Интернет на нещата в образната диагностика и откриване на in silico знания

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Резюме: *Представената статия е фокусирана върху концепцията и значението на IoMIT. Тя включва уеб базирани и облачни платформи за образна диагностика като Nora, Siemens Helthineers и IBM Watson Health, като разкрива техните суперизчислителни ресурси и инструменти за образна диагностика. В доклада са предложени DT CWT базирани алгоритми като решение за класификация на изображения на щитовидната жлеза и рак на гърдата. Представен е сравнителен анализ между CNN и технологията, базирана на извличане на признаци от изображения чрез уейвлети. На базата на получените резултати са добавени заключения и препоръки за използването на двете технологии.*

Ключови думи: *образна диагностика, платформи за образна диагностика, обработка на изображения, класификация на изображения, извличане на признаци от изображения*

The Internet of Medical Imaging Things and In Silico Knowledge Discovery

Stella Vetova

Abstract*: The presented paper is focused on the concept and importance of IoMIT. It includes web-based and cloud-based medical imaging platforms such as Nora, Siemens Helthineers and IBM Watson Health revealing their supercomputing resources and tools for medical imaging. In the paper DT CWT based algorithms are proposed as a solution for thyroid and breast cancer image classification. A comparative analysis between CNN and wavelet features-based technology is presented. On the base of the gained results, conclusions and recommendations for the usage of both technologies are added.*

Key words: *medical imaging, medical imaging platforms, image processing, image classification, image features extraction*

1. CONCEPT AND IMPORTANCE OF RESEARCH AREA

The concept of Internet of Medical Imaging Things (IoMIT) for remote monitoring and control using the Internet infrastructure and remote servers dates back two decades when IoMIT 1.0 emerges. Proving its effectiveness, the preventative model of medical care has established itself as a successful strategy for public health. Both, IoMIT and the preventative model in combination were assessed as a promising direction for advanced medicine.

In 2015 Siemens Healthcare, GE Healthcare, Philips Healthcare launched a new generation of IoMIT. On the one hand, GE Healthcare initiated the network connectivity of 2 000 000 devices on the Health Cloud including patient monitoring, medical imaging equipment, etc. In its essence, the Health Cloud acts as an open ecosystem and for its development for new analytics solutions the IT integrators Capgemini and Tata Consultancy Services joined. Such applications as MR application and ViosWorks are shifted from local processors to the cloud. In addition, GE extends its work covering applications for the operational use cases and delivering enterprise workflow orchestration. The application “Radiology insights” for tracking X-ray repeat or reject rates is the typical IoMIT product for radiography.

On the other hand, Siemens develops the concept of teamplay and provides three use cases used and validated by large customers. The first use case is dose optimization in CT imaging. The second one is asset optimization addressed to CT and MR users and providing options for asset management and financial analysis. The third use case concerns protocol sharing allowing CT and MR users to share protocols and best practices.

In addition, the release of Philips Healthcare’s HealthSuite Digital Platform shows the direction of IoMIT future development. Furthermore, Lumify device is the ultramobile ultrasound tool which makes image data accessible on the cloud HealthSuite. The partnership of Philips with high technological companies as Salesforce, Amazon, Hitachi Data Systems contribute to the development of the cloud.

Nowadays, the considerable growth of high-technology including mobile technologies, virtual reality, communication network infrastructure, cloud computing, big data processing, artificial intelligence is a prerequisite for the rapid development of IoMIT. Contributing to the efficient healthcare, it is a convenient means of providing personalized medical care and diagnostics for people who live in remote districts. The combination of medical imaging and telemedicine is used for early detection and diagnosis.

Taking into account the World Cancer Research Fund International statistics, with its 2 million diagnosed cases in 2018 and representing 6.4% of the total number of diseases, breast cancer is considered to be the fifth cancer disease causing death among women. To reduce the number of cancer cases, progressive improvement in medical treatment strategies is needed. This provides the stage of early detection and diagnose to prevent women from breast cancer. Thus, the combination of mobile communication and devices, the means of artificial intelligence as well as the technology of big data processing, image processing and the software developed for medical purposes appears to be the utility for physicians in their effort for public health care.

