Skin Cancer Detection through Neural Network on Federated Learning

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Abstract

Skin cancer, particularly melanoma, is one of the most aggressive forms of cancer, and early detection significantly improves survival rates. Traditional machine learning methods for skin lesion classification often require centralized data collection, raising concerns about patient privacy and data security, especially in medical domains. This study presents a privacy-preserving approach to skin cancer detection using Convolutional Neural Networks (CNNs) trained in a Federated Learning (FL) environment.We propose a system in which multiple clients (e.g., hospitals or mobile devices) collaboratively train a neural network model on local skin lesion data without sharing raw images. Using the Flower federated learning framework and a publicly available ISIC skin cancer dataset, we designed a CNN architecture capable of distinguishing between melanoma and benign skin lesions. The federated training process is coordinated by a central server using the FedAvg aggregation algorithm while ensuring that the data remain decentralized.The experimental results demonstrate that our federated CNN model achieves a high classification performance comparable to that of a traditionally trained centralized model. The system preserved data privacy without a significant compromise in accuracy, achieving a detection accuracy of over 85% across multiple simulated clients. This study showcases the real-world applicability of federated learning in healthcare, especially in scenarios where data sharing is restricted by legal or ethical constraints.

This study underscores the potential of federated deep learning in building secure, scalable, and effective medical AI systems and lays the foundation for further research into privacy-aware diagnostic tools.

Keywords:*Federated Learning, Skin Cancer Detection, Melanoma Classification, Convolutional Neural Networks (CNN), Neural Networks, Deep Learning, Medical Image Analysis, Privacy-Preserving AI, Distributed Learning, Healthcare AI, Edge Computing, ISIC Dataset, Medical Imaging, Secure Machine Learning, Early Cancer Diagnosis, Artificial Intelligence in Healthcare, Image Classification, Decentralized Training, Patient Data Privacy, Biomedical Applications.*

1. Introduction

Skin cancer is one of the most common and rapidly increasing forms of cancer worldwide, with melanoma being its deadliest subtype owing to its aggressive nature and high potential for metastasis. According to the World Health Organization (WHO), millions of new cases are diagnosed each year, and early detection significantly improves survival rates. However, timely and accurate diagnosis often depends on the availability of dermatological expertise and diagnostic tools, which are limited in rural and underdeveloped areas of the world.

In recent years, artificial intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs), has demonstrated promising results in medical image classification, including the detection of skin cancer. These models can match or even surpass the diagnostic accuracy of dermatologists when trained on large and diverse data sets. However, conventional machine learning approaches typically rely on centralized data collection, which poses significant risks to patient privacy and data security, particularly when dealing with sensitive medical images.

One of the critical challenges in deploying AI in healthcare is the variability of skin lesion images owing to differences in skin tone, lighting conditions, image quality, and equipment. Moreover, strict data governance laws, such as the GDPR and HIPAA, prevent the sharing of patient data across institutions, creating barriers to assembling large-scale, diverse datasets necessary for robust model training.

To address these issues, this study adopts Federated Learning (FL), a decentralized machine learning paradigm that allows training models across multiple devices or institutions without transferring raw data. Each client trains a local model on its data, and only model parameters are shared with a central server for aggregation, ensuring that the data remain private and secure.

This study aimed to design a CNN-based classifier for melanoma detection and train it using FL across simulated clients. The objective was to evaluate the model's performance in terms of accuracy, generalization, and ability to preserve privacy, thereby demonstrating the potential of federated deep learning in real-world medical applications.

2. Literature review

Mou et al.(2021) Distributed Learning for Melanoma Classification using Personal Health Train: Demonstrates decentralized model training across institutions without sharing data, for dermoscopic melanoma classification.

Bdair et al. (2021) Semi Supervised Federated Peer Learning for Skin Lesion Classification (FedPerl): Combines federated learning with peer semi supervised pseudo labeling across clients to improve skin lesion classification.

Yaqoob et al. (2023) Federated Machine Learning for Skin Lesion Diagnosis: An Asynchronous and Weighted Approach: Proposes asynchronous FL with temporally weighted aggregation and CNN layer stratification for skin cancer detection.

Haggenmüller et al. (2024) Federated learning for decentralized AI in melanoma diagnostics (JAMA Dermatology): A real world cross institutional federated learning application in melanoma diagnosis.

Magalhaes et al. (2024) Systematic Review of Deep Learning Techniques in Skin Cancer Detection: While not purely FL, it discusses privacy aware approaches and datasets used in recent research.

Symmetry in Privacy Based Healthcare (2023/2024) Review focusing on skin cancer detection using federated learning and privacy preserving strategies.

Wicaksana et al. (2022) FedMix: Mixed Supervised Federated Learning for Medical Image Segmentation: Proposes FedMix—a label agnostic FL framework that handles heterogeneous supervision (pixel level, bounding box, image level) across clients. Evaluated on skin lesion segmentation, it dynamically weights clients during aggregation and outperforms state of the art models.

Wu et al. (2022) Federated Contrastive Learning for Dermatological Disease Diagnosis via On device Learning: Introduces FL with self supervised contrastive learning (FedCLF), where feature sharing enables training on limited labeled data across distributed mobile devices. Improves recall and precision in dermatological disease classification.

