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Current Challenges in Medical Imaging Informatics Based on Artificial Intelligence

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ABSTRACT*:* This paper reviews state-of-the-art research solutions across the spectrum of medical imaging informatics, discusses clinical translation, and provides future directions for advancing clinical practice. More specifically, it summarizes advances in medical imaging acquisition technologies for different modalities, highlighting the necessity for efficient medical data management strategy the context of AI in big healthcare data analytics. It then provides a synopsis of contemporary and emerging algorithmic methods for disease classification and organ/ tissue segmentation, focusing on AI and deep learning architectures that have already become the de facto approach. The clinical benefits of in-silico modelling advances linked with evolving 3D reconstruction and visualization applications are further documented. Concluding, integrative analytics approaches driven by associate research branches highlighted in this study promise to revolutionize imaging informatics as known today across the healthcare continuum for both radiology and digital pathology applications. It is also projected to enable informed, more accurate diagnosis, timely prognosis, and effective treatment planning, underpinning precision medicine.

KEYWORDS: Medical Imaging, Image Analysis, Image Classification, Image Processing, Image Segmentation, Image Visualization, Integrative Analytics, Machine Learning, Deep Learning, Big Data.

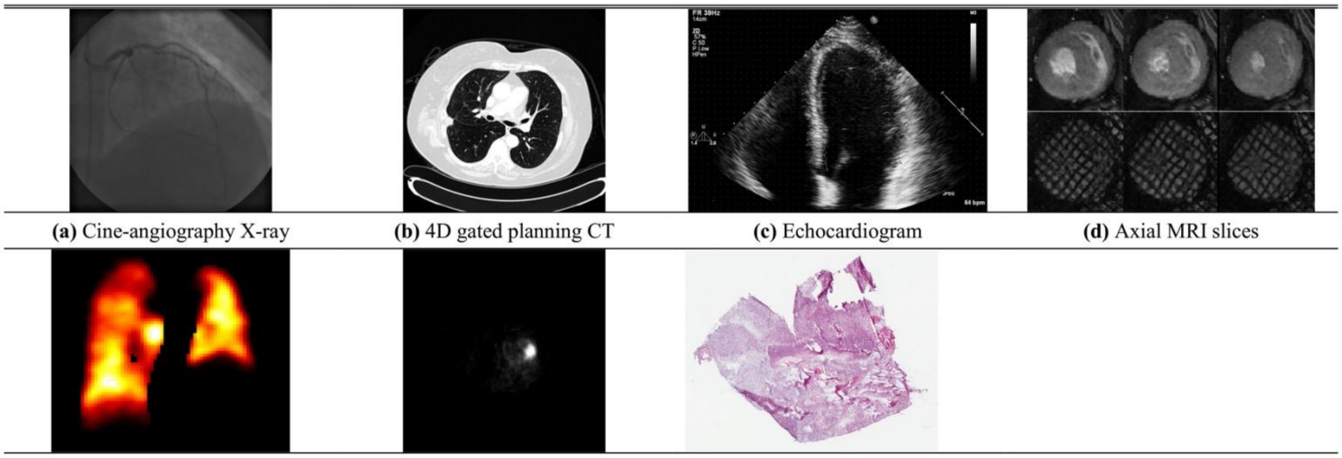
I.INTRODUCTION

The objective of medical imaging informatics is thus, according to SIIM, to improve efficiency, accuracy, and reliability of services within the medical enterprise [3], concerning medical image usage and exchange throughout complex healthcare systems [4]. In that context, linked with the associate technological advances in big-data imaging and electronic application.Biomedical imaging has revolutionized the practice of imaging the human body and high-resolution viewing of cells and pathological specimens. Broadly speaking, images are formed through interaction of electromagnetic waves at various wavelengths (energies) with biological tissues for modalities other than Ultrasound, which involves use of mechanical sound waves. Images formed with high-energy radiation at shorter wavelength such as X-ray and Gamma-rays at one end of the -optical and still longer wavelength - MRI and Ultrasound are nonionizing. The imaging modalities covered in this section are X-ray, ultrasound, magnetic resonance (MR), X-ray computed tomography (CT), nuclear medicine, and high-resolution microscopy [8], [9] (see Table I). Fig. 1 shows some examples of images produced by these modalities.

