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# DATA-DRIVEN DIAGNOSTIC TOOLS FOR BREAST CANCER DETECTION IN CLINICAL DECISION SUPPORT SYSTEMS

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**ABSTRACT** Computer-aided diagnosis (CADx) technology has demonstrated enhanced efficacy in breast cancer (BC) detection, which is particularly crucial during primary care physicians' initial evaluation of patients. The work aims to develop novel, user-friendly auxiliary computer aids accessible directly to frontline medical practitioners, eliminating the need for costly computer systems. The scientific novelty lies in the fact that we have devised a nonrelational database (DB) of factual data designed to house the results of patient studies, which can be harnessed for machine learning in computer-aided BC diagnosis systems. The DB encompasses a heterogeneous vector of primary measurements (metadata, DICOM standard files, alongside other images and data) for each patient, facilitating the construction of a neural network for tumor recognition and preliminary classification. We have populated the database with new, region-specific data pertinent to women in Ukraine amidst severe stress induced by the ongoing war. Additionally, we have developed a new system for concurrent monitoring of ultrasound, computed tomography, and mammography results, complemented by a decision support system for simultaneous cross-verification of neoplasm diagnoses based on density and spatial correlation.
**KEYWORDS:** breast cancer, image processing, neural networks, machine learning, and computer-aided diagnosis.

**I. INTRODUCTION** doctors is crucial. While numerous Computer-Aided Diagnosis and the number of false-negative results interpreting medical data [1-4]. Prospective clinical studies have shown an increase in the effectiveness of detecting breast cancer using CADx, which is especially important during the initial examination of patients by general practitioners. In [7, 8], specific examples of the successful use of CADx systems in breast cancer diagnostics are examined more thoroughly. The present phase in the evolution of breast cancer diagnosis and prevention necessitates the creation of new Computer-Aided Diagnosis (CAD) systems. The work aims to develop innovative, user-friendly computer tools that are readily available to medical practitioners, thus eliminating the dependence on costly computer systems. For efficient and smart archiving, retrieving, and analyzing patient examination data, including digitized MRI, CT, and mammogram images for breast cancer detection, developing a sturdy, knowledge driven system that can offer decision support to primary care incurring substantial costs for both setup and ongoing operation.

The structure of this work is as follows: Section II presents an overview of existing models for BC recognition, methods for working with DICOM files and cloud SAAS models; Section III describes the architecture of the developed system; Section IV describes the configuration and parameters of the decision support system; Section V presents the obtained results and discusses them.

## II. RELATED WORKS

### A. REVIEW OF EXISTING CADX MODELS FOR BC RECOGNITION

The cross-disciplinary domain of computer-aided cancer diagnostics encompasses mathematical modelling, image processing, pattern identification, statistical analysis methods, and clustering [9]. The application of CADx technology for COMPUTER-AIDED diagnosis technology (CADx) is (CAD) systems are available, none provide comprehensive designed to reduce the observational errors of physician's database capabilities and universal applicability without Cancer detection is currently a significant focus in oncology research. Numerous databases provide access to digitized cancer research [10], with DDSM [11] being the most notable. This open dataset, widely used by researchers, includes relevant metadata for each image. Comprehensive metadata is also available in FORDS [12] and BI-RADS [13]. However, DDSM does not offer CADx or search engine capabilities. The UK-based Mammography Image Analysis Society (MIAS) database [14] provides access to images and malignancy data but lacks supplementary information or search functionalities. AMDI, the Indexed Atlas of Digital Mammograms [15], is an online repository of digital mammograms that allows image upload and download, statistical comparison methods, and content-based image searches. IRMA (Image Retrieval in Medical Applications) [16] is a project to develop content-based image retrieval systems, not CADx. The Ljubljana Breast Cancer Dataset (LBCD) is the oldest among several renowned breast cancer datasets, established in 1988 [17]. It illustrates situations where a woman might encounter a blocked node, which could potentially lead to breast cancer recurrence.

