



A Review On Histopathological Image Classification For Breast Cancer Detection Using Federated Learning

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Abstract: Federated Learning (FL) has emerged as a powerful paradigm for privacy-preserving medical image analysis, enabling collaborative training across multiple pathology centers without sharing raw patient data. In breast cancer diagnostics, both histopathological image classification and segmentation are essential for identifying malignant regions and supporting early clinical decision-making. However, the development of high-performing deep learning models is challenged by institutional data silos, staining and scanner variability, annotation inconsistencies, and severe non-IID data distributions across clinical sites. This literature review synthesizes recent advances in FL for histopathology - including encrypted aggregation, differential privacy mechanisms, attention-guided architectures, parameter-efficient modality adapters, and segmentation-driven frameworks for whole-slide imaging. Special emphasis is placed on FedImp, an impurity-based optimization method that adaptively weights client updates using entropy-driven data-quality measures. While originally evaluated in classification scenarios, FedImp directly addresses critical limitations affecting segmentation tasks, such as uneven label availability, morphological heterogeneity, and client imbalance. By prioritizing informative updates and suppressing noisy or skewed contributions, FedImp enhances convergence stability, improves generalization, and reduces communication overhead in multi-center FL settings. Through a comparative review of ten influential studies, this work highlights existing methodological gaps and positions FedImp as a compelling foundation for future federated histopathological breast cancer segmentation pipelines, integrating privacy, robustness, and clinical scalability.

Keywords: Federated Learning, Histopathological Image Analysis, Breast Cancer Detection, Important Deep Neural Network Layers, Non-IID Data, FedImp.

I. INTRODUCTION

Breast cancer detection from histopathological images relies heavily on machine learning models capable of accurately identifying tumor regions. However, deploying such models across pathology centers is difficult due to privacy restrictions on patient data and significant variability in whole-slide images produced by different institutions. Federated Learning (FL) addresses this by enabling collaborative model training while keeping data local, yet its effectiveness in histopathology is limited by non-IID data, heterogeneous staining styles, inconsistent annotations, and class imbalance across clients.

FedImp directly tackles these challenges through an impurity-based weighting mechanism that assigns higher importance to informative, higher-quality client updates rather than treating all contributions equally. This approach is particularly valuable in segmentation tasks, where variations in tissue morphology, slide preparation, and annotation density create highly skewed data distributions. By emphasizing cleaner updates and reducing the influence of noisy gradients, FedImp enhances convergence stability and generalization across diverse clinical environments.

Given the sensitivity of segmentation workloads to domain variability, FedImp offers a strong pathway toward more reliable FL pipelines for breast cancer histopathology. Its impurity-guided aggregation provides a targeted solution for learning effectively from heterogeneous data without compromising privacy. This review uses FedImp as a central reference point to examine how such optimization strategies align with the unique challenges of federated histopathological image segmentation.



II. BACKGROUND AND CONTEXT

Histopathological examination of biopsy slides is the clinical gold standard for breast cancer diagnosis, as it reveals cellular morphology, tissue organization, and tumour boundaries with high resolution. Deep learning has significantly advanced the analysis of these images, enabling automated classification and segmentation of malignant structures. However, training robust segmentation models traditionally requires large, diverse datasets - an obstacle in medical settings where patient confidentiality limits data centralization and institutions operate under strict regulations such as HIPAA and GDPR.

Federated Learning (FL) addresses these constraints by enabling decentralized model training in which local data remain within each medical institution. In FL, only model parameters or gradients are shared, mitigating privacy risks while still allowing multi-center collaboration. Despite this advantage, FL performance is heavily influenced by the heterogeneity of client data. In histopathology, non-IID distributions arise due to variations in staining protocols, scanner types, sample preparation, magnification levels, and annotation quality. These inconsistencies lead to unstable optimization, slow convergence, and reduced accuracy when standard aggregation methods such as FedAvg are employed.

To strengthen FL under such challenging conditions, recent research has explored optimized aggregation techniques, privacy-preserving enhancements, attention-based feature extraction, and domain adaptation mechanisms. Among these developments, the impurity-weighted aggregation strategy introduced in FedImp has gained relevance for medical imaging scenarios characterized by uneven data quality. By measuring dataset impurity through entropy-based metrics, FedImp provides a principled approach for weighting client updates and mitigating the effects of skewed or noisy data partitions.

Within this context, breast cancer histopathological image segmentation represents a domain where FL and impurity-aware aggregation methods can offer substantial benefits. Accurate segmentation demands model stability across diverse clinical environments, making techniques like FedImp particularly valuable for improving performance while maintaining privacy and scalability.

