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Integrating Imaging Bioinformatics in Ophthalmology

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Abstract

Imaging informatics collates the multitude of information into data; allowing research to occur, driving data quality, and ultimately improving patient care. Imaging informatics increases the efficiency of imaging workflows by enhancing productivity and making information accessible to multiple users simultaneously. Consistency of critical data is essential for marrying information together through the process, to save the radiologist time, for consistency, billing, and research.

Introduction

The advancement of computer science and the availability of big data has enabled the emergence of artificial intelligence, which has led to a technological revolution significantly affecting many aspects of our daily life [1-4]. The application of AI in the field of medicine is expanding rapidly [5], mainly due to the advancement of machine learning (ML) that can be utilized for the analysis of medical images and patient data, diagnosis of diseases, and prediction of treatment outcomes [6]. ML is a paradigm of AI that systematically allows computer algorithms to adapt according to a large amount of raw input data and make predictions or determinations using the learned patterns [1,7,8]. The method can be roughly divided into conventional machine learning (CML) and deep learning (DL) [8]. CML algorithms, such as the support vector machine (SVM), random forest (RF), decision tree (DT), and linear regression and logistic regression, generally do not involve large neural networks [8] and have been applied for the construction of predictive algorithms for the diagnosis or classification of diseases based on data from medical records or population-based studies [9]. DL has usually been applied for the analysis of multimedia datasets, including images, sound, and videos [7,8], and involves large neural networks composed of multiple neuron-like layers of algorithms, such as artificial neural networks (ANNs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) [7,8].

In ophthalmology, AI has initially been applied for the analysis of fundus photographs and optical coherence tomography (OCT) images; thus, previous studies have mostly focused on the integration of AI into the diagnostic approach of posterior segment diseases, such as diabetic retinopathy, glaucoma, macular degeneration, and retinopathy of prematurity [5,10–14]. However, as DL algorithms can be utilized for the analysis of imaging the data of anterior segment structures, such as anterior segment photographs (ASPs), anterior segment OCT (AS-OCT) images, specular microscopy, corneal topography, in vivo confocal microscopy (IVCM), infrared meibography, and tear interferometry [2], AI is also expected to assist in the diagnosis and monitoring of various anterior segment diseases. Recently, many studies have been conducted on the application of AI in various anterior segment diseases [2].

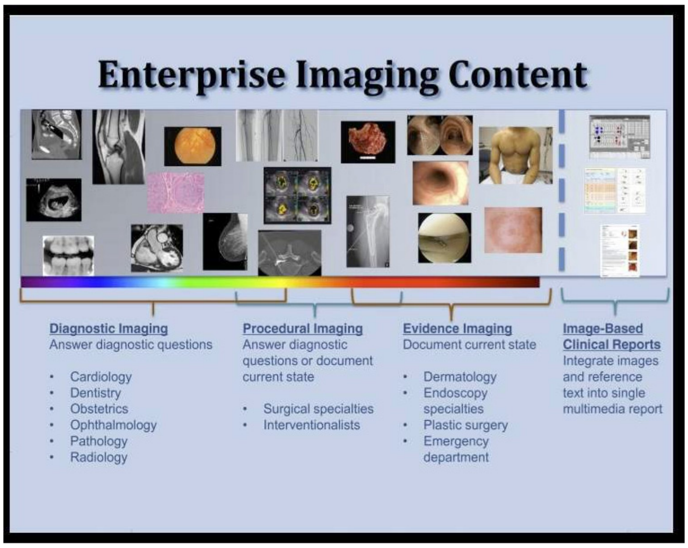
In modern medicine, each medical specialty obtains and consumes images during their delivery of care. These images allow providers of all specialties to better understand the diseases afflicting their patients. Unfortunately, current electronic health records focus only on textual/numeric data and largely avoid imaging data. The enterprise imaging community aims to build the imaging pillar of an electronic health record, raising awareness for the role of imaging and advocating for change.

Enterprise Imaging Community defines enterprise imaging as "a set of strategies, initiatives and workflows implemented across a healthcare enterprise to consistently and optimally capture, index, manage, store, distribute, view, exchange, and analyze all clinical imaging and multimedia content to enhance the electronic health record [15].

Medical images, whether still or in video format, can be acquired for one of three purposes: diagnosis, documentation/evidence, or procedural guidance. Diagnostic imaging is defined as "imaging obtained to elicit a differential diagnosis or confirm a clinical suspicion [15]." Examples of diagnostic imaging include abdomen/pelvis CT obtained in the assessment of right lower quadrant abdominal pain, echocardiogram obtained to assess cardiac function, and whole slide pathology obtained to provide a histologic tumor diagnosis.