The features included in existing databases are as follows:

- Age: This refers to the patient's age at the time of diagnosis.
- Menopause: This is defined as the period 12 months after a woman's last menstrual cycle.
- Tumor size: This indicates the size of the malignant tumor at the time of diagnosis.
- Inv nodes: This represents the number of visible lymph nodes in the armpit showing signs of spreading breast cancer.
- Unit caps: This describes situations where the tumor appears localized on the outside, but there is a risk of metastasis to the lymph nodes.
- Grade of malignancy: This refers to how visible the cancer is under a microscope.
- Chest: This specifies which side of the breast the breast cancer is located on.
- Breast quadrant: This identifies the section of the breast where the breast cancer is located, usually near the nipple.
- Radiation: This denotes the treatment method used to eliminate cancer cells.

Therefore, there is a need to develop a non-relational factual database for breast cancer research that contains current, region-specific data and a comprehensive set of parameters.

### REVIEW OF TECHNIQUE OF DICOM FORMAT FILE HANDLING

The advancement of contemporary imaging technologies in the medical field has resulted in a substantial increase in the quantity of medical images primarily stored in the DICOM (Digital Imaging and Communications in Medicine) format. This format enables the storage, transmission, and sharing of high-quality medical images using a standardized approach. The utilization of DICOM imaging has become a crucial component in various aspects of medical practice, including diagnosis, treatment, and research. The Orthanc DICOM Server [18, 19] allows users to focus on the core of DICOM files by hiding the complexities of the DICOM format and protocol. What distinguishes Orthanc is its provision of a RESTful API, which enables smooth integration from any programming language. Furthermore, Orthanc aids in extracting DICOM tag data into JSON files and allows for the real-time creation of standard PNG images from DICOM instances. Orthanc also provides a plugin mechanism designed to enhance its fundamental functionalities by adding new modules, thereby extending the capabilities of its REST API. Currently, freely accessible plugins include a Web viewer, PostgreSQL and MySQL database backends, and a reference implementation of DICOMweb. One of the top computer recognition systems, which relies solely on mammography data, was introduced in [20]. The highlighted CAD/CADx system is a computer-assisted detection and diagnosis system equipped with a searchable database and network, meticulously designed to enhance mammography in clinical and research settings. It consists of three main components, forming a three-tier distributed system:

- SQL Database: This contains mammograms, treatment records, and relevant cancer patient data (metadata).
- Applications Engine: These are server-based applications specifically designed to detect calcifications, masses, and architectural distortions.
- Client Applications: Currently, the system includes four client applications, and its architecture allows for the smooth integration of additional client applications, including both web-based and standalone versions.

The system operates within a distributed architecture, with a central business logic layer acting as the core of its applications. The data access layer interfaces with the SQL database, while the client applications represent the presentation layer. The database provides access to a wealth of information, including cancer registry data, radiological mammography images, and reports. Furthermore, it offers functionalities such as providing images and data to researchers for CAD algorithm development, enabling radiologists to extract and annotate images, and providing additional information for statistical analysis.

## REVIEW OF SAAS CLOUD MODELS

A significant drawback of existing local systems for early breast cancer diagnosis is the high cost associated with the necessary computing equipment, as well as the process of implementing and operating such systems for use by primary care practitioners nationwide. The most logical solution in this scenario is the SaaS (Software as a Service) cloud model [2123] – a cloud software delivery model where the service provider develops cloud software, ensures its maintenance, automatic updates, and availability, and provides this software to customers over the Internet for a fee proportional to the volume of use. The public cloud provider manages all hardware and standard software, including middleware, software applications, and security measures. This allows SaaS customers to significantly reduce costs, deploy, expand, and update business solutions more quickly compared to onpremises systems and software. Moreover, it enables them to calculate their total cost of ownership with greater accuracy. SaaS applications that integrate artificial intelligence and machine learning are set to improve the effectiveness of early detection systems for breast cancer, thereby increasing the value of SaaS solutions [24].

This study draws on our previous experience in developing computer recognition systems for image processing, computer vision, machine learning and the development of mathematical methods for processing heterogeneous unstructured data [2527]. Despite the challenges associated with using neural networks for breast cancer analysis, ongoing research efforts show promise for improving early detection and prognosis prediction. Addressing issues related to data heterogeneity, interpretability, and limited data availability is crucial to unlocking the full potential of neural networks in advancing breast cancer diagnosis and treatment. Integrating information from multiple imaging modalities through multimodal fusion approaches can enhance diagnostic accuracy and robustness, overcoming the limitations of individual modalities.

