# Privacy-aware multi-dermoscope Skin-Lesion Classification in heterogeneous Federated Learning


### Abstract

Federated learning (FL) enables collaborative model training across medical institutions without sharing sensitive patient data, making it essential in privacy-restricted clinical settings. However, medical datasets vary substantially across devices and centers, leading to divergent client updates that can reduce federated performance. This problem is particularly pronounced in dermatology, where images are acquired with different dermatoscopes—contact polarized, contact non-polarized, and non-contact polarized—introducing device-dependent heterogeneity. Moreover, class imbalance and uneven domain representation, common in medical datasets, further challenge robust model training. We focus on five skin-lesion classes (actinic keratosis, basal cell carcinoma, melanoma, nevus, and seborrheic keratosis) curated from the ISIC Archive, representing a realistic multi-device, multi-center scenario. To address these challenges, we propose a domain-aware FL framework that employs client-specific Batch Normalization layers to handle device heterogeneity and augments each client with class-conditional synthetic data to mitigate class and domain imbalance. Our goal is to approach the performance of a centralized model trained on all private data, and experiments demonstrate that our approach closely matches this upper bound, providing a practical strategy for privacy-preserving dermatological model training under heterogeneous and imbalanced conditions.


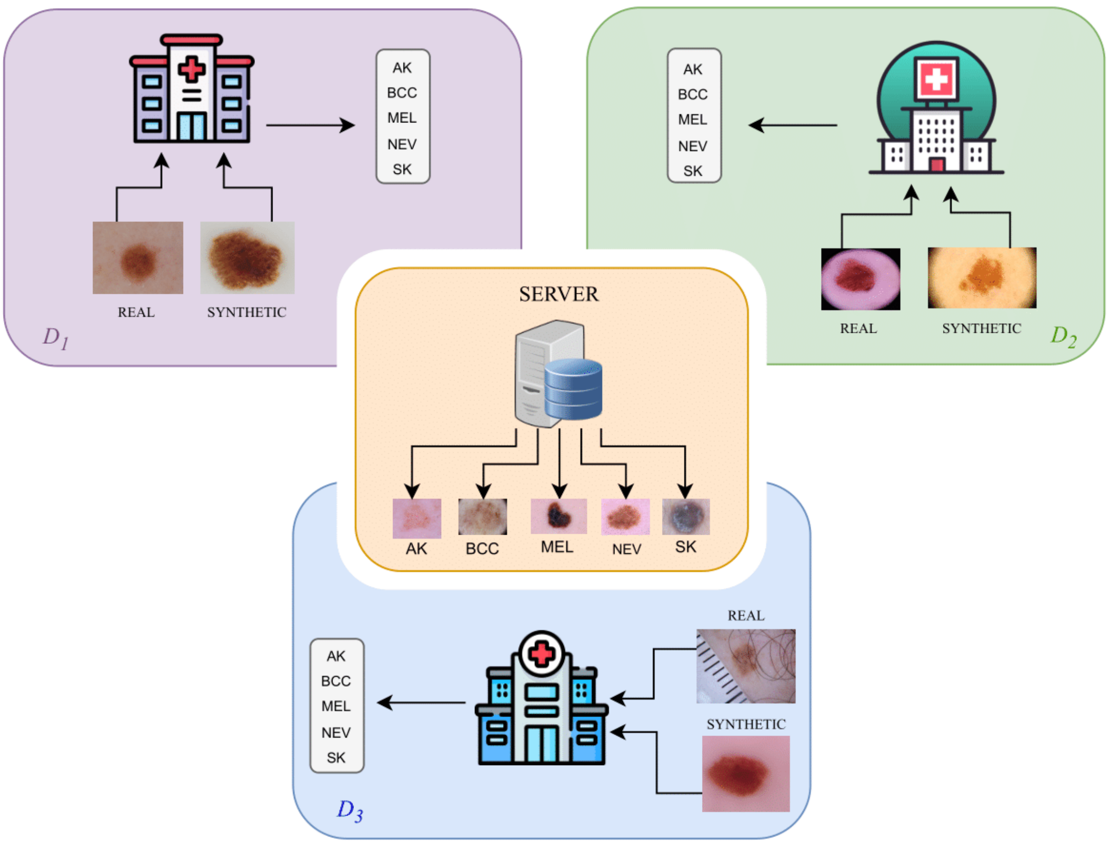


Figure 1: Framework structure of the proposed method.