OPTIMIZING BREAST CANCER DETECTION AND DIAGNOSIS: THE IMPACT OF DEEP LEARNING IN MEDICAL IMAGING

905F3: WIDER TOPICS IN DATA SCIENCE

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ABSTRACT

Breast cancer stands as one of the leading malignancies weighing heavily on healthcare systems worldwide. This essay explores the emergence and implementation of Deep Learning (DL), a subset of artificial intelligence, in breast cancer imaging as detective, diagnostic and therapeutic tools. The discourse encompasses the foundations of traditional imaging modalities, digitization and ultimately the integration and specific applications of Deep Learning algorithms in breast cancer management. Ultimately, it envisions the future trajectory of artificial intelligence in breast cancer imaging, foreseeing early detection, personalized treatment approaches and elevated standards of patient care.

INTRODUCTION

Cancer arises when the normal cell transforms into a tumor cell in a multi-stage process that chaotically progresses from a pre-cancerous lesion to a malignant tumor. There are over 200 different types of cancer, and each is diagnosed in a different way. Breast cancer is a highly heterogeneous neoplasm with distinct subtypes (Fig 1.) and presents a significant challenge in modern healthcare, with approximately 2.3 million women diagnosed and 670,000 deaths globally recorded in 2022 (Sung et al., 2021).

Its rapid progression highlights the critical need for early detection, with imaging and screening playing a pivotal role in comprehensive assessment and management of breast cancer treatment. In recent years, many technological advancements have assisted in automating the means of segregating benign instances from malignant ones with cancerous cells. In this pursuit, the introduction of Deep Learning and computer vision, a subset of artificial intelligence (AI), has emerged as a transformative force in breast cancer imaging. This essay aims to explore the profound impact and added value of deep learning on imaging technologies, shedding light on its potential to revolutionize breast cancer detection, diagnosis, and therapeutic strategies.

To grasp the impact of artificial intelligence, it's important to first understand the landscape and evolution of conventional breast cancer imaging techniques.

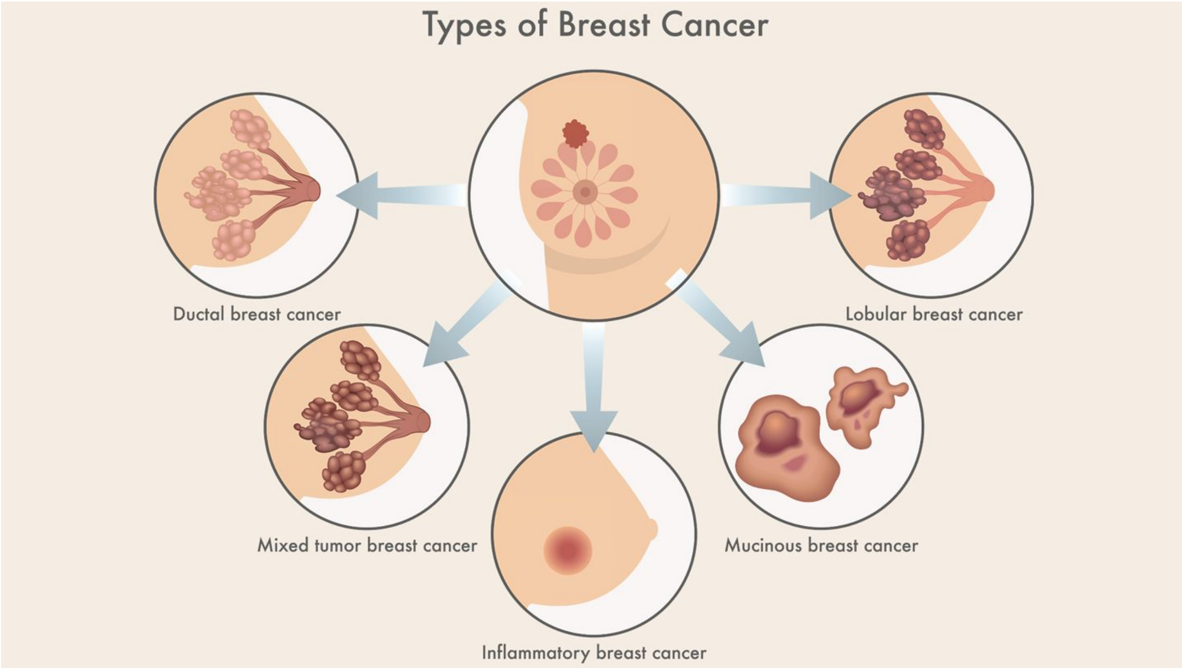

FIGURE 1: VARIATIONS IN BREAST CANCER TYPES.

