Leveraging Evidence from Deep Learning Studies to Develop an Improved MRI-based Model for Breast Cancer Diagnosis

Kamarul Amin Abdullah [1,5], Sara Marziali [1,4], Muzna Nanaa [1], Lorena Escudero Sánchez [1,3], Nicholas R. Payne [1], Minmini Selvam[1,2,6], Fiona J. Gilbert [1,2]

[1] Department of Radiology, University of Cambridge School of Clinical Medicine | [2] Department of Radiology, Addenbrookes Hospital, Cambridge University Hospitals NHS Foundation Trust | [3] Cancer Research UK Cambridge Centre, Li Ka Shing Centre | [4] Istituto Nazionale dei Tumori, Milan, Italy | [5] Universiti Sultan Zainal Abidin, Malaysia | [6] Sri Ramachandra Institute of Higher Education and Research, Chennai, India

INTRODUCTION

- **Breast MRI** is crucial in high-risk cancer screening, but increasing demand creates delays [1,2].
- **AI, especially deep learning (DL)**, can **enhance MRI interpretation** efficiency and accuracy.
- Efficient DL models can reduce delays and improve diagnostic accuracy, particularly in high-risk breast cancer patients.
- This study reviews existing DL models to identify strengths and gaps, guiding the development of an improved breast cancer diagnosis model.

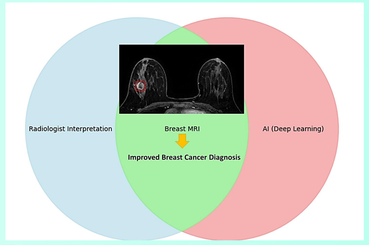


Fig. 1: Synergy between Radiologist Interpretation, AI, and MRI.

METHODOLOGY

- Systematic review and meta-analysis following PRISMA guidelines [3]; protocol registered on PROSPERO (CRD42024485371).
- **Literature Search:** Web of Science, PubMed, IEEE, using keywords like 'Deep Learning,' 'AI,' 'Breast Cancer,' and 'MRI.'
- **Bias Assessment:** QUADAS-2 [4] and MAIC-10 tools [5] ensured study quality.
- **Criteria:** Studies reporting AUC, sensitivity, specificity included."
- **Subgroup Analysis:** Evaluated DL model types, MRI sequences, and study designs to identify trends

RESULTS AND DISCUSSION

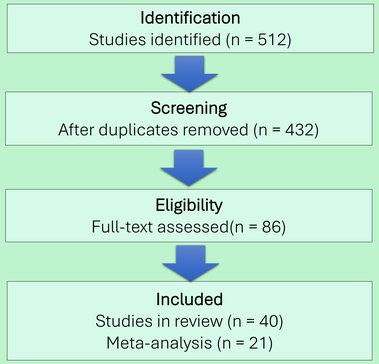


Fig. 2: PRISMA Flowchart (*A simplified version*) shows the included studies.

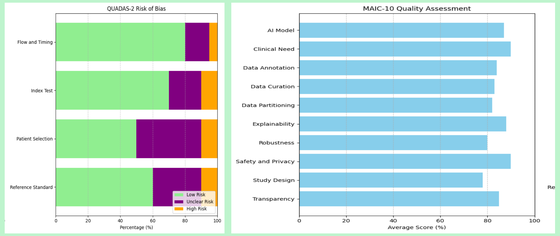


Fig. 3: Average scores of MAIC-10 shows more than 70% for all studies. QUADAS-2 tool shows low risks for included studies more than 50%.

Distribution of DL Models by MRI Sequence

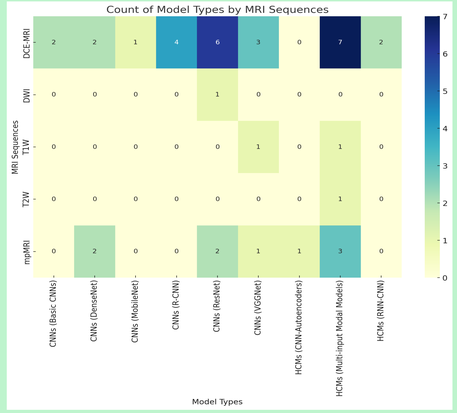


Fig. 4: Predominant use of DCE-MRI highlights the need for multi-parametric MRI integration in breast cancer diagnosis.