i)Image Selection

X-ray imaging's low cost and quick acquisition time has led to it being one of the most commonly used imaging techniques. The image is produced by passing X-rays generated by an X-ray source through the body and detecting the attenuated X-rays on the other side via a detector array; the resulting image is a 2D projection with resolutions down to 100 microns and where the intensities are indicative of the degree of X-ray attenuation [9]. To improve visibility, iodinated contrast agents that attenuate X-rays are often injected into a region of interest (e.g., imaging arterial disease through fluoroscopy). Phase-contrast X-ray imaging can also improve soft-tissue image contrast by using the phase-shifts of the X-rays as they traverse through the tissue [10]. X-ray projection imaging has been pervasive in imaging applications among others [11].

Ultrasound imaging (US) employs pulses in the range of 1–10 MHz to image tissue in a noninvasive and relatively inexpensive way. The backscattering effect of the acoustic pulse interacting with internal structures is used to measure the echo to produce the image. Ultrasound imaging is fast, enabling, for example, real-time imaging of blood flow in arteries through the Doppler is used, hence less harmful to the patient. However, bone and air hinder the propagation of sound waves and can cause artifacts. Still, ultrasound remains one of the most used imaging techniques employed extensively for



(a) Cine-angiography X-ray **(b)** 4D gated planning CT **(c)** Echocardiogram **(d)** Axial MRI slices

(e) Q SPECT lung perfusion **(f)** 2D slice from a 3D FDG-PET **(g)** Magnified, digitized tissue

real-time cardiac and fetal imaging [11].

Harnessing the full potential of available big data for healthcare innovation necessitates a change management strategy across both research institutions and clinical sites. In its present form, heterogeneous healthcare data ranging from imaging, to genomic, to clinical data, that are further augmented by environmental data, physiological signals and other, cannot be used for . The latter is attributed to a number of factors, a non-exhaustive list extending to the data being scattered across and within the research community, and not being well-curated nor semantically annotated. Additionally, these data are typically semi- or un- structured, adding a significant computational burden for constituting them data mining ready.
This direction, many clinical and research sites have developed such data management and exploration tools to track patient outcomes More recently, there has been a much greater emphasis placed(ETL) interfaces. ETLs can accommodate the full spectrum of clinical information, imaging studies and genomic information. Hence, it is possible to interrogate multi-modal data in a systematic manner, guide personalized treatment, refine best practices and provide objective, reproducible insight as to the underlying mechanisms of disease onset and progression

ii)Process of pathology

Medical image analysis typically involves the delineation of the objects of interest (segmentation) or description of labels (classification) examples includes segmentation heart for cardiology and identification of cancer for pathology. To date, medical image analysis has been hampered by a lack of theoretical understanding on how to optimally choose and process visual features. Reamscapes skin lesions brain MRI heart MRI quantitative perfusion , classification of heart disease from statistical shape models [78], retinal blood vessels segmentation , general anatomy (i.e., the VISCERAL project evaluated the subjectivity of 20 segmentation algorithms. segmentation of several organs together (the open and ongoing biomedical challenges appears in . These challenges have provided a footing for advances in medical image analysis and helped push the field forward; however, a recent analysis of challenge design has showed that biases exist

a)Features analytics

There has been a wealth of literature on medical image analysis using signal analysis, statistical modelling, etc.. Some of the most successful include multi-atlas segmentation , graph cuts and active shape models . Multi-atlas segmentation utilizes a set of labelled cases (atlases) which are .Theimageto be segmented is registered to each atlas (i.e., using voxel-based morphometry and the propagated labels from each atlas are fused into a consensus label for that image. This procedure averaged to form a maximum likelihood consensus. A similarity metric can then be used to weight the candidate segmentations. A powerful alternative method attempts to model the object as a deformable structure, and optimize the position of the boundaries according to a similarity metric. Active shape models contain information on the statistical variation of the object in the population and the characteristic of their images These methods are typically iterative and may thus get stuck in a local minimum. On the other hand, graph cut algorithms facilitate a global optimal solution . Despite the initial graph construction being computationally expensive.

