Designing a Federated Learning-Driven Collaborative Diagnostic System for Metastatic Breast Cancer

Reducing Long Diagnosis Delays and Improving Patient Survival Outcomes in Developing Countries

INTRODUCTION

Breast cancer is the leading cause of cancer mortality[1]. Breast cancer patients in developing countries suffer from the highest mortality rates in the world[2].

- These high mortality rates are attributed to long diagnosis delays that could stretch upwards of 15 months [3]. The average number of pathologists per head of population in the Sub-Saharan countries is 50-70 times less than in the US and UK.

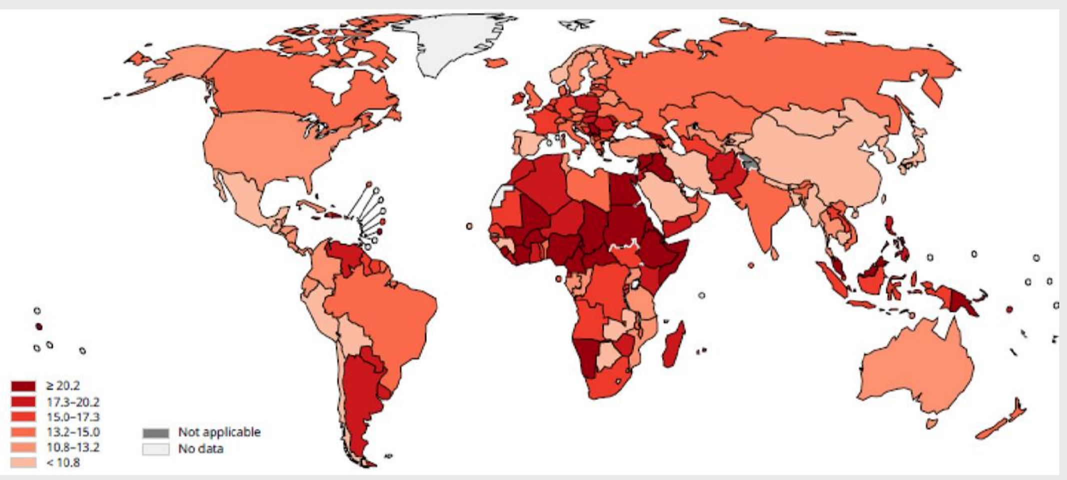


Figure 1. World map of breast cancer mortality rates (all ages), showing high mortality rates in Sub-Saharan Africa, South Asia and South America [2]

CHALLENGE 1

Manual diagnosis is time consuming and sometimes error-prone.

OBJECTIVE 1

Develop a **deep learning (DL)-driven** diagnostic system to **standardize and automate** diagnosis.

CHALLENGE 1

Computational costs and lack of mobile capacity hinder real-world applications.

OBJECTIVE 1

Develop an **efficient** and **mobile-ready** system, enabling applications in various environments.

CHALLENGE 1

Severe shortages of high-quality data and issues of patient privacy.

OBJECTIVE 1

Develop a **privacy-preserving**, federated learning (FL) system to **leverage global data.**