2. MEDICAL IMAGING DEVICES AND IMAGE FORMATS

For the precise diagnosis physicians use a variety of methods and apparatuses for medical imaging. One of the most often used in medical practice are X-Ray, Ultrasound, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). X-ray is appropriate for the cases when areas of concern are available but no symptoms appear. Based on sound waves to produce visual representation of the tissue, the ultrasound [1] reveals the tissue composition and blood flow providing information for the level of suspicion. On the contrary, for the cases of high-risk and advanced stage of disease MRI [2], [3] is the appropriate apparatus. Based on the three dimensional image representation, MRI provides imaging of high quality allowing adequate assessment, treatment, response evaluation and pre-surgery planning. In addition, CT [4], [5], [6], [7], [8], [9] generates medical images for the cases of early detection when no symptoms are available. Unlike the other apparatuses discussed above, this technique can detect very small areas of disease which makes it a powerful tool for the medical experts.

The produced image data using medical imaging apparatuses differs in format, resolution, color space as shown in Fig. 1. Published in 1993, the Digital Imaging and Communication in Medicine (DICOM) format is recognized as a standard for medical imaging transmission, storing retrieval, printing, processing and displaying medical imaging information. DICOM is implemented in a number of medical areas such as radiology, cardiology, radiotherapy, ophthalmology and dentistry. Being compatible with TCP/IP, DICOM is an application protocol used for communication between systems. It can be exchanged between a sender and receiver for the purposes of image and patient data transmission including metadata: patient name, reference number, study number, dates, reports [10]. Furthermore, DICOM standard enables work with variety of software products and apparatuses produced by different manufacturers. In addition, DICOM guarantees data security using the DICOM TLS protocol for encryption [11].

3. MEDICAL IMAGING PLATFORMS

The benefits of web-based medical imaging platforms spread in a wide range. Web-based medical imaging technology enables disease image analysis on the base of web-browser and Internet infrastructure usage.