CONVENTIONAL IMAGING TECHNIQUES FOR BREAST CANCER

Traditional screening modalities like Mammography, Ultrasound, and Magnetic Resonance Imaging (MRI) have been widely regarded as the 'gold standard' in breast cancer detection. Over time, these techniques have evolved significantly, assuming pivotal roles in identifying abnormalities promptly to facilitate timely treatment and reduce mortality rates. This chapter explores the inception, progression, and impact of the three imaging modalities.

1. MAMMOGRAPHY

The introduction of mammography traces back to the early 20th century as documented by (Nicosia et al., 2023) marking its inception as an x-ray imaging method aimed at early detection of breast cancer and other related issues. Initially employing film detectors, mammography has made significant strides with Digital Mammography (DM) emerging as a notable advancement in the field. Digital Mammography employs solid-state detectors to convert x-rays passing through the breast tissue into electronic signals. The computer processes these signals to generate digital images known as mammograms. These images are displayed on a monitor and stored for future reference, enhancing sensitivity and specificity in screening breast tissues.

Mammography screening has reportedly decreased breast cancer mortality rates on a global scale by approximately 40% (Broeders et al. 2012). Although widely regarded as the gold standard, traditional mammography has its limitations, including false positives and cases of undetected breast cancer with prognostic implications. Another challenge is tissue superposition, where different breast tissues overlap in 2D mammograms, potentially masking malignant lesions, and lowering sensitivity. This phenomenon, particularly prevalent in dense breasts characterized by a high density of fibro glandular tissue, contributes to approximately one-third of missed cancers (Mainprize et al., 2016). These complexities highlight the ongoing need to refine and improve breast imaging techniques to enhance detection accuracy and ultimately optimize patient outcomes.

To address these limitations, Digital Breast Tomosynthesis (DBT) was introduced into clinical practice. DBT involves capturing multiple X-ray scans from slightly different angles, resulting in a partial tomographic three-dimensional mammogram with reduced superposition compared to Digital Mammography (DM). This pseudo-tomographic technique produces a stack of 2D slices of the breast tissue, offering some vertical resolution and reducing the masking effect of superimposed tissues. Studies, such as Zackrisson et al. (2019), have demonstrated an increased cancer detection rate with DBT, often accompanied by a reduction in the recall rate compared to DM screening. However, a notable drawback of DBT is its longer interpretation time relative to DM. This extended time is primarily attributed to the larger number of images that need to be reviewed in DBT. This poses a challenge as the objective is to streamline the detection and diagnostic process, aiming for efficiency and timeliness.