SYSTEM DESIGN

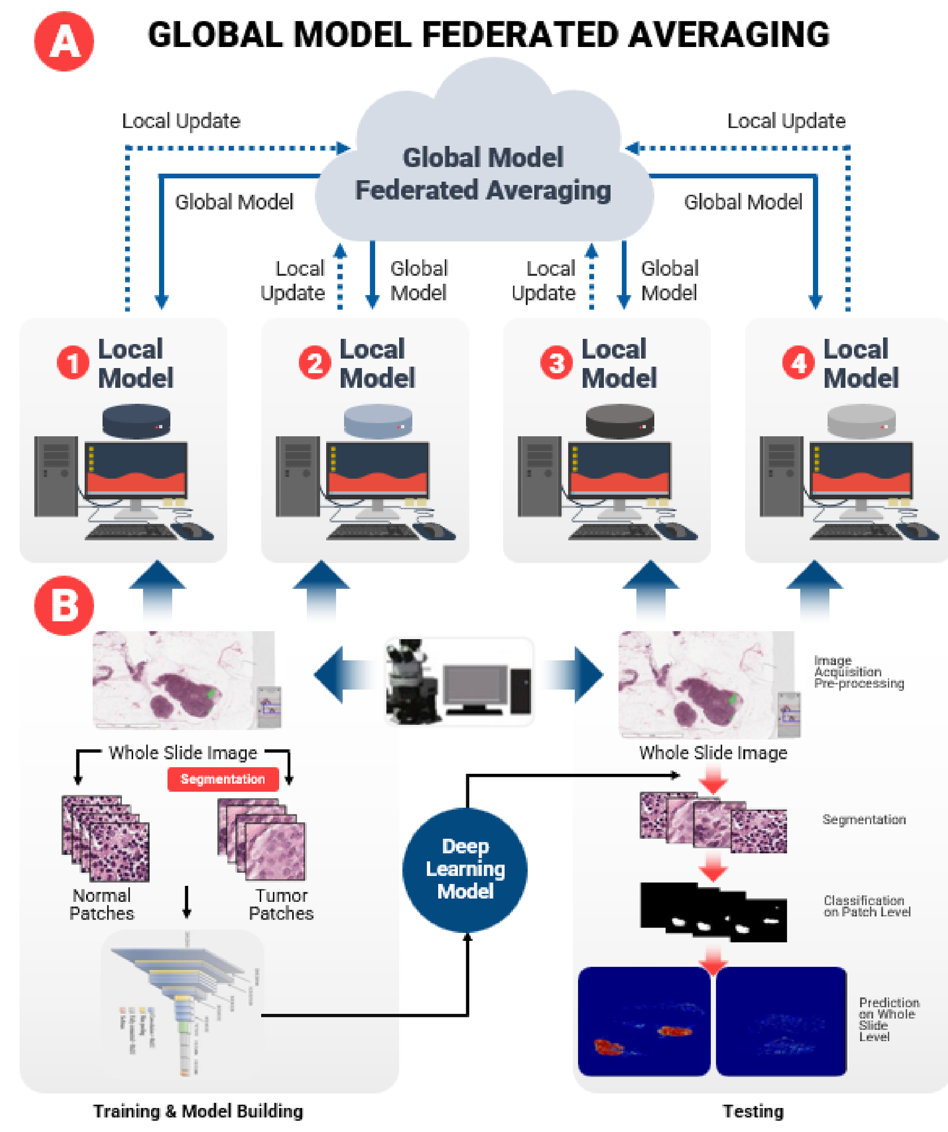
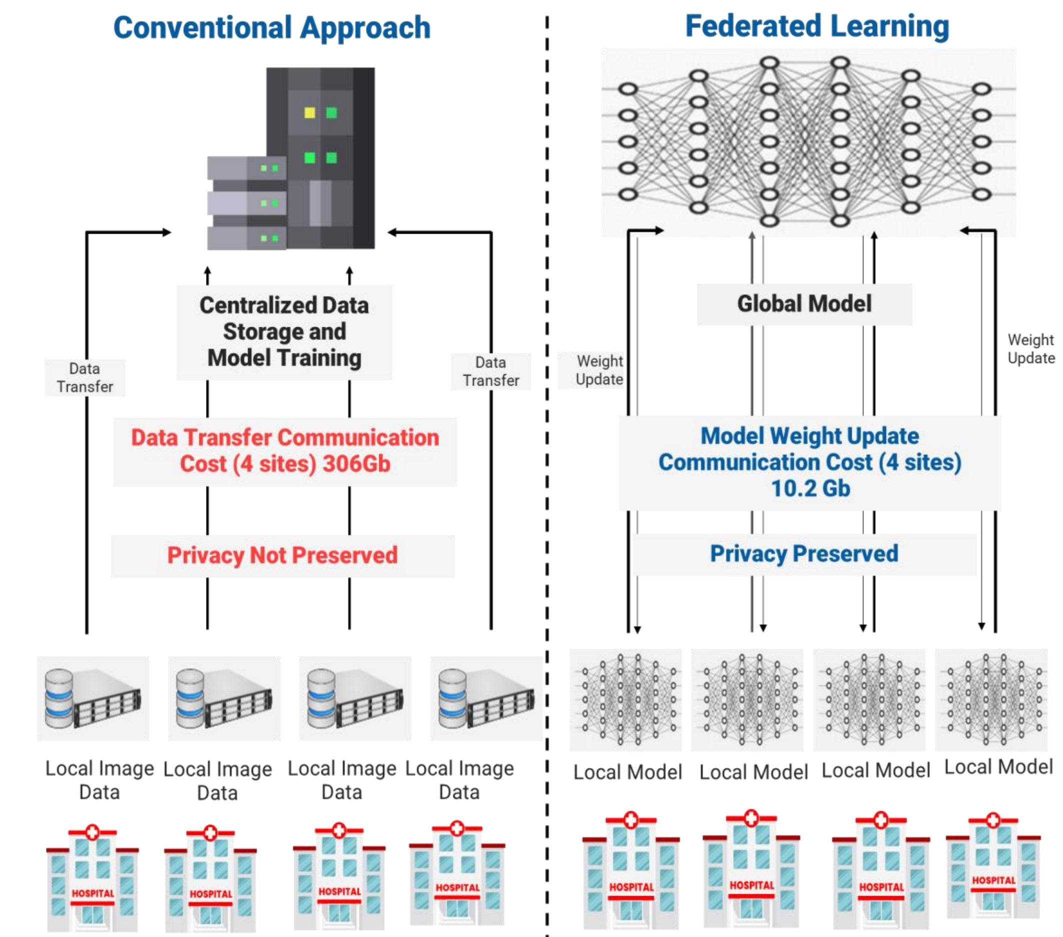