b) **Machine Learning**

Machine learning (prior to deep learning which we analyze below) involves the definition of a learning problem to solve a task based on inputs . To reduce data dimensionality and induce necessary invariances and covariance's (e.g. robustness to intensity changes or scale) early machine learning approaches reliedonhand-crafted features store present data. Inimagingdata several transforms have been used to capture local correlation and disentangle frequency components spanning from Fourier, Cosine or Wavelet transform to the more recent Gabor filters .

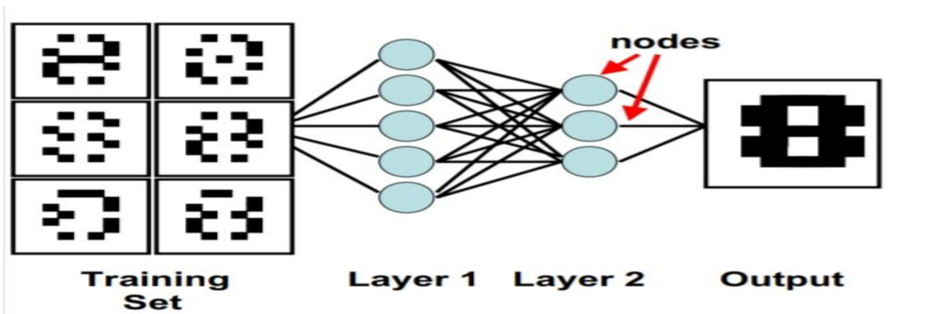


Figure2: An example of how a machine learner is trained to recognize images using a training set (a corrupted image of the number 8 which is labeled or identified as the number 8

II. CNN INTERPRETABILITY

one of the earliest applications of convolutional neural networks(CNN currently most used form of deep learning) has appeared as early as 1995, where a CNN was used for lung nodule detection in chest x-rays . Since then, fueled by the pathology has witnessed a revolution (see also Table II), where for some tasks now we observe human level performance . In this section, we aim to analyze key works and trends in the area, while we point readers to relevant, thorough reviews in the major draw of deep learning and convolutional architectures is the ability to learn suitable features and decision functions in tandem. While Alex Net quickly set the standard for classification (that was profusely adapted also for classification of medical tasks, see next subsection) it was the realization that dense predictions can be obtained from classification networks by that enabled powerful segmentation algorithms. The limitations of such approaches for medical image segmentation were quickly realized and led to the discovery of U-Net , which is even today one of medical image segmentation.

Alternative approaches directly exploit the 3D data by using architectures that perform 3D convolutions and then train the network from scratch on 3D medical images . Other notable techniques include slicing 3D data into different 2D views before fusing to obtain a final classification score . Learning lung nodule features using a 2D auto encoder .

III.VISUALIZATION AND NAVIGATION

A. Biomedical 3D Reconstruction and Visualization

Three-dimensional (3D) reconstruction concerns the detailed 3D surface generation and visualization of specific anatomical structures, such as arteries, vessels, organs, body parts and abnormal morphologies e.g. tumors, lesions, injuries, scars and cysts. It entails meshing and rendering techniques are used for completing the seamless boundary surface, generating the precise position and orientation of the patient's anatomy, 3D visualization can contribute to the

Design of aggressive surgery and radiotherapy strategies, with realistic testing and verification, with extensive applications in spinal surgery, joint replacement, neuro-interventions, as well as coronary and aortic stenting . Furthermore, 3D reconstruction constitutes the functionality, diffusion processes, hemodynamic flow and fluid dynamics in arteries, as well as mechanical loads and properties of body parts, tumors, lesions and vessels, such as wall / shear stress and strain and tissue guy displacement .In medical imaging applications with human tissues, registration of slices must be performed in an elastic form . To that respect, feature-based registration appears more suitable in the case of vessels' contours and centerline , while the intensity-based registration can be effectively used for image slices depicting .