## III. CADX SYSTEM

### A. SYSTEM CLOUD ARCHITECTURE

The OncoAssist system's architecture comprises a unique structure of elements and their encompassing shell. The shell establishes the reasons for selecting an appropriate architectural style, its elements, and its boundaries [28]. The architecture is designed to meet the requirements of the system being developed, adhering to the "form follows function" principle, and represented in Figure 1.

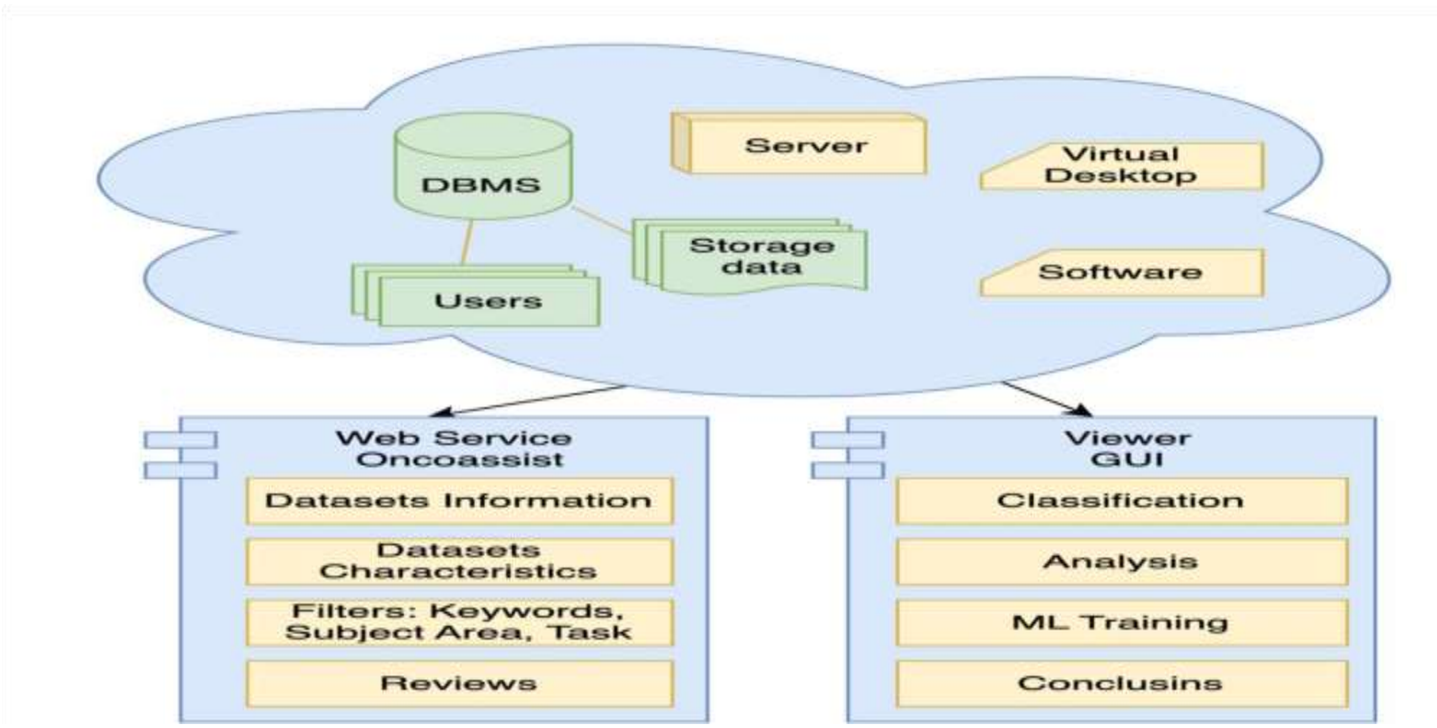


Figure 1. Blueprint of the decision-support infrastructure that utilizes CADx

The OncoAssist system comprises several key components:

- “Cloud OncoAssist”, which encompasses the following subsystems:

o “DBMS”: This request processing subsystem generates a client request with the data processed by the system. The creation mechanisms and their actions can be modified as the project evolves. o “Storage Data”: This is an integrated repository of substantial data of various formats, leading to classification based on the same criteria.

o “Server, Virtual Desktop, and Software”: The server component is installed and configured on a dedicated service with the necessary software package for the system architecture's operation.