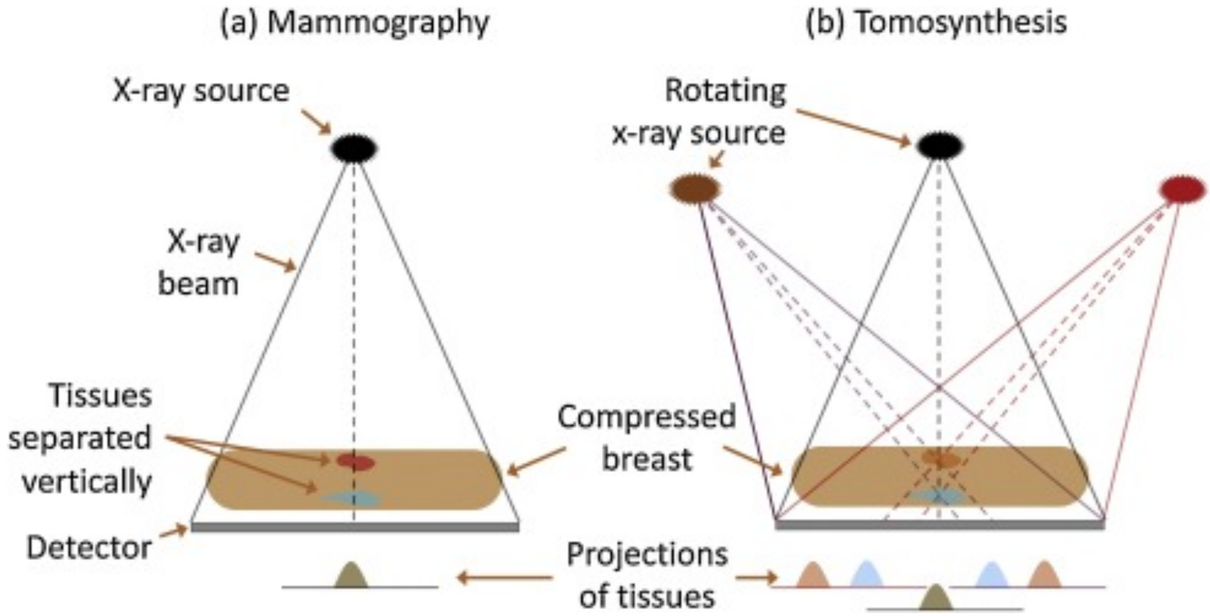

Figure 2: Comparison of breast cancer screening techniques: digital mammography vs. Digital Tomosynthesis.

2. ULTRASOUND TECHNOLOGY

Ultrasound complements mammography in evaluating breast health, offering numerous benefits for both screening and diagnosis. Its precision in distinguishing between benign and malignant tumours, especially those with irregular borders, minimizes the necessity for unnecessary biopsies. Widely available, non-invasive, and cost-effective, ultrasound has become a crucial tool in breast imaging.

Technological improvements such as Colour Doppler imaging and ultrasound contrast agents provide valuable insights into the anatomical and vascular characteristics of breast lesions (Svensson, 1997). Research consistently confirms ultrasound's accuracy in detecting and differentiating between benign and malignant masses, particularly in dense breast tissue, reducing the need for unnecessary interventions (Chen et al., 2003; Costantini et al., 2006).

However, interpretation heavily relies on the radiologist's expertise, making it an operator-dependent modality. While ultrasound exhibits higher sensitivity than mammography, particularly in detecting invasive cancers, its limitation in detecting small breast calcifications restricts its role in breast cancer screening.

Nonetheless, its speed, repeatability, and non-ionizing nature make it increasingly favoured for breast cancer diagnosis and evaluation (Geisel et al., 2018). It is relevant to recognize that ultrasound applications are not to replace mammography but rather to complement it in comprehensive breast imaging protocols.

3. MAGNETIC RESONANCE IMAGING

MRI screening has been crucial in detecting and diagnosing breast cancer lesions for nearly three decades (Heywang et al., 1989). However, its higher cost and limited availability compared to ultrasound and mammography pose limitations. Additionally, interpreting MRI images requires extensive radiologist expertise and is time-consuming (Meeuwis et al., 2010).

Scaranelo (2021) emphasizes the valuable role of breast MRI in managing breast cancer, especially when combined with mammography, particularly for patients with dense breasts. MRI has higher sensitivity in detecting breast neoplasms compared to mammography and ultrasound, making it effective for investigating cancer recurrence, even in women with prostheses.

In terms of imaging dimensionality, MRI offers 3D scans, distinguishing it from DM, DBT, and ultrasound, which produce 2D images Some reports indicate high sensitivity and negative predictive value for breast MRI, with Schoub et al. highlighting figures of 98-100% and around 100%, respectively, particularly useful in confirming the absence of neoplasia. However, other studies caution that while MRI exhibits high sensitivity, it may have lower specificity for both benign and malignant lesions.

Given the limitations, it is optimal to use MRI in conjunction with ultrasound and mammography for optimal outcomes, rather than as a standalone modality.