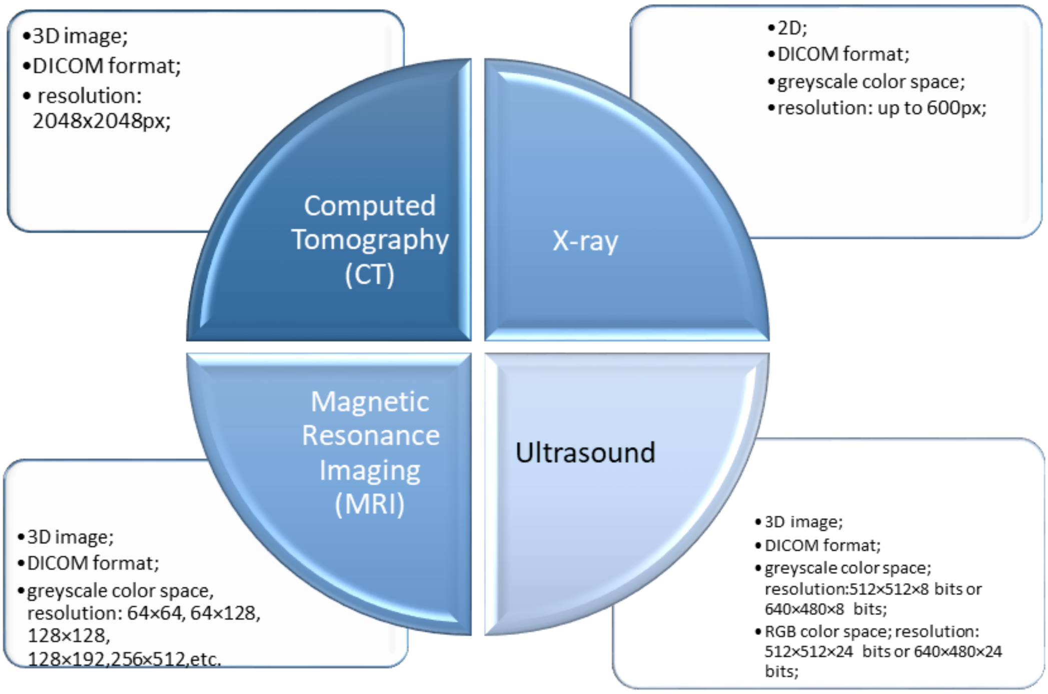


Fig.1. Medical imaging apparatuses and image characteristics

This determines its simplicity. Furthermore, it is time-saving providing the user access to supercomputing resources, experts' knowledge and experience as well as the provided option for distributed resources access. A typical platform representative is Nora (http://www.nora-imaging.com/). The major idea for its development is to bring research and clinic together in cooperation in the effort to guarantee patients' high quality of life. Nora is a multi-user platform which allows visualization, automation, data organization, processing and sharing in an intuitive manner. On the other hand, Nora is designed in two versions: as a stand-alone system or as a web-service in the cloud. In regard to visualization, the functionality of Nora covers features as real-time image resclinic (MPR), overlays, ROIs, 3D surface rendering and connectome. In addition to the typical image formats it supports including DICOM, NIFTI, BRUKER, the framework allows work with JSON, JPEG, PNG, PDF file formats too. Based on the drag-and-drop technology, the viewer is a stand-alone tool which works in an offline mode providing the option for automatically datasets loading. On the other hand, Nora is designed as a processing framework. In addition to image management, visualization, processing and analysis, it acts as an integrator too. Nora can include data from different inhomogeneous sources including PACS system. For the purposes of image processing, the framework is enriched with many tools. It allows work with toolboxes SPM, FSL or FreeSurfer and others without the need of programming in command line. In addition, the pipeline design and parallel processing are also supported as well as instant computer aided diagnosis (CAD). Fig. 2 illustrates Nora viewer for the case study of breast cancer.

The other branch of medical imaging platforms is the cloud-based one. The technology of cloud computing is based on the network access to a shared pool of configurable computing resources which can be rapidly provisioned and released with minimal management effort or service provider interaction [12], [13].

In the presented paper Siemens Helthineers and IBM Watson Health breast cancer platforms are on focus.

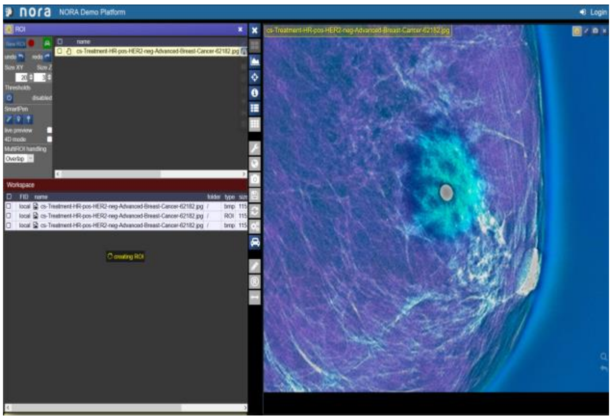


Fig.2. Nora graphical interface and options

For successful functioning, Siemens Helthineers (https://www.siemens-healthineers.com/) requires minimal resources as follows: 3,0 GHz Dual Core Intel CPU; 8GB RAM; NVIDIA or Intel GPU; Windows 7 or Windows 10. To simplify the diagnosis process and provide advanced visualization, and routine reading, the tool syngo.via is developed. Based on latest innovations and artificial intelligence, it guarantees productivity and efficiency. In addition, the three dimensional imaging product syngo.via produces photorealistic clinical images in DICOM format and provides workflow imaging solutions. In addition, Siemens Healthineers supports tools and options for decision making, full interactive remote support, back-up and restore to initial settings, integrated feedback tool.