Figure 2. (A) Design of the federated learning-driven collaborative diagnostic system **(B)** Image processing and training the DL model (Generated by William Gao).



Conventional Approach
Requires direct patient data transfer but restricted by privacy regulations.

Federated Learning (FL)
Decouples model training from direct access to raw patient data [4,5].

Figure 3. Comparison of the conventional and FL approach for model training (Generated by William Gao).

EXPERIMENT 1: Federated Learning Integrates Data to Improve Cancer Diagnoses

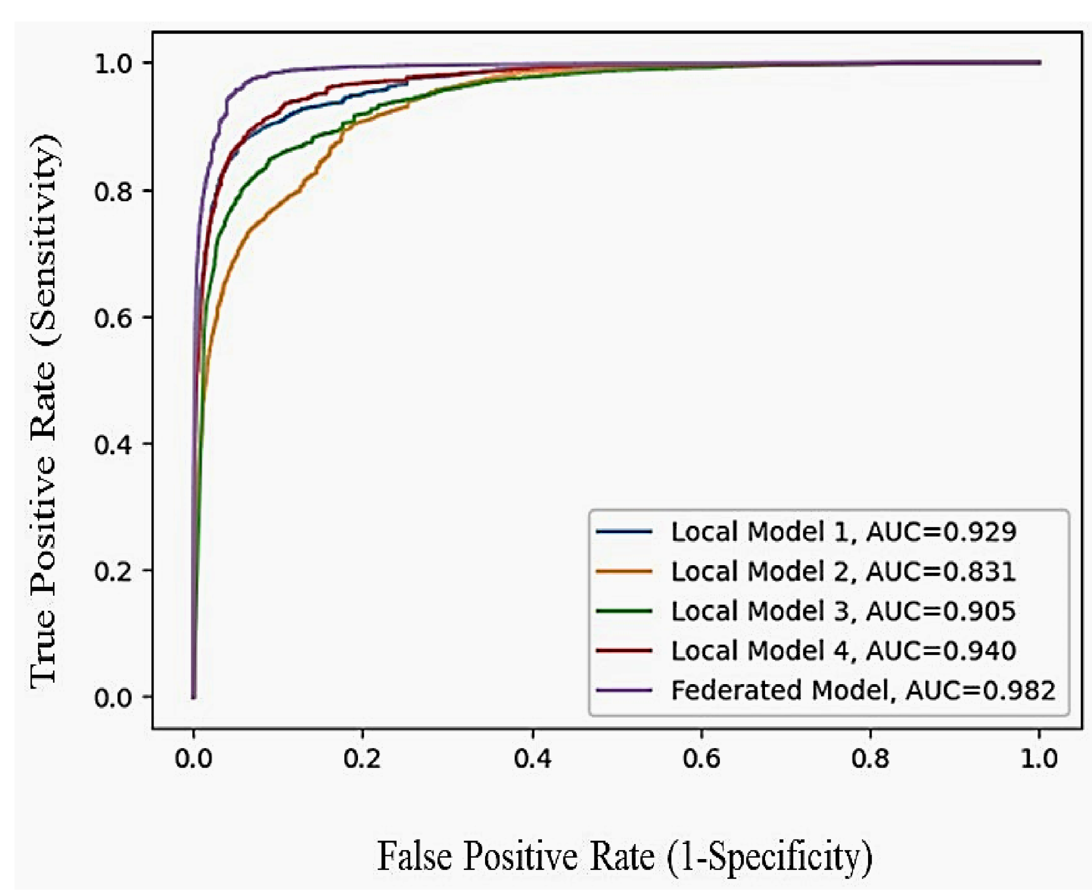


Figure 4. Receiver Operating Characteristic (ROC) curve: FL model vs. local models for prediction on unseen images. The FL model outperformed local models, demonstrating ability to overcome data shortages by integrating data from multiple sites (Generated by William Gao).