INTRODUCTION TO ARTIFICIAL INTELLIGENCE

Artificial intelligence serves as the overarching term encompassing algorithms capable of performing tasks that typically require a level of intelligence. Within this domain, machine learning (ML) emerges as a subset, where algorithms learn from data to enhance their performance. Data inputted into a machine learning program can take two primary forms: features, which represent quantifiable variables like lesion length, or raw data, such as digital mammography, ultrasound, or MRI scans in breast cancer imaging.

At its core, deep learning utilizes neural networks inspired by the structure and function of the brain. These networks are proficient in handling large datasets and identifying intricate patterns, making them well-suited for analysing images, such as those in breast cancer imaging. DL algorithms utilize extensive collections of annotated images to understand nuanced features associated with malignancy, thereby improving diagnostic precision.

When raw data serves as the input, algorithms must autonomously identify features. While learned features generally yield superior performance compared to manually crafted features, this task poses challenges for traditional ML algorithms. To address this, a subset of ML techniques collectively referred to as deep learning (DL) can be employed. In deep learning (DL), features are represented in terms of simpler features. DL algorithms, often called deep neural networks (DNNs), comprise multiple layers of interconnected neurons. A notable subtype of DNNs is convolutional neural networks (CNNs), designed to extract meaningful features from images. CNNs are tailored for image analysis tasks and are extensively applied in breast cancer imaging.

MACHINE LEARNING: COMPUTER-AIDED SYSTEMS

The integration of novel machine learning (ML) systems into medical diagnostics has revolutionized the field of oncology, particularly in the detection and diagnosis of breast cancer. The more traditional imaging modalities highlighted so far i.e. mammography, ultrasound, and MRI, while effective, have inherent limitations in accuracy, efficiency, and consistency.

Computer-aided detection and diagnostic systems (CAD) have emerged as pivotal tools in radiology, designed to leverage vast datasets and sophisticated algorithms to improve diagnostic processes. CAD systems employ conventional; machine learning algorithms and classification models to analyse imaging data autonomously, identify suspicious lesions and assess their characteristics.

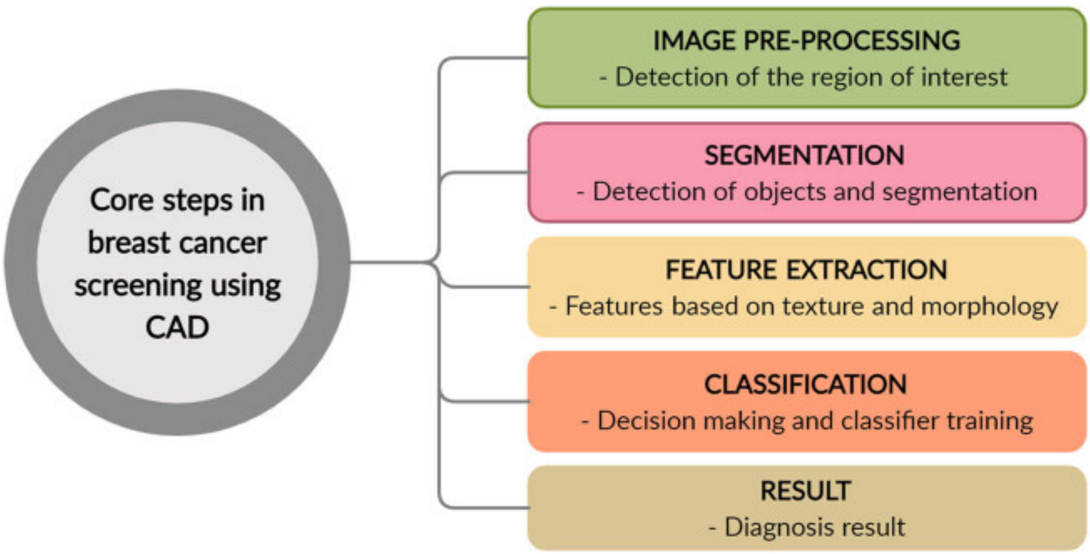

Figure 3: Core steps employed in breast cancer screening with the help of cad systems.

