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Federated Learning Models for Privacy-Preserving Cervical Cancer Screening in Low-Resource Healthcare Systems

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Abstract

Cervical cancer remains a leading cause of cancer mortality among women in low- and middle-income countries (LMICs), largely due to insufficient screening coverage and infrastructural limitations. With the increasing digitization of healthcare data and the rise of artificial intelligence (AI) in medical imaging and diagnostics, machine learning (ML) presents new opportunities for improving early detection and intervention. However, data privacy concerns and lack of centralized infrastructure pose significant barriers to traditional ML implementation. Federated learning (FL) offers a novel, privacy-preserving solution by allowing decentralized model training on distributed datasets without transferring sensitive patient data. This article explores the implementation of FL-based cervical cancer screening models in low-resource settings, examining their technical frameworks, privacy safeguards, benefits, challenges, and long-term potential for scalable, equitable care delivery.

Keywords: AI for cervical cancer detection; Privacy-preserving healthcare AI; Edge computing in cancer screening; Distributed machine learning in low-income countries; Digital health equity; Secure machine learning in global health; Collaborative model training in healthcare; Federated neural networks for image classification; Low-bandwidth AI healthcare solutions; Mobile-based cervical cancer screening AI; HPV screening using distributed AI

Introduction

Cervical cancer is both preventable and curable when detected early, yet it continues to claim the lives of over 300,000 women annually, with more than 85% of deaths occurring in LMICs [1]. The disparity in outcomes is primarily due to inadequate screening coverage, shortage of trained medical personnel, and limited access to pathology services and follow-up care [2]. Traditional screening methods Pap smears, visual inspection with acetic acid (VIA), and HPV DNA testing while effective, require infrastructure, continuous workforce training, and system-level coordination that may be unavailable in resource-constrained settings [3]. Cervical cancer remains one of the most preventable yet deadly forms of cancer affecting women globally, with a disproportionate burden in low- and middle-income countries (LMICs) [4]. Despite the availability of effective screening tools such as Pap smears, HPV DNA testing, and visual inspection with acetic acid (VIA), many health systems in resource-constrained environments face barriers to implementation, including lack of infrastructure, trained professionals, and patient follow-up mechanisms [5]. These systemic challenges contribute to late-stage diagnosis and high mortality rates in regions least equipped to respond.

Artificial intelligence (AI) has demonstrated immense potential in improving the reach and quality of cervical cancer screening by automating diagnostics, enhancing accuracy, and enabling early detection [6]. However, a critical limitation remains: the need for large volumes of high-quality, diverse medical data to train reliable AI models. In LMICs, healthcare data is often fragmented, limited in scale, and stored locally in paper-based or siloed digital systems [7]. Moreover, ethical concerns surrounding patient privacy, data sovereignty, and informed consent restrict the centralization of sensitive health data, particularly in cross-border collaborations.

Artificial intelligence, particularly deep learning models applied to digital cytology and visual inspection images, has shown promise in automating cervical cancer screening with high accuracy. However, the deployment of centralized AI models raises ethical and logistical challenges around data privacy, cross-border data sharing, and equitable representation in model training. These barriers are especially acute in LMICs, where data governance frameworks may be underdeveloped or absent [8].

Federated learning (FL) is an emerging approach that addresses these limitations by training models directly at data sources (such as rural clinics or regional hospitals) and aggregating only the model updates not the raw data on a central server. In doing so, FL offers a pathway for building robust, generalizable AI models while preserving patient confidentiality and supporting data sovereignty. In the context of cervical cancer screening, FL can empower low-resource clinics, rural hospitals, and national health programs to collectively contribute to and benefit from AI development, even in the absence of robust digital infrastructure or cloud connectivity. From automated Pap smear classification to HPV risk prediction, FL enables the creation of inclusive, privacy-conscious diagnostic models that can adapt to diverse populations and healthcare settings.

Understanding federated learning

Federated learning is a distributed machine learning paradigm wherein multiple clients (e.g., healthcare facilities) collaboratively train a shared model without exposing local data. Each client computes local model updates using its own data and shares only the encrypted parameters (e.g., weight gradients) with a coordinating server, which aggregates them to update the global model.

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Several pioneering projects highlight the feasibility of FL in healthcare:

Flower (Federated Learning Framework) and Tensor Flow Federated (TFF) have been used in medical image classification in collaborative studies. In India, federated models have been tested in rural health centers for diabetic retinopathy screening. The World Health Organization's Digital Health Strategy encourages the exploration of AI and privacy-preserving technologies for global health equity. In cervical cancer, pilot FL projects in Latin America and Sub-Saharan Africa are exploring cytology model development without centralized data transfer, showing early promise in balancing performance and privacy.

Conclusion

Federated Learning holds transformative potential for privacy-preserving, AI-enabled cervical cancer screening in low-resource healthcare systems. By enabling decentralized model training across geographically dispersed institutions, FL addresses key barriers to data sharing, enhances model diversity, and empowers under-resourced clinics to contribute to and benefit from AI advancements. Its implementation aligns with the principles of digital equity, patient autonomy, and ethical AI, making it a compelling approach for global health innovation.

With continued investment in digital infrastructure, collaborative governance, and capacity building, FL can become a cornerstone of smart, inclusive cervical cancer control strategies bringing life-saving diagnostic tools to the women who need them most, regardless of geography or economic status.

Federated learning stands as a promising enabler of AI-powered cervical cancer screening in low-resource healthcare systems. It aligns technological innovation with ethical responsibility, offering a scalable and secure model for expanding access to early cancer detection and ultimately saving lives across the globe.

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