Similarly, IBM Watson Health (https://www.ibm.com/) [14] provides solutions for smart health combining data, technology and expertise in a symbiosis. It integrates massively parallel POWER7 processors guaranteeing resources to store, achieve, transfer and analyze medical images. To increase the efficiency of clinical process, IBM develop a platform which supports the entire clinical workflow as follows [https://www.ibm.com/watson-health/solutions/enterprise-imaging]:

1. To create a patient profile before the patient's visit, all the relevant information and images from previous studies, modalities and the EHR are compiled into a single interface.
2. The options for viewing the status of the pending studies in real-time by the radiologists and for quick location of important information supported by the AI solutions implementation are designed.
3. The process of diagnosing and treatment is facilitated through AI solutions implemented allowing providers to locate important information about drug dosing or disease management or for potential cancer treatment.
4. After the patient's visit, the reports are formatted into templates containing the his/her health information and study results.
5. The patient reports and images can be securely shared.

Fig. 3 graphically illustrates the clinical workflow stages supported by IBM Watson Health.

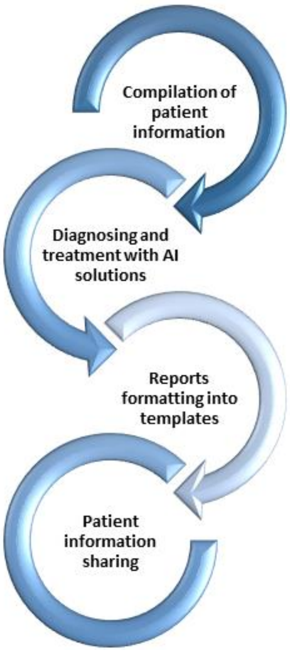


Fig.3. IBM Watson Health clinical workflow stages

Being a PaaS, IBM Watson Health supports imaging solutions for radiology, cardiology, orthopedics, eye care, financial management. In their effort to find solution for breast cancer problem, Watson designed an application using MRI Computer Aided Detection called Merge CADstream. Its functions are addressed to data visualization and segmentation, analysis, diagnosis and therapy opportunities. In addition, Merge CADstream supports tools for patients' exams with less rescanning; automatic analysis of MRI studies improving the interpretation and reporting; time reduction and ease of decision taking; ease of ROIs classification and abnormalities detection using MIP, angiography map, and MPR tools; archive and easy access to patient files of diagnosis, monitoring and analysis to obtain notion of disease running; confidence increasing in planning interventional activities; ability to differentiate low signal intensity malignities and fibrous tumors of high intensity; use of DICOM image formats.

Acting as a gateway to European biological and biomedical imaging, Euro-BioImaging project (https://www.eurobioimaging.eu/) [15] provides tools, resources, services and support needed in the research process. Based on the basic idea to overcome the fragmentation, the project comprises over 205 universities, research councils, ministers, industrial partners. Euro-BioImaging is built on 21 nodes located in 9 European countries. Each of the nodes has experts to support the researchers in their research projects including imaging pipeline, study design, image acquisition, storing and interpreting. Also, the node experts provide training courses covering different levels of expertise. Providing image technologies of highest quality, Euro-BioImaging provides a wide range of imaging from the nano- to the tissue-scale. In addition, the project provides high-impact technologies to assist researchers. The list of technologies includes Coherent Anti-Stokes Raman Scattering microscopy (CARS), Quantative Phase Imaging (QPI), Mass spectrometry-based imaging (MSI) for biological and medical applications, PhotoAcoustic Imaging (PAI), Structured Illumination Microscopy (SIM), Atomic Force Microscopy (AFM). In addition, Euro-BioImaging expands its functionality working in collaboration with the cluster projects CORBEL and EOSC-Life. On the base of Euro-BioImaging project expertizes and best practices, repositories of methods, tools, protocols, software applications and image data are shared for future use by other users of the project. To guarantee data security, the project provides data storage protection and analyses standards.

