

## Review of contemporary computing technology to enhance breast imaging

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### Introduction

Computers have revolutionized the field of diagnostic imaging and are absolutely essential in modern radiology practices [1]. First introduced into the radiology department in the 1960's, computers' role drastically expanded with the development of Radiology Information Systems (RIS). The earliest uses of computer technology related to imaging acquisition were nuclear medicine, digital subtraction angiography, computerized tomography (CT) in the 1970's, and magnetic resonance imaging (MRI) in the 1980's. The next major development was the picture archiving and communication systems (PACS). By the 2000's, many practices had converted to voice recognition software from transcriptionist. Also in the 2000's screening mammography computer aided detection (CAD) was reimbursed by insurance companies which precipitated its widespread adoption [2-4]. An area of current opportunity in the breast imaging world is the intersection several newly available technologies. Simultaneously, the American College of Radiology (ACR) has created a campaign to guide radiology called "Imaging 3.0." This program emphasizes the importance of adding value on behalf of all stakeholders including patients, hospital systems, and payers. Application of several new technologies may help achieve the goals of Imaging 3.0.

### The Cloud

Cloud based computing is the process of using remotely located computer servers to store, process, and transmit data. Traditionally hospitals and radiology departments each maintained their own individual servers. In the breast imaging department there are several opportunities to improve performance using cloud computing. Mammography has been shown to reduce cancer mortality by up to approximately 40% [5-9]. Cancers detected with the aid of available comparison mammograms have more favorable characteristics than when prior exams are not available [10]. Comparison with previous examinations is associated with a significant decrease in the frequency of axillary node metastasis and the cancer stage for screening mammography<sup>11</sup>. These benefits are attributable to the ability to accurately detect subtle incremental mammographic changes which may otherwise be overlooked. Therefore, tremendous effort is expended to obtain prior images. Patients often have their exams located at multiple facilities in various geographic locations. Hospitals and outpatient imaging centers spend significant time and money tracking and compiling prior patient records, creating and mailing compact discs (CD), and importing images from discs into PACS results in substantial cost to the facility [12-14]. Additionally, approximately 30% unnecessary additional work per case is created when reports addendums are issues as prior outside exams become available and must be re-read [15].

A universally available cloud database is an attractive solution to solving the problem of access to old images. However, there are numerous other benefits. Reduced patient radiation doses will be realized since repeat images may be avoided. Additional radiation exposure is estimated at 1 mSv per diagnostic mammogram [16]. When practicing the "As low as reasonably achievable" (ALARA) principle, available prior exams should be sought before repeating additional images. Also, a universal database is more economical than every hospital maintaining their own hardware with associated IT staff. This would be especially useful for practices that cover multiple locations and for patients that switch facilities. The cloud enhances interoperability for patients choosing to access to web-based portals for results and also allows increased access to their own imaging record. Cloud-based archiving also provides an efficient solution for the PACS requirement of a second-copy digital archiving.

### Artificial intelligence

A neural network is a computer programing paradigm which enables a computer to learn from observational data. Deep learning refers to a powerful subset of machine learning techniques that detects patterns and creates learning within a neural network. The final product is a computer program that teaches itself how to learn from a tremendous amount of data which is provided to it. These technologies fall under the umbrella of artificial intelligence (AI). Importantly, the more data available to the program, the more data it has to learn from, and the more accurately it can perform.

This technology is currently being used to assist internet search results, voice recognition, and data analysis, but has not extended meaningfully into the medical imaging industry. Computer aided detection in the future will not involve teams of developers creating rules to help the computer find edges/pixels as in traditional CAD. Rather, a large amount of known data will be provided to a computer and software will learn to detect patterns. Currently available traditional CAD has led to no significant improvement in any performance metric, including sensitivity, specificity, positive predictive value, recall rate and benign biopsy rate [17].

However, there is much potential for the prospects of machine learning and neural networks. There are several possible applications of this technology. In addition to assisting with final diagnosis, another

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potential use would be AI algorithms that identify “quick negative” exams. This would be useful in high volume screening settings. If even 10% of the normal chest x-rays, mammograms, and lung CT screens could be immediately identified as normal, a substantial amount of radiologist time and effort could be reallocated. A standardized report would be automatically generated for review and sign off. This concept is only viable if AI's performance could result in a sensitivity approaching 100%. The concept of the “quick negative” would also be useful in underserved countries without easy access to local medical expertise.

## Cloud plus AI

Although in concept these technologies have existed for some time, their proliferation is increasing its pace since huge amounts of data are now available in the correct format. The cloud and AI reinforce each other in a positive feedback loop. A cloud based image database could provide secure, patient-portable accessibility of prior exams for more accurate and timely interpretation of mammograms with objectively improved patient outcomes at reduced costs [18]. Also cloud based image database of normal and abnormal mammograms would be the ideal training resource to teach computers to find breast cancer using the current techniques of AI. Ultimately this concept is scalable to the entire radiology department as ideals of Imaging 3.0 are put into action [19].

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