III. RELATED WORKS

Federated Learning (FL) has gained significant attention in medical imaging, particularly for breast cancer histopathology where privacy, dataset heterogeneity, and multi-institutional collaboration are major concerns. Several studies have explored FL-based frameworks to enhance classification and segmentation accuracy while addressing confidentiality and data governance constraints.

Federated Learning Approach for Breast Cancer Detection Based on DCNN applies DCNNs in a privacy-preserving FL pipeline (with HE considerations) to mammography, achieving very high detection accuracy across VINDR-MAMMO, CMMD and INBREAST ^[1].

Enhancing Breast Cancer Classification through Attention-Based VGG-19 and FL uses attention-augmented VGG-19 plus federated multi-center training and domain-adversarial tuning to improve cross-center classification robustness ^[2].

Enhancing Breast Cancer Classification in Histopathological Images through Federated Learning Framework proposes an encrypted FLF pipeline (Extended ElGamal) with C2T2Net capsule-attention model optimized by swarm algorithms for BreakHis classification ^[3].

Federated Learning Empowered Breast Cancer Detection using YOLO and ResNet-50 Fusion Client-side YOLO detection and ResNet-50 classification fused via FL to yield high accuracy under IID client distributions ^[4].

Federated Fusion of Magnified Histopathological Images for Breast Tumor Classification (IoMT) Fuses multi-magnification features in FL using a residual network to boost BreakHis classification for IoMT deployment ^[5].

Federated Cross-Assessment & Dynamic Aggregation for Histopathology Segmentation (FedSODA) introduces synthetic cross-assessment and dynamic stratified-layer aggregation to handle sample imbalance and heterogeneity across seven segmentation datasets ^[6].

Privacy-preserving FL for Histopathology Image Segmentation (FedDP) injects differential-privacy noise into federated segmentation updates to prevent gradient inversion while keeping Dice/Jaccard drops minimal ^[7].

FL with Differential Privacy for Medical Images empirically explores DP along with FL tradeoffs showing dataset-dependent accuracy/privacy results (e.g., Brain Tumor = 0.78, OASIS = 0.91) ^[8].

Federated Histopathological Classification for Oral SCC applies standard FedAvg CNN pipeline to OSCC histology, evaluating IID and non-IID splits and reporting approximately 90.18% on non-IID ^[9].

Secure and Collaborative Breast Cancer Detection Using FL demonstrates FL on DDSM mammograms achieving approximately 95.3% and emphasizing privacy-preserving collaborative detection ^[10].



Federated Learning for Enhanced Cell Nuclei Segmentation in Histopathology comparative study of FedAvg, FedMix, FedST, FedRGD, LL on nuclei segmentation (MoNu*, MICCAI etc.), finding FedAvg most balanced overall ^[11].

FedImp impurity-based aggregation that weights client updates by entropy to accelerate convergence and improve robustness under severe non-IID distributions. ^[12]

Decentralized FL with XAI (colorectal) trains multiple CNN backbones in a decentralized FL setting and integrates superpixel-based XAI, achieving 96.05% FL accuracy on NCT-CRC-HE-100K ^[13].

Personalized FL for Histopathological Lung-Cancer Prediction proposes a personalized FL framework using client-specific autoencoders plus hierarchical clustering to handle non-IID histopathology data, reporting dramatic improvements over vanilla FedAvg on LC25000 ^[14].

FL-based Histopathology Classification (HAM10000) applies a VGG16-based federated classifier to the HAM10000 dermatology dataset, obtaining approximately 82.04% accuracy and highlighting scope for aggregation improvements beyond FedAvg ^[15].

IV. SYSTEMATIC ANALYSIS

A systematic analysis of existing work on histopathological image classification for breast cancer detection shows that while various Federated Learning, deep learning, and stain-normalization techniques have been proposed, each involves specific trade-offs in accuracy, privacy, computational cost, and robustness to non-IID data. In this section, we critically evaluate the performance, strengths, and limitations discussed in the related works.

Reference no.	Methodology	Dataset(s)	Accuracy	Merits	Demerits
H. AlSalman [1]	FL with DCNNs; considers Homomorphic Encryption	VINDR-MAMMO, CMMD, INBREAST	98.9%	Very high accuracy; privacy-aware design.	HE computes overhead; clinical Validation needed.
C.Valarmathi [2]	Attention VGG-19 and FL with domain-adversarial fine-tuning	(multi-center mammography/biopsy sets)	91.9%	Better localization & cross-center generalization.	Dataset details limited; not segmentation-focused.
J. Peta [3]	Encrypted FL (Extended ElGamal), C2T2Net capsule-attention; swarm optimizers	BreakHis	95.68%	Strong confidentiality, high accuracy.	Single dataset; heavy custom crypto/optimizers.
N. K. Trivedi [4]	Client-side YOLO, ResNet fusion aggregated via FL	Public datasets	98.73%	High performance when IID; detection and classification combo.	Assumes IID; limited non-IID handling.
B. L. Y. Agbley [5]	Multi-magnification feature fusion in FL with ResNet backbone	BreakHis	95.70%	Leverages scale info; IoMT deployment focus.	Complexity; non-IID scenarios need more study.