4. IN SILICO KNOWELEDGE DISCOVERY

For the case study of thyroid, an algorithm for image classification using image features extraction with the Dual-Tree Complex Wavelet Transform (DT CWT) is proposed. It consists of seven main steps and comprises scaling, color space conversion, image subdivision, DT CWT performance, features storing, query-image submission and classification. The whole process runs in a sequence as follows:

1. The source image (*I*), is resized to the size of *MxN* for *M=N=512* where *M* - number of rows, *N* – number of columns. The obtained result is the image I'.
2. The image I' is converted from RGB into grayscale color space;
3. The image (I') is divided into $n \times n$ $(n = 8)$ non-overlapping subimages $(I_1' \div I_{64}')$.
4. DT CWT is performed on each of the subimages $(I_1' \div I_{64}')$ generated in step 3 at level $l = 4$ to decompose them and produce their lowpass and bandpass components.
5. The extracted wavelet features form the image feature vectors which are stored in a classification database. Fig. 4 presents the entire process of image decomposition using DT CWT in a consistent manner from step 1 to step 4.
6. The user is given the option to submit a classification query-image (Q) which is decomposed using the first four steps of the algorithm and thus form a query-image feature vector.
7. To compute the similarity distance between the query-image feature vector and each of the image feature vectors in the classification database, Hausdorff Distance [16, 17, 18, 19, 20, 21, 22, 23, 24] executes according to the following equation:

$$H(A,B) = \max(h(A,B), h(B,A)), \quad (1)$$

where: $A = \{a_1,...,a_m\}$, $B = \{b_1,...,b_n\}$ are two finite point sets and:

$$h(A,B) = \max_{a \in A} \min_{b \in B} \|a - b\|, \quad (2)$$

The experiments are performed on the base of thyroid specialized image dataset TIRADS. It is designed in 6 image groups depending on the disease degree and 97 RGB images in total. The efficiency of the proposed algorithm for the case study of thyroid is estimated using accuracy (3):

Fig.4. DT CWT features extraction process

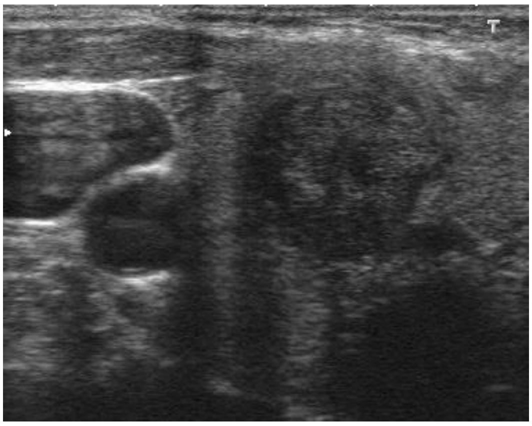
$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}, \qquad (3)$$

where,

- TP – True Positives – a class of images defining the cases when the actual output fits the prediction parameter and both have YES value;
- TN – True Negatives – a class of images defining the cases when the actual output fits the prediction and both have NO value;
- FP – False Positives – a class of images defining the cases when the predicted observations are evaluated as negatives (NO value) and the actual output is positive (YES value). Thus, there is no fit between both parameters.
- FN – False Negatives – a class of images defining the cases when the predicted observations evaluated as positives (YES value) and the actual output is negative (NO value) with no fit between both parameters.

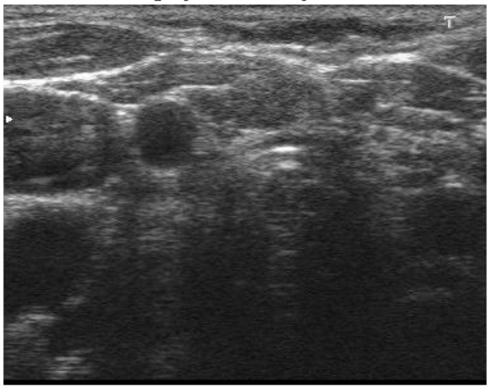
The category membership of the classified query-image is determined using Hausdorff distance on the base of the category membership of the nearest image.