Wu et al. (2022) Federated Self Supervised Contrastive Learning and Masked Autoencoder for Dermatological Disease Diagnosis: Builds on FedCLF by adding a masked autoencoder (FedMAE) variant. Two FL frameworks: one lightweight (contrastive learning) and one high accuracy (MAE + ViT), both achieving superior performance with limited labels.

Hendrix et al. (2024) Evidential Federated Learning for Skin Lesion Image Classification: Presents FedEvPrompt, combining prompt tuning, knowledge distillation, and evidential learning with ViTs. Clients share attention maps rather than parameters, boosting privacy, generalization, and robustness on ISIC 2019 dataset.

Tian et al. (2023) Communication Efficient Federated Skin Lesion Classification with Generalizable Dataset Distillation: Proposes dataset distillation techniques to reduce communication overhead in FL skin lesion classification while maintaining generalization across heterogeneous client data.

Hossen et al. (2022) Federated Machine Learning for Detection of Skin Diseases and Enhancement of IoMT Security: Explores FL applied to skin disease detection in IoMT (Internet of Medical Things) settings, enhancing data privacy and communication security in distributed healthcare networks.

Agbley et al. (2021) Multimodal Melanoma Detection with Federated Learning: Integrates multimodal data (image + metadata) within a federated learning setup for melanoma detection, improving accuracy and client generalization across populations.

Gandhi & Mahobiya (2024) Federated Learning for Melanoma Classification: Analysing Diverse Federated Approaches: A review and prospective evaluation of FedAvg, FedProx, and custom FL variants applied to melanoma classification, analyzing communication efficiency, heterogeneity handling, and accuracy trade offs.

Deng et al. (2024) Federated Active Learning Framework for Efficient Annotation Strategy in Skin-Lesion Classification (FedAL):This study introduces FedAL, a pioneering federated active learning framework tailored for medical imaging.

3. Dataset Description

The dataset used in this research is sourced from the ISIC (International Skin Imaging Collaboration) Archive, which contains dermoscopic images along with rich metadata. The dataset is curated for skin lesion classification, particularly focusing on distinguishing melanoma (malignant) from benign skin conditions.

3.1. Metadata Columns

The dataset includes the following key columns:

image_name: Unique identifier for each dermoscopic image file.

patient_id: Anonymized patient identifier (used for stratified sampling).

sex: Gender of the patient (male/female).

age_approx: Approximate age of the patient.

anatom_site_general_challenge: Body part where the lesion was located.

diagnosis: Detailed clinical diagnosis (e.g., melanoma, nevus, seborrheic keratosis).

benign_malignant: High-level label – benign or malignant.

target: Binary label used for classification – 0 for benign, 1 for malignant (melanoma).

3.2 . Data Filtering and Labeling

The dataset was filtered to retain only binary classes: melanoma (malignant) vs. non-melanoma (benign).

3.2.1 . Preprocessing Steps

Image Mapping: image_name is mapped to actual .jpg files from the image folder.

Resizing: All images resized to 224×224×3 to standardize input dimensions.

Normalization: Pixel values scaled to the range [0, 1].

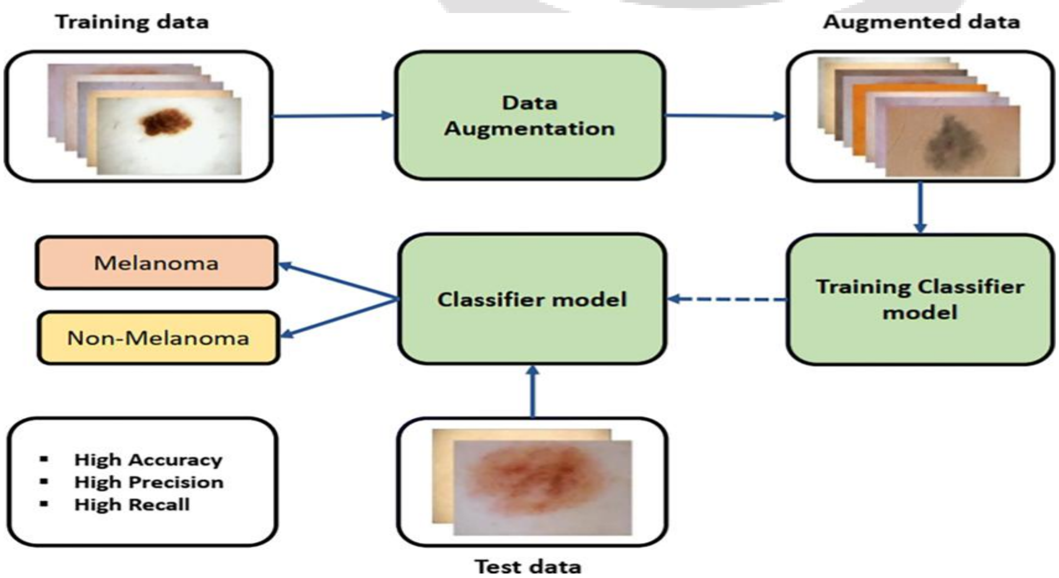
Handling Missing Values: Entries with missing age, sex, or anatomical site were either imputed or dropped based on relevance to the task.