Y. Zhang [6]	Synthetic cross – assessment with dynamic stratified-layer aggregation	7 datasets (CoNSeP, CPM-17, CRAG, CryoNuSeg, Glas, Kumar, TNBC)	92.52%	Tackles imbalance and heterogeneity; strong segmentation gains.	Added complexity; synthetic ops maintenance.
L. Pan [7]	FL segmentation, Differential Privacy (noise in updates)	LungCancerWSS S4LUAD	91.09%	Protects against gradient inversion; small utility loss.	DP can harm fine boundaries; tuning needed.
M. H. Mehmood [8]	Fed and Differential Privacy study; measures epsilons v/s accuracy	Brain Tumor, OASIS	Brain Tumor: 0.78; OASIS: 0.91	Concrete privacy-utility tradeoffs; guiding DP tuning.	DP often reduces performance for fine tasks.
S. Rajit [9]	FedAvg CNN pipeline on OSCC histology	OSCC dataset (5192 images)	90.18% (non-IID)	Practical non-IID evaluation; privacy preserved.	Classification focused; not WSI segmentation.
J. Sharma [10]	FL with privacy emphasis applied to mammograms	DDSM	95.3%	Demonstrates FL can exceed some centralized baselines.	Details sparse; segmentation applicability unclear.
M. Usai [11]	Comparative analysis: FedAvg, FedMix, FedST, FedRGD, LL	MICCAI, BNS, MoNuSeg, TNBC, MoNuSAC	FedAvg up to Acc 97.3 (BNS)	Thorough segmentation comparison; practical insights.	Some methods are unstable; generalization gaps on MoNuSAC.
H. A. Tran [12]	Entropy/impurity-based client weighting for aggregation	Benchmarks: EMNIST, CIFAR-10 (and proposed medical use)	Faster convergence; higher accuracy under non-IID	Improves robustness in severe non-IID; reduces comm rounds.	Mostly validated on natural images; privacy/DP interplay must be studied.
M. S. Tahosin [13]	Decentralized FL with multiple CNN backbones, superpixel XAI for interpretability.	NCT-CRC-HE-100K	FL Acc 96.045% (ResNeXt local 99.53%)	High accuracy; integrated interpretability increases clinical trust.	Class imbalance noted; not segmentation-focused; balancing needed.
B. J. Ayekai [14]	Personalized FL: client autoencoders, hierarchical clustering; personalized aggregation	LC25000 (Lung/Colon)	100% (reported)	Strong personalization for non-IID; large performance gain vs FedAvg	Extremely high reported perf – risk of overfitting or experimental bias; reproducibility concerns.



M. Yenilmez [15]	VGG16 local models, FedAvg aggregation	HAM10000 (skin lesions)	82.04%	Resource- efficient; privacy preserved; comparable to prior work	Relatively modest accuracy; suggests improved aggregation needed.
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V. CONCLUSION AND FUTURE WORK

Federated Learning has emerged as a strong paradigm for collaborative histopathological image analysis by enabling multi-center training without compromising patient privacy. Across the reviewed studies, FL proved capable of matching or exceeding centralized performance when enhanced with secure aggregation, attention mechanisms, stain normalization, multi-modal fusion, personalized optimization, and differential privacy. However, challenges such as severe non-IID distributions, staining variability, domain shifts, annotation inconsistencies, and the complexity of whole-slide images continue to hinder reliable segmentation performance. In this context, FedImp stands out as a promising optimization strategy; its entropy-based impurity weighting directly addresses data heterogeneity, reducing the influence of noisy clients and improving convergence stability, generalization, and communication efficiency - making it well suited for federated histopathological breast cancer segmentation pipelines.

Although FedImp effectively improves federated learning performance on heterogeneous histopathology datasets by aligning important neural network layers, several enhancements can further strengthen its accuracy, robustness, and real-world applicability. Future research may explore dynamic selection of multiple important layers, integration of stronger backbone models such as EfficientNet-B5 or Vision Transformers, and advanced data augmentation or hyperparameter tuning to boost classification performance. Incorporating differential privacy and secure aggregation would significantly improve the method's privacy and deployment readiness for medical institutions. Moreover, adding model explainability (e.g., Grad-CAM), simulating realistic client conditions such as dropouts, can enhance reliability when implemented. These extensions would make FedImp more accurate, secure, and suitable for real-world federated medical imaging scenarios.

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