- "Web-service OncoAssist": This subsystem enables data network capture, filtering by a set of criteria, metadata review, and importing a data set from code, among other things.
- "Viewer": This is a data display subsystem with a graphical user interface (GUI), offering advanced features such as data visualization and classification using human intelligence to identify abnormal areas in the image, among others.

## DATABASE AND HYBRID CLOUD

The architecture of an information system and database involves organizing its core components, including their volume, capacity, interfaces, and communication protocols. The type of architecture chosen depends on such factors as system development, availability, cost, maintenance effort, and practicality [17, 29]. The database is crucial for providing strong data support for the CADx system. It is a comprehensive repository containing images, patient information, pathology records, disease types, and more. It also enables secure data retrieval and allows data to be matched against specific criteria. Information can be accessed within the organization (medical/government authorities) and among the community (registered doctors/patients). Medical records can be analyzed and reviewed for physicians, doctors, and administrators to understand patient conditions and illnesses. Patients have the option to deny access to their health history. This creates a hybrid system, integrating various components connected through technology and facilitating the management of programs with associated data.

The system design provides information about cancer registration, imaging, and radiological mammography signals. The model is designed to enhance the efficiency and scalability of the database. The hierarchical database architecture incorporates diverse standards and data from multiple sources, structured within a three-tier architecture with interfaces connecting each level. Confidential information from cancer registries is stored at the highest tier, including patient details, cancer diagnoses, comorbidities, disease stages, treatments, etc. Some elements in this tier can be expanded to include additional cancer diagnoses. The intermediate tier contains information specific to breast cancer, including symptoms, pathology, and imaging, with more granular data extending to mammary gland skin cancer, though lacking the core information from the next tier. The lowest tier consists of entities related to images and pathology, forming the foundational level of the architecture. This hierarchical structure allows the essence and content of the database to flow from the hidden to the private. Parent and child models are designed to create a more efficient and scalable database.

## SYSTEM GENERAL ARCHITECTURE

The proposed decision support system (DSS) relies on Computer-Aided Detection/Analysis eXpert (CADx) technology. From a components point of view, the system consists of two sub-systems: OncoAssist and OncoAssist MLOps. Figure 2 shows system environments and components.

OncoAssist Software Environment. A cloud-based cluster running software modules and components as containerized applications in the cloud.

OncoAssist Web Interface Module. A web application that provides users full functionality via a web browser, utilizing OncoAssist Storage to manage and store medical data. This module comprises three components:

- Medical Data Catalog Explorer Component: allows users to upload scan files and enables Radiologists/Oncologists to manage and browse the medical data catalog.
- Scans Viewer Component: provides a web interface for Radiologists/Oncologists to view and analyze scan files alongside medical records.

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- CADx Suggestions Viewer: displays suggestions produced by the ML Model via the ML Inference API, allowing users to provide feedback on these suggestions.

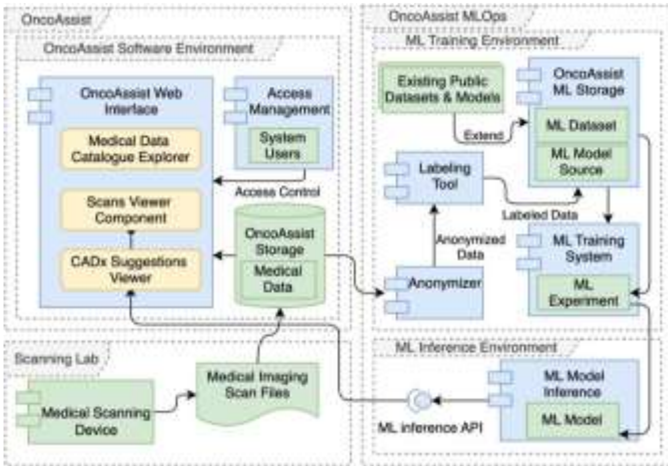


Figure 2. System general architecture

ML Training Environment. A cloud studio facilitating ML model training and inference, comprising several modules that support the MLOps process. It consists of the following components:

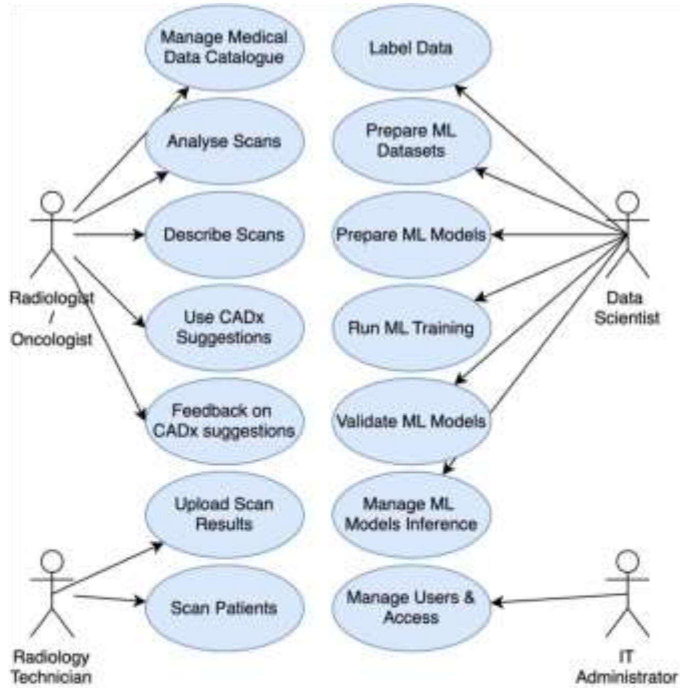


Figure 3. System actors and use cases

- OncoAssist ML Storage: stores ML Datasets and ML Model Sources developed by Data Scientists.
- Labeling Tool: extends existing public datasets and collected ones with labeled data using anonymized medical data from OncoAssist Storage.
- ML Training System: runs training experiments and stores training results.

ML Inference Environment. An environment executing ML Models using ML Model Inference software, providing an API for generating CADx Suggestions.

ACTORS AND USE CASES

Figure 3 illustrates the System actors and use cases.

Radiologist/Oncologist. This actor utilizes the OncoAssist system through a web interface, which offers all necessary functionalities for managing medical data, analyzing scans, and providing feedback on CADx suggestions. The

Radiologist/Oncologist can:

- browse and manage patient medical records;
- view scan files and analyze them alongside medical records;
- Provide feedback on CADx suggestions generated by the system.

Data Scientist. This actor is responsible for developing, training, and performing inference on ML models for CADx suggestions. Their tasks include:

- Developing and training ML models
- Integrating ML models into the system's architecture
- Evaluating and refining ML model performance
- System Environments and Components management and setup

Radiology Technician. This actor operates various scanning devices at the Scanning Lab to perform patient scans. They ensure that scan files are properly processed, formatted and uploaded to the system.

IT Administrator. They are responsible for managing user accounts and permissions.

D. IMAGE PROCESSING STAGES

The screening stage of cancer diagnosis includes mammography, MRI, and CT scans, which are used for visual detection of tumors in images and series of images based on optical density distribution. The most used format for medical imaging is DICOM. Figure 4 shows image processing stages from imaging files to model training datasets. The process of image processing includes the following steps:

- Input data is collected from input sources and organized as input storage for raw data.
- Data anonymization is the first step of preprocessing, files content is anonymized, cleaning all identifying data.
- Imaging data preprocess starts with cleanup and reformat:
  - At this step, images are cleaned up from unused visual information, like imaging artifacts, extracting only the areas of interest.
  - Reformat is needed to transform imaging data from DICOM format to imaging formats used for further processing by some models.
  - Labeling tools are used, pre-labeling is done with ML assistance.
- The data labeling step is done to label images with regions of interest and their specification and classification.
- The data augmentation step is done in two ways: augmenting with non-imaging data from medical reporting, like tumor classification and specification. The second step is augmenting using techniques like rotation, perspective changes, etc.

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- Prepared dataset is split into train/test/validate sub-datasets.
- Dataset is stored in the format compatible with the model which will be trained.