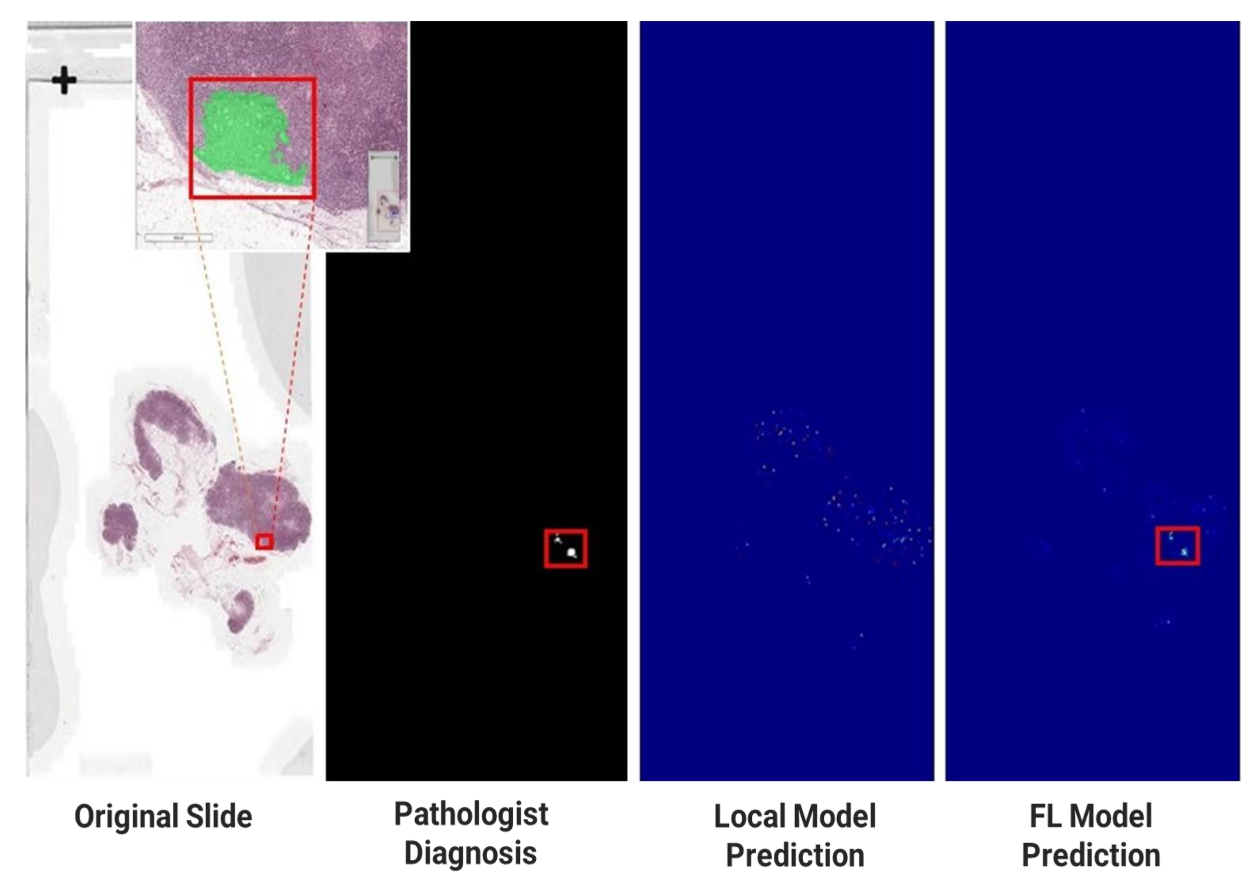


Figure 5. Visual comparison between FL vs. local model prediction on cancerous regions in whole slide images, with the pathologist's diagnosis as ground truth. The FL model alone was able to successfully identify the small cancerous region (Generated by William Gao).

