance from the nipple. For example, the total breast density can be considered an artifact of laterality.

Many nosological forms have been described. They are divided into normal, benign, suspicious, and potentially suspicious. Each nosological form has a probability distribution of occurrence by age. The nosological form has features, they are also artifacts, which are formalized according to the same template as the study.

The probabilities of occurrence of the nosological form are very rarely described in the literature. Therefore, we had to use the real experience of doctors - to get several invaluable consultations from specialists in their field. Also from the literature [8], descriptions of nosological forms and probabilities of occurrence of each artifact and its properties in this form were taken.

To describe the research in the graph structure, the concepts were formalized. The knowledge base stores tags and their values as sets, and specific study cases as regular nodes. Each set has a description and an identification number, all of which can be viewed through the user interface.

## IV. RESULTS

To solve this problem, it was decided to develop a problem solver. The problem solver is a graphodynamic sc-machine (memory uses a semantic network as a model of knowledge representation), consisting of two parts:

- graf-dynamic sc-memory;
- sc-operations systems.

The system of operations is agent-oriented and is a set of sc-operations, the condition for initiating which is the appearance of a certain structure in the system memory. In this case, the operations interact with each other through the system's memory by generating constructs that are the conditions for initiating another operation. With this approach, it becomes possible to ensure the flexibility and extensibility of the solver by adding and/or removing a certain set of operations from its composition.

There are currently four agents:

- probability counting agent;
- an agent that creates a report on the patient's passport data;
- the agent that creates the study report;
- the agent that generates the general report.

To create a group of agents, you need to develop a module and connect it, create the necessary command launch buttons in the user interface. After that, you need to write the agents. Only one agent is launched from the user interface - the agent that generates the general report.

During the process of writing the agent, you need to use the C++ libraries to work with OSTIS. To get data from graph structures and work with them, you need to use iterators. There are different iterator constructs: a three-element iterator and a five-element iterator. The three-element structure consists of two nodes and a directional arrow between them. The five-element structure consists of two nodes connected by a directional arrow, to which another arrow is connected, directed from the third node. The agent that creates the general report runs all the other agents, waits for the result from them, and then groups all the got data into one big report, which is finally visible to the user.

The agent that creates the patient report is passed through the part of the study graph that contains the passport data using iterators. The agent finds the nodes connected by various relationships with the patient and finds in which sets they consist. Takes the IDs of these sets and uses them to generate a report with the patient's passport data.

The agent that creates the research report works with the part of the graph that describes the artifacts in the images. The agent searches for graph constructs that describe artifacts and their attributes. Just like in the previous agent, we search for nodes by relationships and then look at the sets that contain them. The set IDs are used to generate the report.

The last agent calculates the probabilities of the existence of nosological forms. Calculations are made based on the theory of probability. First, data on all the artifacts found and their properties, as well as the age of the patient, are collected from the graph of the study of a particular patient. The agent then goes through the entire tree of nosological forms and selects its artifacts and attributes for each form. After that, it compares the data found for each nosological form and, if they were the same, the agent accesses the node describing this artifact or property at the address, finds its probability, which it multiplies by the already existing probability. Also, the nosological form has a probability of spreading among different age groups, so the agent takes this into account in calculating the probability.

The result is a list of nosological forms and their probabilities of presence in this study sorted in descending order.

In the future of development, you can add to this system:

- neural networks that will find artifacts and their attributes in images;
- an agent that forms a graph structure from the data received from neural networks;
- a module of agents that implement various verifications of the correct operation of neural networks;
- a more intuitive interface for the end-user (doctor).

## V. CONCLUSIONS

For the main method of breast cancer prevention-screening, there is currently no CAD system that can work on the "white box" principle. False positives also reduce the confidence of doctors with the CAD system. Also, there are no systems for monitoring the laying of the breast for an X-ray technician. The development of CAD systems in mammology is mainly carried out using computer vision technologies, while the proposed solution uses not only computer vision but also a knowledge base for verifying the output of neural networks and production output, taking into account the probabilities of the appearance of signs of the disease. This approach is quite flexible and scalable – knowledge can be both accumulated and obtained, and recognition modules can be added or retrained. Changing the knowledge base allows you to show the doctor based on which knowledge the pathological formation was determined. But most importantly, knowledge base agents in the future can connect to the hospital information system (HIS) and independently request the data necessary for the preparation of the study report. This approach allows you to fully simulate the activities of a diagnostic doctor.

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