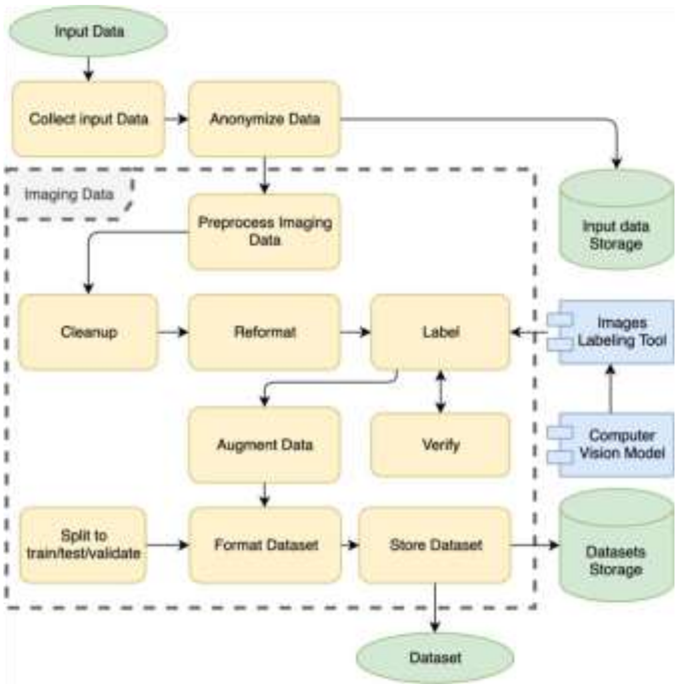


Figure 4. Data processing flow

F. USER INTERFACE

The OncoAssist Web Interface (viewer) is a tool to be used by Radiologists and oncologists to combine management and Reviewing the medical imaging together with reviewing CADx System-produced Findings, Data, And Recommendations. It is Developed as a web interface to a cloud-based system to Provide a Secure, Fast, and Comfortable way to Work With Imaging data and system recommendations.

User Interaction is Split Into Two Steps, Illustrated In Figure 5.

specific range of densities (see Figure 7).