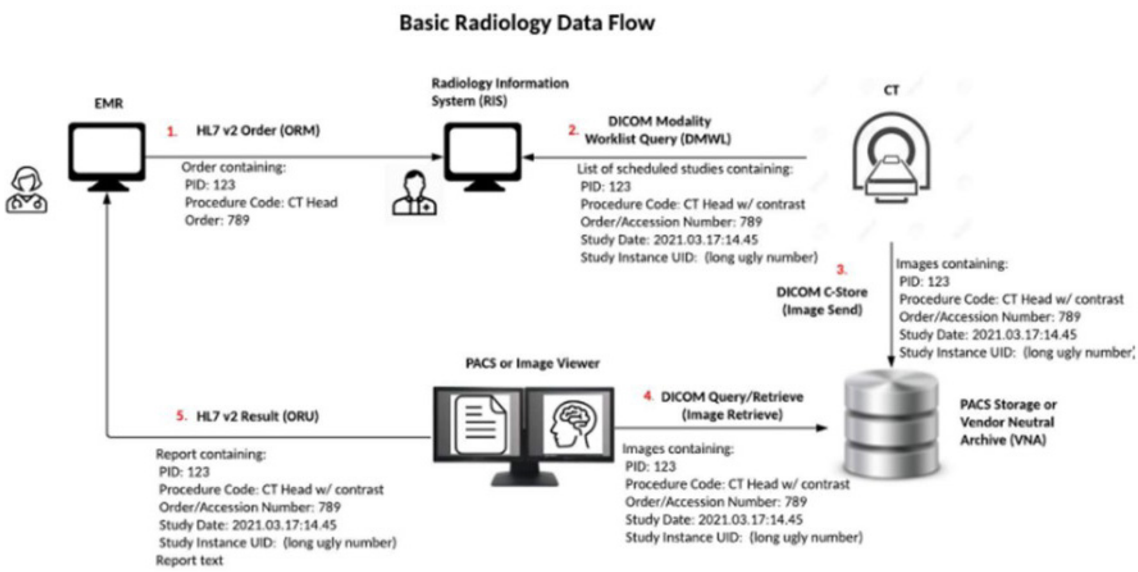
Images obtained for documentation/evidence purposes are defined as those "images captured primarily for documentation of a patient's current state [15]." Examples of documentation/evidence photos include photographs of the skin showing the current state of infection, a video showing a patient's gait after diagnosis of Parkinson's disease, and photographs in the emergency room showing the effect of trauma. Forensic images are a special type of document/evidence images obtained to be used as a part of legal proceedings.

Finally, procedural images are images "obtained before, during, and after surgical and percutaneous invasive procedures. These images are intended to establish relevant procedure anatomy, guide a surgical approach, document timestamps of salient procedure events using modality-generated metadata, or confirm post-procedure conditions such as stent deployment [15]." Examples of procedural images include ultrasound images obtained during a renal biopsy, fluoroscopic images obtained during orthopedic hardware placement, and photographs obtained during arthroscopic knee surgery.



The next component of enterprise imaging to explore are the "strategies, initiatives, and workflows." These terms represent the work needed to plan, design, implement, and support enterprise imaging. Governance is crucial for each of these steps as imaging informaticists must balance the needs of the organization with those from each specialty.

Finally, the verbs to "capture, index, manage, store, distribute, view, exchange, and analyze [15]" represent all of the actions that must be accounted for when developing, implementing, and supporting an enterprise imaging program.



Healthcare Information and Management Systems Society (HIMSS)

The Digital Imaging and Communications in Medicine (DICOM) Standard is the digital backbone of modern radiology. Universally supported by radiology and cardiology equipment (and, increasingly, radiotherapy, ophthalmology, dental, pathology, dermatology, veterinary, and other imaging specialties), the Standard is designed to cover routine clinical practices from scheduling exams, to acquiring, storing, processing, displaying, reporting, and distributing images and related data.

Metadata is what turns a bunch of pixels into a medical record. The DICOM metadata captures details about the patient, the order, the procedure performed, and the imaging technique so the image can be properly interpreted.

Abbreviations: RIS: Radiology Information System; **HIS:** Hospital Information System; **PACS:** Picture Archive And Communication System; **VNA:** Vendor Neutral Archive; **HL7:** Health Level 7; **FHIR:** Fast Healthcare Interoperability Resources; **IHE:** Integrating The Healthcare Enterprises; **DICOM:** Digital Imaging And Communications In Medicine; **CDA:** Clinical Document Architecture; **CCD:** Continuity Of Care Documents; **MPPS:** Modality Performed Procedure Step; **SC:** Storage Commitment; **PID:** Patient Identifier; **Uids:** Unique Identifiers; **Iods:** Information Object Definitions; **PHI:** Protected Health Information; **CDA:** Clinical Document Architecture; **CCD:** Continuity Of Care Document; **SCN:** Study Content Notification; **AI:** Artificial Intelligence; **ML:** Machine Learning; **CML:** Conventional Machine Learning; **DL:** Deep Learning; **SVM:** Support Vector Machine; **RF:** Random Forest; **DT:** Decision Tree; **ANN:** Artificial Neural Network; **RNN:** Recurrent Neural Network; **CNN:** Convolutional Neural Network; **OCT:** Optical Coherence Tomography; **ASP:** Anterior Segment Photographs; **AS-OCT:** Anterior Segment Optical Coherence Tomography; **IVCM:** In Vivo Confocal Microscopy; **LASEK:** Laser-Assisted Epithelial Keratomileusis; **LASIK:** Laser In Situ Keratomileusis; **SMILE:** Small Incision Lenticular Extraction; **DMEK:** Descemet Membrane Endothelial Keratoplasty; **AUC:** Area Under The Receiver Operating Characteristic Curve; **LASSO:** Least Absolute Shrinkage And Selection Operator; **LR:** Logistic Regression; **RANSAC:** Random Sample Consensus; **MRF:** Material Recovery Facilities; **MG:** Meibomian Gland; **MGD:** Meibomian Gland Dysfunction; **Map:** Mean Average Precision; **GAN:** Generative Adversarial Network; **CNF:** Corneal Nerve Fiber; **DC:** Dendritic Cell; **AUPRC:** Area Under Precision-Recall Curve.

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