The test experiments are performed for each of the thyroid image categories. On the one hand, the statistics on the experimental results shows accuracy of 77,15%. On the other hand, the algorithm has the ability to detect both alternating smooth transitions between areas with lower pixel intensity towards higher pixel intensity and sharp transitions between areas of small size. Moreover, the detected images have the orientation and localization of the object in the query-image. The graphic results also show that the algorithm can detect images by sharp transitions and homogeneous areas where the pixel intensity is close to zero which makes the proposed algorithm appropriate for recognition by shape. Fig. 5 shows the classification result (b) of image from TIRADS 4b group (a).



(a)

Category 4b, Accuracy=76,9%



(b)

Fig. 5. Image classification result for TIRADS Category 4b
(a) TIRADS 4b category query-image;
(b) the nearest image from TIRADS Category 4b

For the design of tools addressed to early breast cancer detection, diagnosis, localization, treatment and monitoring typically two techniques are used: image classification using extracted image features composing feature vectors and using similarity evaluation and the one based on deep learning using convolutional neural network (CNN). On the base of them both a great number of techniques are developed using Discrete Wavelet Transform [25], Gabor Wavelet Transform [26], [27], [28], Dual-Tree Complex Wavelet Transform [29], Contourlet Transform [30], [31], Curvelet Transform [32], 3D Fourier Transform [33], color histogram [34], [35], [36], color moments [37] and correlogram [38], Harris Corner Detector [39], Barnard Detector [40], Contour-based shape features [41], [42], [43], Hough Transform [44], modificated Hough Transform and edge detection as a base for extraction of peaks of Hough image and used for shape matching [45], etc. In addition, on the base of CNN and DL, the classifiers are trained for a new classification task [46], [47]. Used for human face detection [48], biological data identification [49], object recognition [50], disease assessment based on medical images, CNN and ML are preferred for the development of solutions on the breast cancer [51], [52], [53], [54], [55]. Furthermore, the researchers' efforts reach to the area of cybersecurity in medical science where strategies and methods for data protection against phishing attacks [56], spam, malicious links [57] and network and software-based attacks [58] are proposed.

A comparative analysis between CNN and wavelet features-based technology is proposed for the case study of breast cancer classification. To this end, a modified version of the algorithm described above is used. Its modifications comprise the Dual-Tree Complex Wavelet Transform (DT CWT) performance on the entire image and the usage of Euclidean distance for similarity estimation. For the test experiments, a test dataset on Invasive Ductal Carcinoma (IDC) of 502 images in RGB color space and PNG format with size of 50 x 50 px is used. The dataset consists of two categories 0 and 1 where the images are categorized according to the disease degree. Thus, category 0 includes the IDC negative cases and the category 1 includes the IDC positive ones. To estimate the efficiency of both approaches, accuracy, precision and recall metrics are calculated. The gained results show close values for the three metrics speaking of comparability. However, for precision the wavelet features-based technology demonstrates a better result than CNN, exceeding by 1.8% which makes it appropriate for the cases when the cost of a false positive is very high while the one of the false negative is low. On the other hand, CNN shows better results for recall than the wavelet-based technology meaning that CNN is appropriate for the cases when a false negative is high. Fig. 6 and Fig. 7 illustrates the image classification result for two of the performed experiments.

(a)

(b)

Fig.6. Image classification result for experiment 3, (a) Submitted classification image, (b) Classified image

(a)

(b)

Fig.7. Image classification result for experiment 5, (a) Submitted classification image, (b) Classified image

6. CONCLUSION

The presented paper discusses the concept and the importance of IoMIT in the modern world and the tools it uses to meet the requirements for efficiency in the medicine. The overview of the web-based and cloud-based medical imaging platforms shows the range of supercomputing resources and options they provide. In addition, the progress of Euro-BioImaging project is discussed. Moreover, the paper includes proposed solutions for the case study of thyroid and breast cancer using DT CWT as well as comparative analysis between the CNN approach for image classification and the wavelet features-based one on the same problem. The gained results show comparability and are reason to conclude that the wavelet features-based approach is appropriate for the cases when the cost of a false positive is very high while the one of the false negative is low and that the CNN is appropriate for the cases when a false negative is high.

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