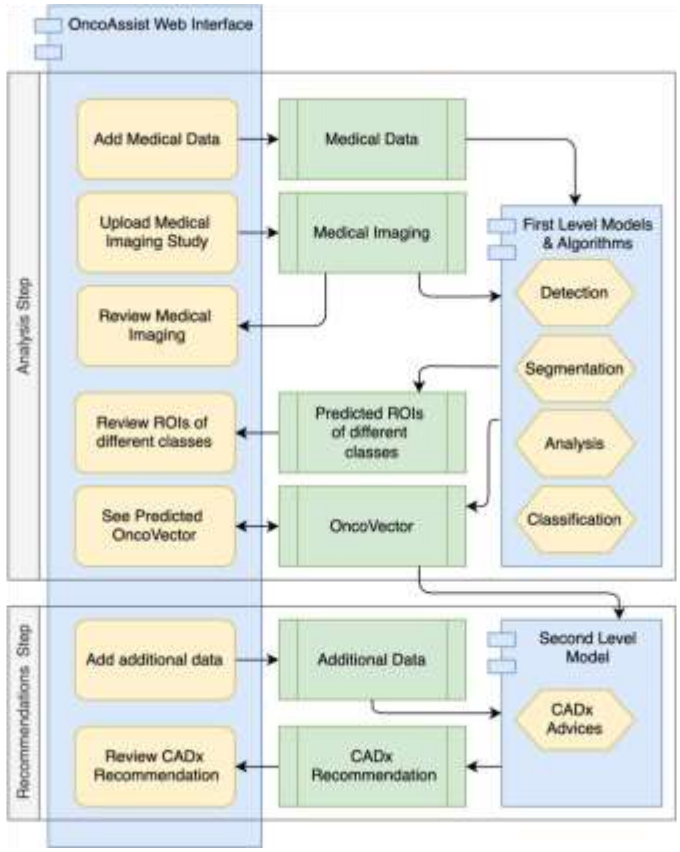


Figure 5. Viewer software architecture

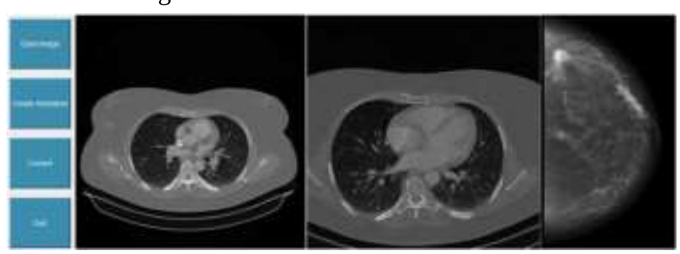

Figure 6. Parallel data viewer window for the same part of the

Analysis Step. It includes imaging and medical data management and review in the viewer. When new data is uploaded, it is processed by modular backend processing, including ML models and algorithms processing. This processing produces ROIs definitions which can be shown in viewer, including segmentation, positioning and classes. Also, it produces the OncoVector, vector of data, predicted and calculated by backend processing. The OncoVector is shown in the viewer to allow users to review, adjust and verify the data. Recommendations Step. At this step, users work with CADx recommendations, starting with additional data management which can be needed for CADx recommendations. When data is prepared, it is combined with OncoVector from the Analysis Step and processed by the second-level CADx model, which produces recommendations for the next steps. With the Viewer users can review, verify and adjust the recommendations. To enhance diagnostic accuracy, it is possible to directly compare the graphical results of these studies for the same body area on one screen, as shown in Figure 6. Since the studies are conducted on different devices, monochrome images are normalized across


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various series, and the image brightness is linked to the physical density of the tissues, highlighting a patient body Identifying the size of a breast tumor from MRI, CT and mammogram data in the form of a series of slice images in DICOM format includes several stages [7].

1. DICOM Data Upload. First, it is needed to upload a series of DICOM images and convert them into a format that is easy to process. An array of voxels of a three-dimensional image is created (Figure 7a).

2. Normalization of image brightness for body tissue density. To improve the image quality, a brightness conversion filter is applied to the range of optical density from bone (white) to adipose tissue (black), as shown in Figure 7b.

3. Tumor Segmentation. For tumor segmentation, the threshold segmentation of the optical density of the seal is used.

4. Tumor Size Measurement. After segmentation, tumor size is measured using voxel data: tumor volume and linear tumor dimensions (Figure 7c). To calculate the linear dimensions of the tumor (length, width, height), we find the minimum and maximum coordinates of tumor voxels along each axis simultaneously for all three types of research (Figure 6).

## IV. CONFIGURATION AND PARAMETERS OF THE DECISION SUPPORT SYSTEM

### A. BUILDING OF THE NEURAL NETWORKS USING DEEP LEARNING

Using neural networks and machine learning for cancer diagnosis has become one of the most prevalent methods for detecting cancer [3, 9, 24, 32-35]. Our system is designed as a deep learning system that utilizes multiple algorithmic layers in the form of neural networks [36-40].

Our system is designed as a deep learning system that utilizes multiple algorithmic layers in the form of neural networks. The key feature of using neural networks is the application of a set of models for cancer feature detection and analysis, the results of which are combined for use in the system's second (DSS) layer.

The models are trained using supervised learning with datasets described in Section III. The images are preprocessed by resizing, normalizing, and applying data augmentation. The networks processes input images through CNN-based architectures based on multiple convolutional layers. The models are optimized using Gradient Descent.

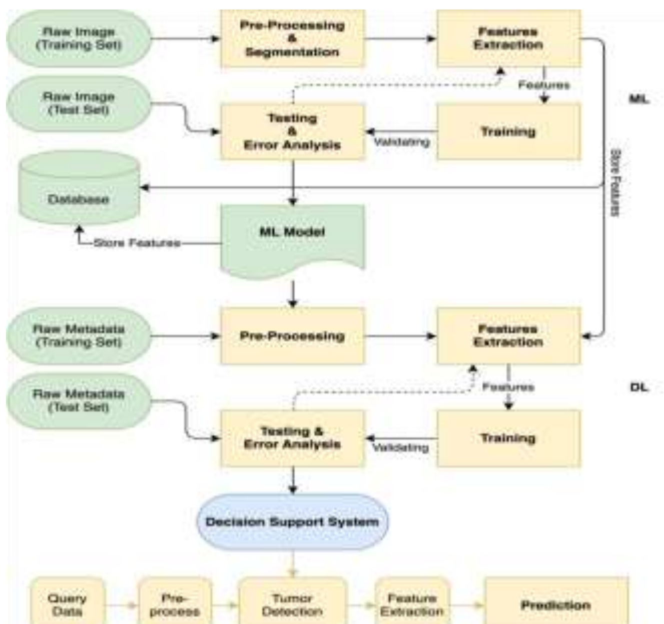


Figure 8. Image preprocessing deep learning algorithm for

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Figure 7. Image preprocessing and suspicious tumor decision support system

Detection: a – automatic breast image selection, b – size and Prominent deep-learning models utilized in computer brightness normalization, c – tumor accentuation vision have notably enhanced the performance of CAD Systems, particularly Convolutional Neural Networks (CNNs), transfer learning techniques, and deep learning-based object detection models [2].