B. Data Management, Visualization and Processing in Digital Pathology

Digital pathology is an inherently interactive human-guided activity. This includes labeling data for algorithm development, visualization of images and features for tuning algorithms, as well as explaining findings, and finally gearing systems towards clinical applications. It requires interactive systems that can query the underlying data and feature management systems, as well as support interactive visualizations. Such interactivity is a prerequisite to wide-scale adoption of digital pathology in imaging informatics applications. There are a v of open source systems that support visualization, management, and query of features, extracted from whole slide images along with the generation of whole slide image annotations and markups. One such system is the Quip software system. These metrics include computational biomarkers with regions of interest from large datasets of images. Together, these technologies will enable investigators to conduct analysis of tissue microarrays composed of large patient cohorts, store and mine large data sets and generate and test hypotheses .

C. In Silico Modeling of Malignant Tumors

Applications of in-silico models evolve drastically in early diagnosis and prognosis, with personalized therapy planning, noninvasive and invasive interactive treatment, as well as planning of pre-operative stages, chemotherapy and radiotherapy (see Fig. 2). The potential of inferring reliable predictions on the macroscopic usetumor growth is of paramount importance to the clinical practice, since the tumor progression dynamics can be estimated under the effect of several factors and the application of alternative therapeutic schemes. Several mathematical and computational models have been developed to investigate the mechanisms that govern cancer progression and invasion,

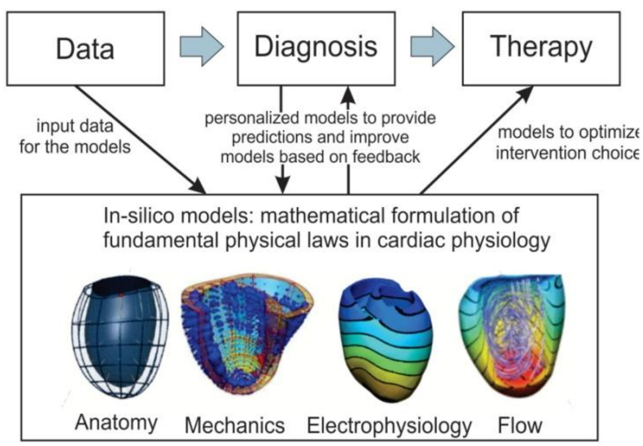
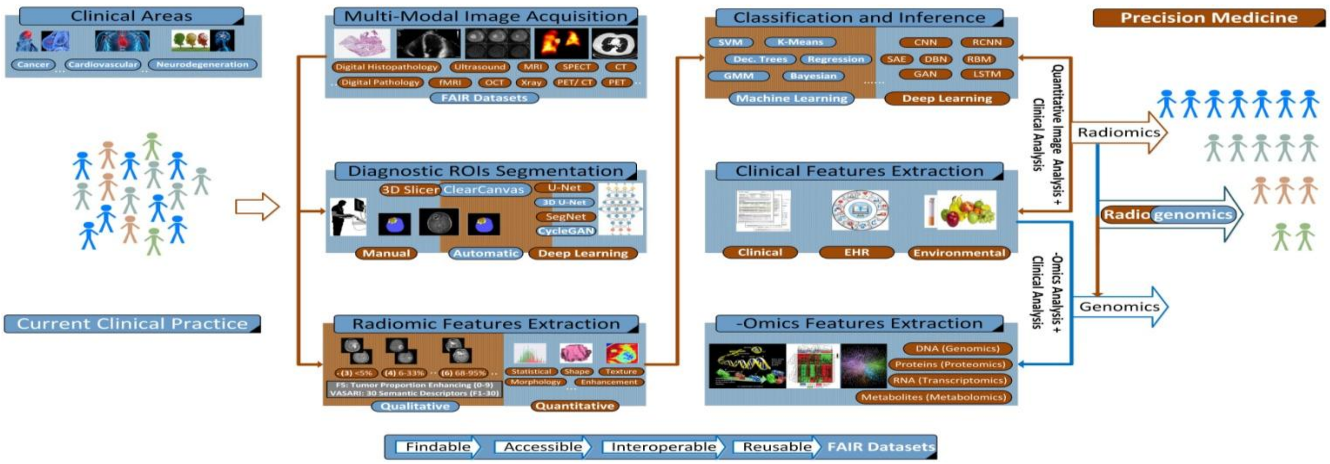


