ODELIA – European swarm learning project for AI in breast cancer MRI

(presented on behalf of ODELIA partners)

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INTRODUCTION

Background

Breast MRI is a powerful tool for cancer detection, but the adoption of AI faces two major barriers: data privacy and inter-hospital collaboration.

Swarm Learning (SL) allows institutions to train AI models without sharing patient data, improving diagnostic accuracy while maintaining confidentiality.

Each site trains a model locally, and only model parameters are merged periodically, ensuring data privacy.

Objective

To demonstrate that SL can enhance AI performance in breast MRI across multiple hospitals, improving cancer detection while ensuring privacy.

METHODS AND MATERIALS

Data Collection

Datasets:
Duke = Duke University Hospital (Public dataset)
USZ = Universitaetsspital Zurich, Switzerland
CAM = Cambridge University Hospitals, UK
MHA = Mitera Hospital, Athens
UKA = Aachen Hospital, Germany

Five datasets ('Duke', 'USZ', 'CAM', 'MHA', and 'UKA') comprising of MRI scans and clinical data were used. Duke, USZ, and CAM were used for training while UKA and MHA served as external test cohorts.

Data remained at each hospital; only AI model updates were shared.

Swarm Learning Framework

Local Training: Each centre trained an AI model using its own data.

Model Merging: AI model weights from the different centres were periodically shared, with the newly merged weights used in the next training round.

Experiment Details

3D-ResNet101 deep learning model to detect cancer in MRI scans. Trained using Weakly Supervised Learning (WSL) to reduce reliance on manually labelled data.

Definitions:
1. **3D-ResNet101:** A deep learning model designed for analysing 3D medical images, such as breast MRI. It processes volumetric data, identifying patterns that help differentiate between cancerous and non-cancerous tissues.
2. **Weakly Supervised Learning (WSL):** A machine learning approach that uses **partially labelled** data instead of requiring extensive manual annotations. In this study, it helps train AI models using existing clinical labels without needing precise lesion markings.

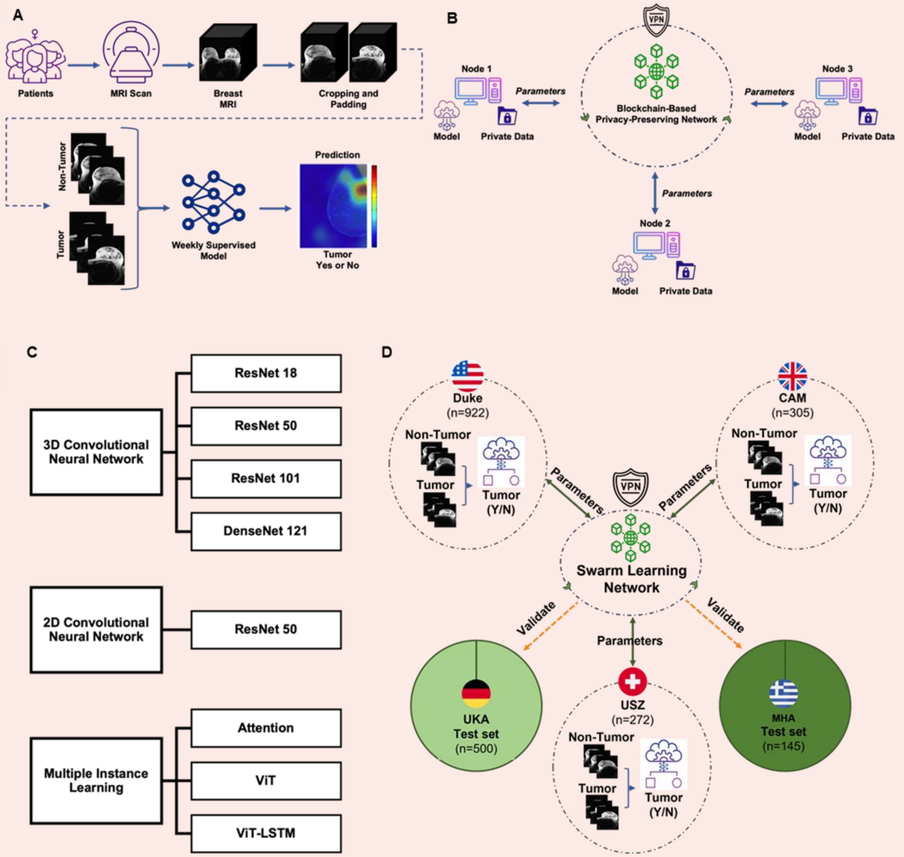


Figure 1: Schematic of the Weakly Supervised Learning (WSL) and Swarm Learning (SL) workflow. **(A)** Schematic representation of the Deep Learning-based WSL workflow for breast cancer tumour detection on Magnetic Resonance Imaging (MRI) data, **(B)** Overview of the SL setup for a 3-node network, **(C)** Graphical representation of techniques and models architecture for benchmarking WSL with breast cancer 3D MRI data, **(D)** Combined representation of real-world SL-based WSL for Breast Cancer Tumour Detection and Data Split Ratio

RESULTS

Performance Metrics

1. **Accuracy Improvement:** The Swarm Learning AI model demonstrated better diagnostic performance than locally trained models.
2. **Key Metrics:**
   - UKA AUROC: 0.807 [±0.024] (↑ compared to local models)
   - MHA AUROC: 0.821 [±0.013] (↑ compared to local models)
   - Statistical significance: AI improvements were significant ($p < 0.05$, DeLong's test).

Clinical Takeaway

Swarm Learning models outperformed traditional AI models, suggesting better cancer detection across different hospitals.

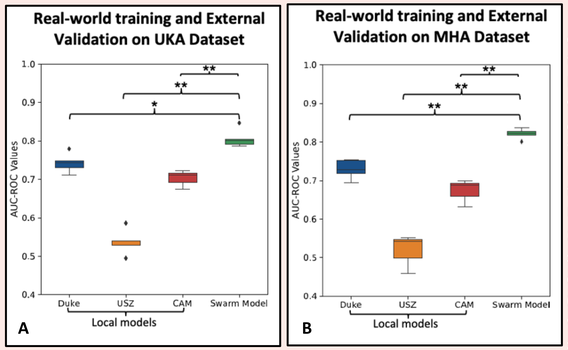


Figure 2: Performance evaluation of the 3D-ResNet101 model trained with Swarm Learning on Duke, USZ, and CAM cohorts, validated on UKA and MHA datasets. **(A)** AUROC and DeLong's test were used to compare local models with the swarm model on the external validation cohort, UKA. Significance levels: $p < 0.05$ (*), $p < 0.001$ (**). Median patient scores from five repetitions confirmed superior performance. **(B)** Same evaluation for the MHA validation cohort, following the same methodology.

CONCLUSION

Swarm Learning enables hospitals to train AI models collaboratively without sharing patient data. This approach improves diagnostic accuracy, enhances AI generalization across different MRI protocols, and ensures privacy compliance. The ODELIA public challenge in 2025 will further validate these findings with larger datasets.

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References
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