Computer-aided detection (CADe) locates suspicious lesions like soft tissue masses or calcification clusters by normalizing images, identifying potential lesion areas (ROIs), and assessing the probability of lesion presence. Conversely, computer-aided diagnosis (CADx) determines lesion malignancy without using a threshold. Conventional CADe/CADx systems rely on predefined features to identify and assess lesion suspicions based on specific characteristics. Efforts to improve CADe involve analyzing data across different breast views and matching views of both breasts, resulting in notable performance enhancements.

For instance, Engeland & Karssemeijer (2007) introduced a two-view mass detection algorithm integrating it into a CADe program, achieving a false positive rate of 0.1 per image and statistically significant improvements in lesion sensitivity from 56% to 61%. Despite these advancements, some analyses suggest CAD tools, like CADe, may reduce specificity and positive predictive value without significantly increasing sensitivity.

To address this, CAD is recommended as a supplementary tool alongside human expertise, combining machine learning capabilities with human judgment to enhance diagnostic accuracy. While there is room for improvement, this dual approach holds promise for future advancements in breast cancer detection.

DEEP LEARNING IN BREAST CANCER MANAGEMENT

The integration of deep learning into breast cancer detection marks a significant leap forward in clinical care. By leveraging analyses of traditional methods such as mammography, ultrasound, and MRI images, deep learning models can discern subtle abnormalities indicative of malignancy with unparalleled accuracy. Multiple studies attest to the superiority of deep learning algorithms in lesion detection compared to traditional image processing and analysis methods. Moreover, these models show potential to streamline interpretation processes and reduce discrepancies between observers, ultimately enhancing diagnostic efficacy.

Deep learning (DL) sets itself apart from conventional machine learning approaches, particularly in handling large volumes of data. The term "Deep" derives from the usage of multiple hidden layers, tiers, or stages to capture hierarchical abstractions within the data, enabling the construction of complex computational models. While training deep learning models may require substantial time due to the large number of parameters involved, the testing phase is relatively quick compared to other machine learning algorithms.

Before going into specific applications of deep learning techniques in breast cancer detection, it's essential to highlight the foundational principles of deep learning and the underlying neural networks.

WHAT ARE NEURAL NETWORKS?

The concept of deep learning as a part of machine learning, originates from artificial neural networks (ANN). A typical neural network comprises numerous interconnected processing units known as neurons, each generating a sequence of real-valued activations corresponding to the desired output. These networks facilitate both supervised/discriminative and unsupervised/generative learning paradigms.

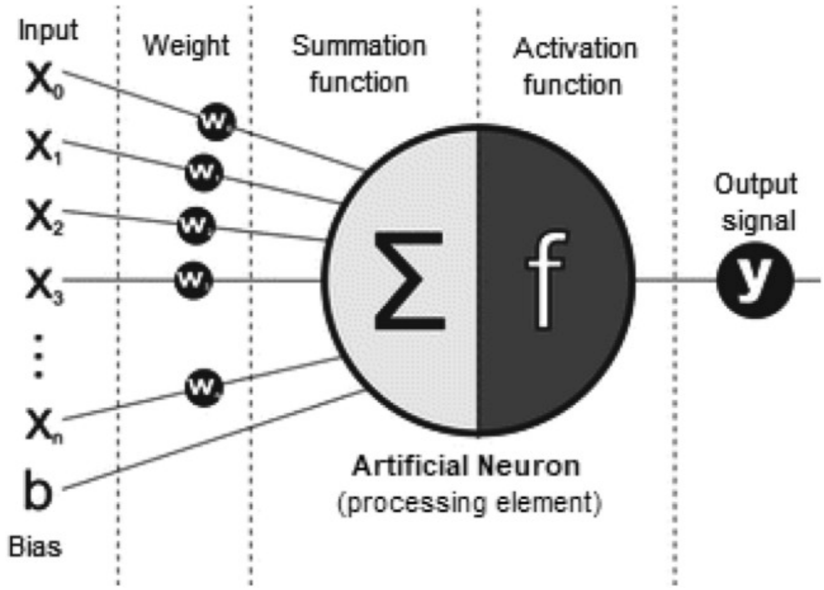

Figure 4: Schematic representation of the mathematical model of a processing element (artificial neuron)

This essay goes on to explore Convolutional Neural Networks and Generative Adversarial Networks as detective and diagnostic tools for breast cancer.

CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs) operate by processing images through a series of sequential stages, known as layers. These layers utilize basic mathematical operations like convolutions and down sampling to merge spatially correlated data within images. Through this multi-stage process, the data undergoes progressive transformation into various representations, enhancing the neural network's ability to accurately recognize and interpret the image.

CNNs have become fundamental in medical image analysis, particularly in breast cancer detection and diagnosis. They excel in extracting intricate features from medical images, enabling precise identification of suspicious regions indicative of malignancy. By leveraging extensive datasets of annotated mammograms, CNNs can learn to differentiate between benign and malignant lesions with remarkable accuracy. Furthermore, their capability to process images at different resolutions makes them invaluable tools for detecting subtle abnormalities that may elude human detection.

Unlike traditional CAD systems, these new AI-based image classification algorithms autonomously identify which image features indicate the presence of a lesion during their training, without relying on input from human programmers. Essentially, the algorithm learns to recognize characteristics of breast cancer, such as size, shape, or texture patterns, on its own through exposure to numerous examples of images with and without cancers. Each image is labelled with its actual status, and during training, the deep learning network adjusts its internal parameters to minimize the difference between its predicted status and the true status for each image. This iterative process enables the network to identify the image features that suggest a malignant lesion.

A remarkable example of this can be found in a study by Lotter, Sorensen, and Cox (2017). They propose an innovative approach to classify mammograms, combining Multi-Scale Convolutional Neural Networks (CNNs) with Curriculum Learning. This technique gradually exposes the model to more complex examples during training. Initially, patch-level CNN classifiers are trained across various scales to detect patterns within small image 'patches'. These classifiers are then used as feature extractors, applied across the entire mammogram in a sliding-window manner to build an image-level model. Through extensive training, the model adjusts its parameters to improve its performance on the classification task. To evaluate its effectiveness, the study then evaluates the model on images obtained from the open-source Digital Database for Screening Mammography

(DDSM)[1], achieving an AUROC of 0.92 compared to final pathology outcomes. Diverging from traditional mammogram classification pipelines, which involve sequences of processes like Region of Interest (ROI) proposal and feature extraction, this approach trains the entire system "end-to-end," leading to significant improvements in classification accuracy. Overall, this research reveals the potential of deep learning neural networks, particularly curriculum learning, in advancing mammogram classification accuracy and simplifying the diagnostic process.

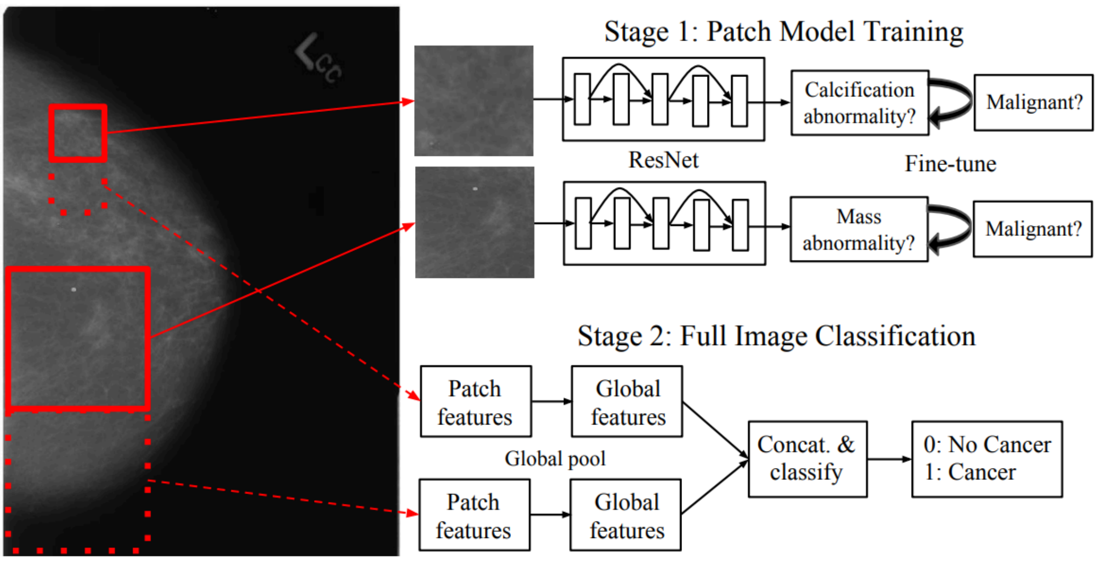

Figure 5: Schematic of patch classifier training and full image classification.