Fig. 3. In silico modelling paradigm of cardiovascular disease with application to heart.

D.Digital twins:

In this form, the digital equivalent of a complex human functional system enables the consideration of event dynamics, such as tumour growth or information transfer in epilepsy network, as well as a systemic response to therapy, such as response to pharmacogenomics or targeted radiotherapy



IV.CONCLUSION

Advances in associate research branches highlighted in this study promise to revolutionize imaging informatics as known today across the healthcare continuum enabling informed, more accurate diagnosis, TIMELY prognosis, and effective treatment planning. Among AI-based research-driven approaches that have obtained approval from the Food and Drug Administration (FDA), a significant percentage involves medical imaging informatics.FDAistheUSofficialregulatorofmedicaldevicesandmorerecentlysoftware-as-a-medical-device(SAMD). These solutions rely on machine- or deep-learning methodologies that perform various image analysis tasks, such as image enhancement (e.g. Subtle PET/MR, IDs-DR), segmentation and detection of abnormalities (e.g. Lung/LiverAI, OsteoDetect, Profound AI), as well as estimation of likelihood of malignancy (e.g. Transpires). Radiology images are mostly addressed in these FDA-approved applications, and, to a lower degree, digital pathology images (e.g. Paige AI). Table III summarizes existing FDA-approved AI-based solutions. We expect significant growth in systems obtaining FDA-approval these numbers in the near future.

V.FUTURE SCOPE

Imaging researchers are also faced with challenges in data management, indexing, query and analysis of digital pathology data. One of the main challenges is how to manage relatively large-scale, multi-dimensional data sets that will continue to expand over time since it is unreasonable to exhaustively compare the query data with each sample in a high-dimensional database due to practical storage and computational bottlenecks. The second challenge is how to reliably interrogate the characteristics of data originating from multiple modalities.

In that sequence, data analytics approaches have allowed the automatic identification anatomical the description of physiological phenomena, towards in-depth understanding of regional tissue physiology and pathophysiology. Deep learning methods are currently dominating new research endeavors. Undoubtedly, research in deep learning applications and methods is expected to grow, especially in in view of documented advances across the spectrum of healthcare data, including EHR , genomic physiological parameters , and natural language data processing . Beyond the initial hype, deep learning models managed in a short time to optimize critical issues pertaining to methods generalization, overfitting, complexity, reproducibility and domain dependence.

At the same time, we should highlight a key difference in the medical domain. Deep learning-based computer vision tasks have been developed on "enormous" data of natural images that go beyond Image Net (see for example the efforts of Google, and Facebook). This paradigm is rather worrying as in the medical domain matching that size is not readily possible. While in medicine we can still benefit from advances in transfer learning methods and computational efficiency in the future we have to consider how can we devise methods that rely on fewer data to train that can still generalize w.ell. From an infrastructure perspective, computational capabilities .conclusion, medical imaging informatics advances are projected to elevate the quality of care levels witnessed today, once innovative solutions along the lines of selected research , and thus potentially transforming precision medicine.

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