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MMS Membership Number: 6537 Word count: 488

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What is the most significant advancement in medical imaging in the last 10 years ?

Artificial Intelligence-Enhanced Computer Aided Diagnosis in Mammography and Digital Breast Tomosynthesis

Introduction

Breast cancer screening mammography reduces mortality from breast cancer by 20%, however, interpretation of millions of mammograms places workload pressures on radiologists (1). The reported sensitivity of mammography is 80% and specificity is 90%, albeit the risk of false-negatives remain (2). Thus, a large proportion of people present with interval cancers, which in retrospect, were visible on screening mammograms (3). Although digital breast tomosynthesis (DBT) detects 30-40% more cancers than full-field digital mammography, interpretation time is greatly increased and cognitive errors can still occur (3). Therefore, to maximise cancer detection rate and address workload issues, artificial intelligence (AI) plays a vital role.

AI-enhanced computer aided diagnosis (CAD) is better than conventional CAD. The use of AI-enhanced CAD in breast cancer screening is the most significant advancement in medical imaging in the last decade, as it has evidence-based potential to be deployed in screening programmes worldwide.

Conventional CAD

Conventional CAD systems present their findings as prompts on a mammogram, allowing a radiologist to decide whether its nature is malignant (3). However, approximately 1000 prompts must be analysed to detect one additional cancer and it cannot learn abstract or intermediate representations of data (4). Although conventional CAD has a higher detection range, evaluation times are longer and do not improve diagnostic accuracy due to high false positive prompts.

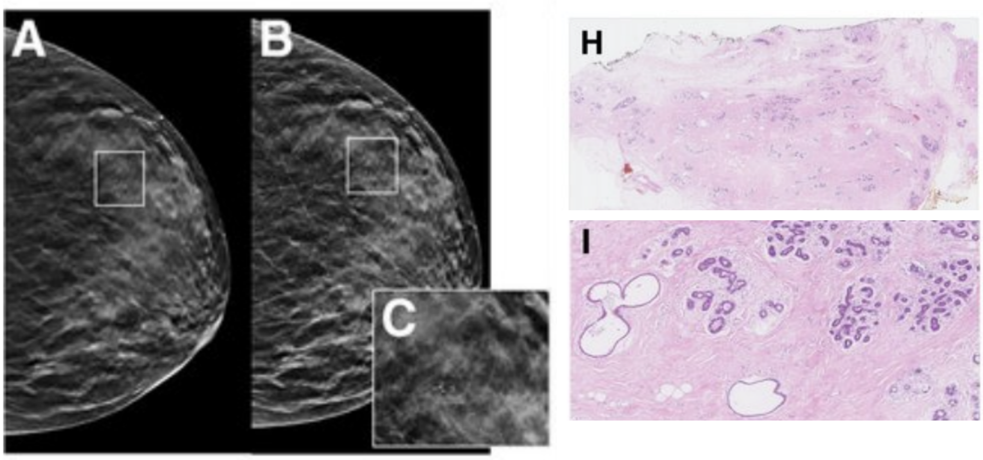

Figure 1: An example of a false positive prompt by Conventional CAD

Screening DBT (A, B, C) demonstrating clustered calcification in the left upper quadrant. Histology findings of DBT guided biopsy revealed sclerosing adenosis and no atypia (H, I). Image courtesy Kuhl et al (5).

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AI-enhanced CAD

AI-enhanced CAD involves convolutional neural network (CNN), which is a type of deep learning (DL) that is better able to learn abstract and intermediate representations of data before classifying the entire image (3). CNN uses layers of filters to read an image, identifying changes in tissue density, unusual shapes and clusters of cells (3). CNN then predicts the probability of a lesion being present and highlights suspicious areas for a radiologist to review (3).

Deep learning models have been used in large data sets to achieve a sensitivity of 87%, which is on par with the 88% sensitivity of radiologists with the same data set (6). A human-like AI system can be used as an independent second reader for screening mammograms, thereby halving the workload for any screening programs where double reading is standard practice (3). Examples of landmark studies which have proven near human performance of AI based systems are outlined in Figure 3.

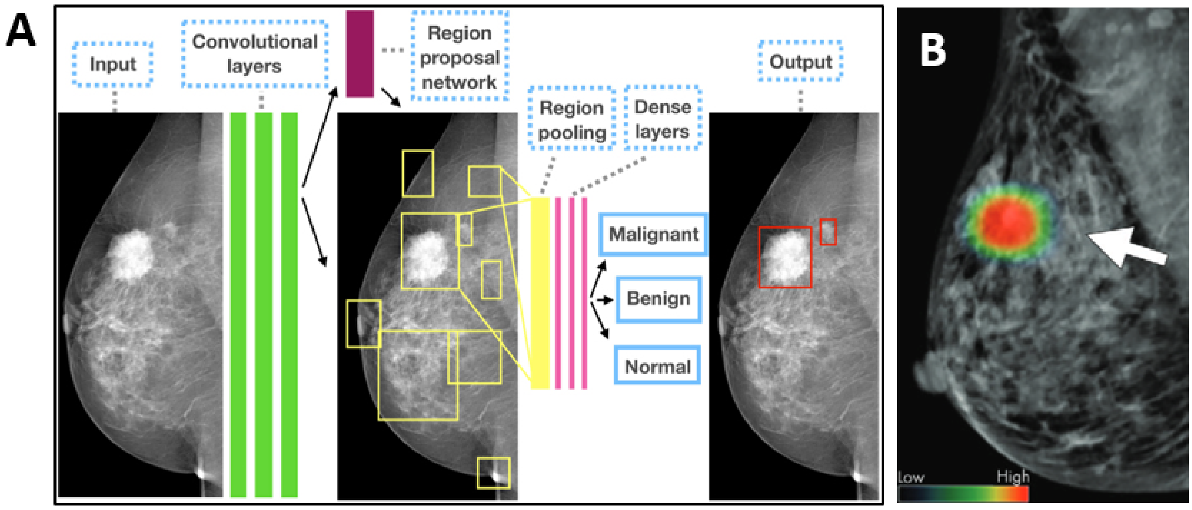

Figure 2: (A) An outline of CNN being used to analyse a screening mammogram. (B) An example of CNN output presenting the probability of cancer presence through heatmaps.
Image courtesy Ribli et. al (7) and Geras et. al (3)

Studies outlining statistical evidence that AI-enhanced CAD systems achieve near human performance in mass detection	Results & Conclusions
Kooi et al. 2017 (8)	Model has equal performance (0.85) to that of radiologists
Schaffter et al. 2020 (6)	Model sensitivity of 87%, on par with radiologists at 88% on the same data set.
Rodriguez-Ruiz et al. 2019 (9)	Model achieved non-inferior performance when compared to 101 radiologists

Figure 3: Examples of landmark studies outlining evidence of AI-enhanced CAD in detection of lesions on screening mammograms.

Conclusion

AI-enhanced CAD in Mammography and DBT is the most significant advancement in medical imaging in the last decade due to its near-human performance. In the near future, AI-enhanced CAD systems have the ability to be seamlessly integrated into current screening programmes and increase efficiency by reducing the number of follow-up tests due to false positive results.

Its higher degree of precision acts as a reliable safety-net to reduce cognitive errors by radiologists, meaning that false negatives are less likely to occur. It maximises the rate of early cancer detection and therefore has the ability to significantly improve treatment outcomes and survival rates.

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