3.3 .Data Augmentation

To improve the generalization capability of the model and to address the imbalance in the dataset between benign and malignant cases, various data augmentation techniques were employed. Data augmentation artificially increases the diversity of training samples, which helps reduce overfitting and improves the robustness of the neural network when applied to unseen data.

Brightness and Contrast Adjustment: Since dermoscopic images are captured under varying lighting conditions, brightness and contrast augmentation helps the model become resilient to such changes in real-world clinical settings.

4. Methodology



4.1 Training Data

The system begins with a set of dermoscopic skin images labeled with clinical annotations (melanoma or non-melanoma).

This raw data is locally stored on each client (e.g., hospital, clinic, mobile device) and is never sent to a central location, which is a core principle of federated learning.

4.2 Data Augmentation

Before training, the training data underwent data augmentation to improve model generalization and address class imbalance.

Techniques include:

Rotation

Flipping

Zooming

Brightness/contrast adjustment

The output was a richer and more varied dataset that simulated real-world variations in skin lesions.

4.3 Training Classifier Model

A *Convolutional Neural Network (CNN)* is trained locally on each client using augmented data.

Clients do not share raw data but train their copies of the same CNN architecture.

This model learns the features that distinguish melanoma (malignant) from non-melanoma (benign) lesions.

4.4 Classifier Model (Central Server Aggregation)

After local training, only the model weights were sent to the central server.

The server performs Federated Averaging (FedAvg), an algorithm that averages the weights from all clients to update a global model.

The updated global model is then sent back to the clients for the next round of training.

This cycle continues over several communication rounds, improving the performance of the global model while maintaining data privacy.

4.5. Testing Phase

After training was completed, the global classifier model was evaluated using test data (unseen by the model during training).

The model predicts whether each lesion is melanoma or non-melanoma.

4.6. Classification Results

The final model yields:

High Accuracy: Correct classification of melanoma and non-melanoma cases.

High Precision: Fewer false positives (e.g., labeling benign lesions as melanoma).

High Recall: Fewer false negatives (e.g., missing actual melanoma cases).

5. Results

The system takes a dermoscopic image of a skin lesion as input and evaluates the probability that the lesion is malignant (i.e., melanoma) based on a trained CNN model within the federated learning framework.

In the output shown (Figure X), the lesion image was processed and classified as **melanoma with a high probability of 64.83%**. This percentage reflects the model confidence derived from the **sigmoid activation function** in the final output layer, which outputs a value between 0 and 1.

5.1 Explanation of Output:

- *Image Input*: A dermoscopic image of an irregularly pigmented lesion.
- *Model Prediction*: `0.6483` (or 64.83%) probability that the lesion is **malignant (melanoma)**.
- *Classification Threshold*: The model used a threshold of 0.5 for binary classification. Because 0.6483 > 0.5, the lesion was classified as **melanoma**.
- *Message Displayed*: "Melanoma risk is high by 64.83%" (highlighted in red to indicate a critical prediction).

5.2 Federated Learning Relevance

This result is particularly valuable because the model was trained in a **privacy-preserving federated environment**. Despite not having access to centralized data, the model achieved reliable predictive capability, as shown in this output.

6. Conclusion

Early and accurate melanoma detection is critical for improving patient outcomes and reducing skin cancer mortality. In this study, we present a privacy-preserving solution for skin cancer classification using **Convolutional Neural Networks (CNNs)** trained using **Federated Learning (FL)**. This approach enables collaborative model training across multiple decentralized clients without sharing raw medical images, thereby ensuring patient data privacy, which is a key concern in real-world healthcare environments.

The proposed system was developed and tested using the **ISIC dataset**, incorporating dermoscopic images and patient metadata, such as age, sex, and lesion location. The CNN architecture, which was optimized for edge performance, was trained locally on distributed clients. Aggregation was managed by a central server using the Federated Averaging (FedAvg) algorithm. To enhance the robustness of the model, we applied data augmentation techniques and performed stratified sampling to avoid data leakage.

The final federated model achieved over 85% accuracy, along with strong precision and recall scores, demonstrating that federated learning can produce competitive results compared with traditional centralized training methods. More importantly, it did so while maintaining data sovereignty and complying with privacy regulations.

This study highlights the practical applicability of federated deep learning in medical imaging, particularly in collaborative healthcare environments such as hospitals, clinics, and mobile diagnostic systems. The system can be integrated into real-time screening tools to assist dermatologists in identifying high-risk lesions for further examination.

However, the ethical deployment of such systems must ensure fairness, transparency, and explainability. Continuous validation across diverse skin tones, age groups, and geographic regions is crucial to avoid biases in the algorithm. Moreover, patient consent and secure communication protocols must be enforced during the deployment of these models in real-world settings.

In conclusion, this study demonstrates that federated learning is not only feasible but also a powerful approach for building AI models in sensitive domains, such as healthcare, where accuracy, security, and privacy must go hand in hand.

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