EXPERIMENT 2: Federated Learning Adapts to Lower-Quality Images at Local Sites

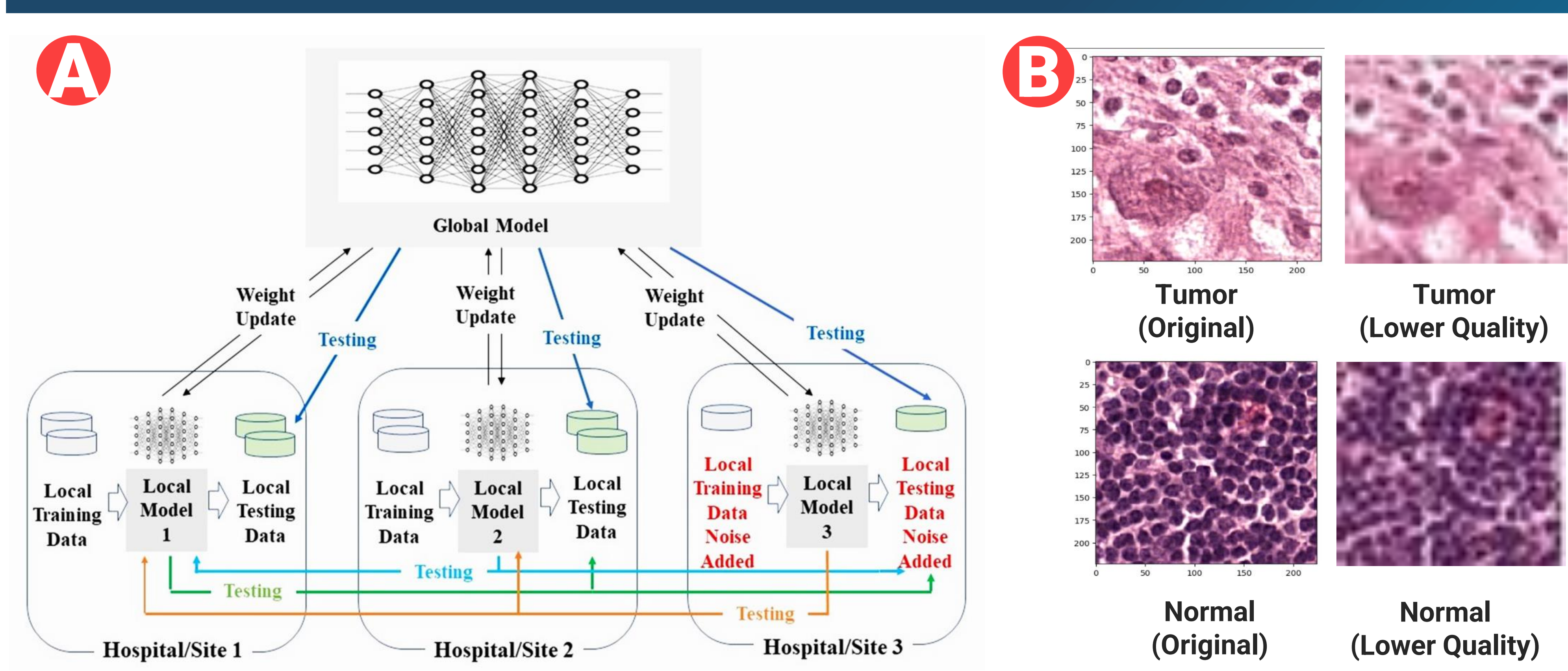


Figure 6. (A) Experiment design to evaluate the local diagnosis on lower-quality images. Clinical sites C1 and C2 generated images of normal quality while C3 images were of lower quality. Site C3 images were simulated by adjusting JPEG image quality to a random value between 6 and 9. **(B)** Original and Augmented (lower quality) images used in the experiment. (Generated by William Gao)

Table 1. Diagnostic performance of local models and the federated model (average ROC AUC ± Standard Deviation), tested on respective image data at individual sites (Generated by William Gao)

	C1 Model	C2 Model	C3 Model *	Federated Model
C1 Test	0.867 (± 0.068)	0.913 (± 0.031)	0.783 (± 0.097)	0.955 (± 0.022)
C2 Test	0.927 (± 0.031)	0.947 (± 0.012)	0.848 (± 0.049)	0.979 (± 0.005)
C3 Test *	**0.612 (± 0.082)**	**0.688 (± 0.038)**	**0.868 (± 0.074)**	**0.961 (± 0.018)**