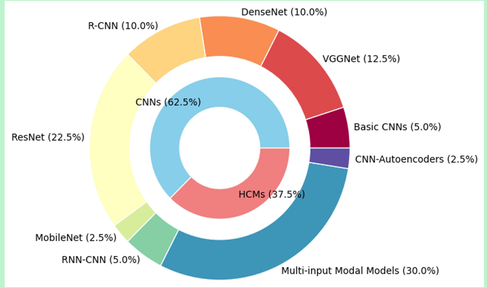


Fig. 5: CNNs dominate in current studies; ResNet and HCMs provide opportunities for segmentation improvements.

Definitions of MR Sequences:

- **DCE-MRI (Dynamic Contrast-Enhanced MRI):** Captures changes in tissue contrast over time.
- **mpMRI (Multi-parametric MRI):** Combines multiple MRI sequences (e.g., T1W, T2W, DWI).
- **DWI (Diffusion-Weighted Imaging):** Visualise tumour cell density.
- **T1W (T1-Weighted):** Highlights fat and contrast agents.
- **T2W (T2-Weighted):** Highlights water content and lesion oedema.

Current Trends in DL Models and MRI Sequences for Breast Cancer Diagnosis

- Most studies focused on **DCE-MRI** as the primary sequence, while **mpMRI**, which integrates multiple sequences, was less common. **mpMRI** combines sequences, potentially improving diagnostic accuracy for complex cases.

Model Performance

- CNNs performed well in lesion-based assessments **(AUC: 0.89–0.93; Sensitivity: 88–91%)**, indicating their suitability for accurate lesion detection in clinical practice.

Why Mask R-CNN is the Better of Breast MRI Diagnosis

- Current models struggle with multi-lesion detection and segmentation. Mask R-CNN's architecture supports both, providing a robust foundation for future model improvement.
- Enhanced segmentation capabilities could lead to fewer missed lesions and faster diagnosis, reducing delays in high-risk patient screening.
- Mask R-CNN offers a path toward faster and more reliable multi-lesion detection, which can improve patient care outcomes.

Future Directions

- Future work will focus on validating **Mask R-CNN** on multi-parametric MRI data and assessing its performance in **multi-lesion detection** for clinical applicability.

CONCLUSION

- This study establishes a foundation for advancing breast MRI diagnostics using AI, bridging gaps in multi-lesion detection, and supporting **more efficient, accurate clinical workflows.**

References

[1] Batchu S, Liu F, Amireh A, Waller J, Umair M (2021) A review of applications of machine learning in mammography and future challenges. Oncology 99:483-90; **[2]** Wuni A-R, Botwe B, Akudjedu T (2021) Impact of artificial intelligence on clinical radiography practice: futuristic prospects in a low resource setting. Radiography 27:S69-S73; **[3]** McInnes MD, Moher D, Thombs BD, McGrath TA, Bossuyt PM, Clifford T, et al (2018) Preferred reporting items for a systematic review and meta-analysis of diagnostic test accuracy studies: the PRISMA-DTA statement. JAMA 319:388-96; **[4]** McInnes MDF, Moher D, Thombs BD, McGrath TA, Bossuyt PM, P-DTAG, et al (2018) Preferred reporting items for a systematic review and meta-analysis of diagnostic test accuracy studies: The PRISMA-DTA statement. JAMA 319:388-96; **[5]** Cerda-Alberich L, Solana J, Mallol P, Ribas G, Garcia-Junco M, Alberich-Bayarri A, Marti-Bonmati L (2023) MAIC-10 brief quality checklist for publications using artificial intelligence and medical images. Insights Imaging 14:11

Acknowledgment

We would like to thank the library team at the University of Cambridge Clinical School for their guidance and the Ministry of Higher Education Malaysia (MOHE) for supporting the K.A.A. postdoctoral fellowship. This research was supported by the NIHR Cambridge Biomedical Research Centre (BRC-1215-20014; NIHR203312). One of the authors, M.S., would like to thank the European School of Radiology (ESOR) for the fellowship in hybrid imaging at the University of Cambridge.

Disclosures of conflicts of interest : None | Contact Information: ka602@cam.ac.uk / kamarulaminab@unisza.edu.my