GENERATIVE ADVERSARIAL NETWORKS

Generative Adversarial Networks (GANs), designed by Ian Goodfellow (Goodfellow et al., 2014), can artificially synthesize medical images that closely resemble real patient data. These networks operate by autonomously learning patterns in input data, allowing them to generate new examples that resemble the original dataset. GANs are comprised of two neural networks: a generator (G) tasked with generating data similar to the original, and a discriminator (D) responsible for discerning between genuine and generated data. In GAN

[1] This database is commonly used for research in breast cancer detection and diagnosis.

modelling, both the generator and discriminator engage in competitive training. The generator's objective is to produce increasingly realistic data to deceive the discriminator, while the discriminator aims to accurately differentiate between genuine and fake data created by the generator.

In the context of breast cancer diagnosis, GANs can be utilized to augment limited datasets by generating synthetic mammograms with diverse pathological characteristics (Fig 7). This synthetic data augmentation helps overcome the challenge of dataset scarcity, enabling more robust training of deep learning models.

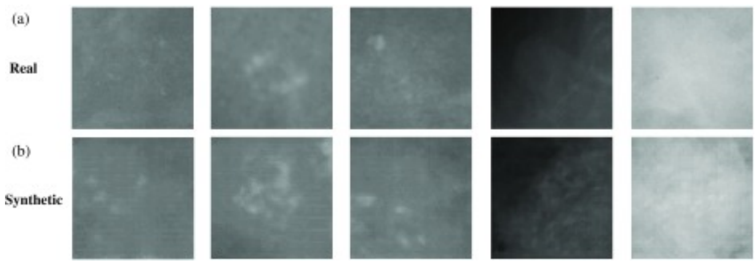

Figure 6: (a) real abnormal ROIs; (b) synthetic abnormal ROIis generated from a generative adversarial network.

Following a similar training approach as the previously mentioned Multi-Scale CNN study, (Guan, 2019) also gathered images from the DDSM to create artificial mammographic images using GANs. They selected two regions of interest (ROIs) from the DDSM images: normal (no cancer) and abnormal (cancer), which served as training data for the model. After generating the synthetic images, the model's performance was compared to that of affine transformations for image augmentation (such as rotation, shifting, scaling) on a CNN classifier. The results suggest that incorporating GAN-generated ROIs in the training data helped the classifier avoid overfitting and achieved approximately 3.6% higher validation accuracy than affine transformations for image augmentation.

Additionally, GANs can also be employed in image-to-image translation tasks, transforming mammograms from one modality to another (e.g., ultrasound or MRI), i.e. training other thereby facilitating multi-modal analysis for enhanced diagnostic accuracy (Armanious et al., 2020)

These studies along with many others highlights the significant potential of GANs as promising augmentation strategies to explore, interpolate between, and generate realistic but unseen imaging data. This consequently expands the sample space and enables imaging algorithms to detect and diagnose breast cancer more accurately and in a timely manner.

CONCLUSIONS

In conclusion, the integration of Artificial Intelligence (AI), particularly Deep Neural Networks (DNNs), into the field of medical imaging represents a significant advancement in breast cancer detection and diagnosis. Through techniques such as transfer learning, adversarial training, data augmentation, and hybrid model implementations, deep learning offers promising avenues for advancing breast cancer care. As we integrate AI technologies into clinical settings, it is imperative to prioritize ethical deployment, ensuring fair and transparent access of human data while maintaining rigorous oversight. Collaboration and interdisciplinary approaches are essential to fully harness the potential of deep learning, paving the way for personalized medicine and improved patient well-being.

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