The initial layer is a convolutional neural network (VGGNet) that identifies suspicious lumps inpatient study images. Typically, breast cancer on a mammogram appears as an intense shadow – a bright white "star," as seen in Figure 6. It stands out against the general background, which is the case in most instances. The primary goal of this first layer is to construct a deep architecture with numerous convolutional layers to extract features from the images efficiently. This ensures high recognition accuracy by specializing the network for a specific type of image, thereby reducing the number of false positives. The deep learning model for the decision support system (DSS) is trained using the database described in Sections 3.1 – 3.2, as shown in Figure 8. The second layer is designed to support the decision support system (DSS). It performs clinical classification of the lumps identified in the first layer and generates recommendations for further research and treatment protocols. In the deep learning process, the second layer utilizes the compaction data from the first layer and metadata from the database. The existing DSS faces significant challenges in recognizing suspicious lumps based on mammography data. Our neural network architecture for DSS addresses this by incorporating multiple images (2 or 3) in the first layer, including CT, MRI, and mammography results, to enhance the accuracy of lump detection. These images are scaled to a uniform size corresponding to their physical location in the patient's body, and a statistical agreement criterion is applied to the seal contour points with a specified confidence level. In [4], the limitations and risks of applying CADx technologies to breast cancer were investigated on a large dataset, demonstrating the advantages of an AI-generated model over a human radiologist in both performance and overall accuracy of analyzing screening mammography cases. However, there were limits to the effectiveness of computer-generated tumor recognition and an increase in false positives. Our deep learning application can overcome these limitations by analyzing three types of studies and other patient data. It can perform in-depth analysis of large datasets and discover new insights it may not have been specifically trained to find.

**B. IMPLEMENTATION OF DSS**

To implement the system architecture, the following technology stack is utilized:

- Microsoft cloud services, providing 5 TB of storage
- Server capacities from Dnipro University of Technology
- Auxiliary software such as ORACLE DBMS and Viewer

Currently, the system is in the process of creating an updated database, which includes the latest survey results of women in Ukraine, considering the ongoing war and changes in environmental parameters. Primary data from 350 patients, including mammograms and multiple slices of CT and MRI images, have been uploaded. The preprocessing of images involved normalizing the brightness of monochrome images for a density range from adipose tissues (DA = $0.9\text{x}10^3$ kg/m$^3$, corresponding to black) to bone tissues (DB = $1.713\text{x}10^3$ kg/m$^3$, corresponding to white). This allows tumors to be immediately visually distinguished, as can be seen in Figure 7a.

**RESULTS AND DISCUSSION**

The viewer was adjusted to highlight the density range of DC = $0.1\text{x}10^4$-$0.11\text{x}10^4$ kg/m$^3$, corresponding to tissues that may indicate compaction. All patient studies were uploaded to a storage system based on an Orthanc server.

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This server was deployed in the research environment as a standalone server. Orthanc server provides a REST API for the OncoAssist viewer and offers a UI for uploading and basic management of studies. The OncoAssist Viewer is currently under development. It uses the Orthanc REST API to display medical imaging with specific density range settings and show model prediction results. The results indicate that the OncoAssist architecture aligns well to create an effective, publicly available SaaS service for primary breast cancer diagnosis. Further research is needed to address issues related to system deployment across various cloud configurations, communication channel throughput, service efficiency, application speed, and scalability.

## CONCLUSIONS

The CADx OncoAssist SaaS system being developed aims to enhance the primary diagnosis of breast cancer (BC) compared to current market solutions. OncoAssist's utility combine's precise machine learning algorithms for BC detection and cloud computing capabilities. We have incorporated a highlevel user interface that enables the simultaneous analysis of various examination types for a single patient, with a system for highlighting suspicious formations based on decision support. The following features have been added:

- ability to comment on mammograms and other DICOM files during examination;
- access to a cloud database and cloud computing from any device with proper authorization;
- a query-based interface for identifying and selecting specific categories of information;
- Content-based image search, allowing radiologists to find similar patient image files.

The unique aspect of the CADx system lies in its availability as a Software as a Service (SaaS) model, accessible from nearly any computer hardware. It combines functionalities typically found in mammogram databases and CADx systems while integrating a deep knowledge database enriched with patient metadata. This system can aid in primary diagnosis and support research on the early detection of BC.

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