The FL model showed **improved diagnostic performance on lower quality test images** at site C3 compared to the local models built at C1, C2, and C3. FL models can improve local diagnosis on lower quality images by leveraging data from other sites to **adapt to variations in local data.**

Global Applications in Developing Regions

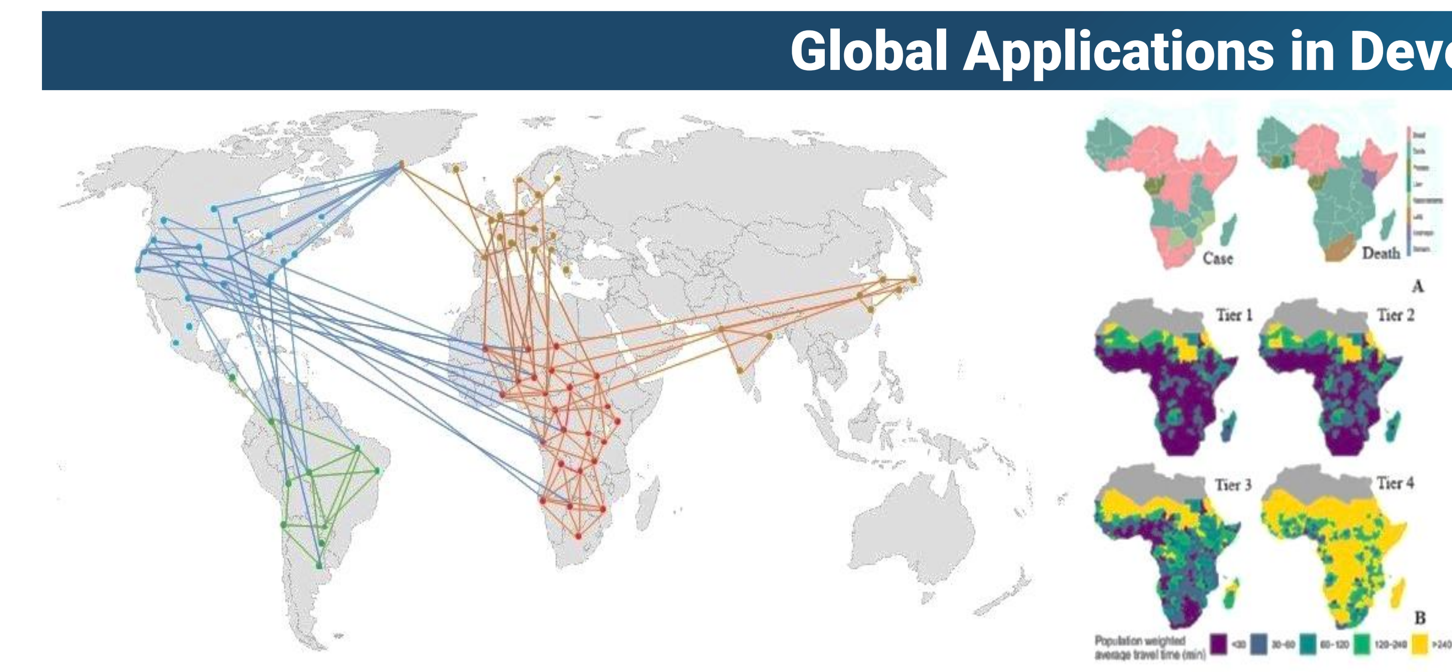


Figure 7. Left: The FL-driven collaborative diagnostic system can be scaled globally to connect healthcare institutions. **Right:** Application of the system can connect all tiers (Tier 1 – 4, large to small institutions) healthcare facilities (B)[6] to reduce the diagnosis delays (A)[3].

Applications in High Mortality Risk and Resource-Constrained Regions:

- **Connect** all tiers of healthcare facilities, especially Tier 1 and 2 facilities in remote and resource-constrained areas, to build global breast cancer diagnosis networks.
- **Develop** more accurate and generalizable FL models that leverage data resources from all participating facilities, adapt to local populations, and preserve patient privacy.
- **Provide** standardized and automated systems to reduce long diagnosis delays and improve survival outcomes.

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