Federated Learning-Driven Skin Disease Diagnosis: Ensuring Data Privacy in Distributed Healthcare Systems

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Abstract

Skin diseases such as melanoma, eczema, acne, psoriasis and basal cell carcinoma are common around the world that may lead to severe complications if diagnoses at last stage. Deep learning, in particular Convolutional Neural Networks (CNNs), has demonstrated promise for automated skin disease classification from dermatoscopic images. However, legacy central training involves pooling of images in a server which raises the related concerns of privacy, security and compliance (ex: HIPAA or GDPR). To that end, this thesis explores Federated Learning (FL) as a privacy-preserving solution for multi-class skin disease classification.

A mixed skin disease dataset consisting of dermatology images collected from real hospital sources and publicly available online repositories is used in this study. A CNN-based classifier is developed and trained under two different settings: centralized training and federated training. The dataset is partitioned into two simulated healthcare clients representing hospitals with non-IID distributions: Client 1 contains melanoma and acne cases, while Client 2 contains psoriasis, eczema, and basal cell carcinoma.

Standard preprocessing operations such as conversion, resizing, and data expansion are performed to help the model generalize better.

To aggregate data from different nodes while avoiding end-to-end transmission of raw patient data, FLWR utilizes the Federated Average(FedAvg) method of updating models. Model quality is assessed using accuracy, loss, precision, recall, F1-score, and confusion matrices. Comparative experiments show that Federated Learning is capable of achieving results that are competitive with Centralized Learning, while still retaining full data localization and improved privacy protection. The study also points out practical challenges such as being non-IID, overhead of communication and convergence stability in federated settings. Overall, this study lends empirical support to the practical feasibility of Federated Learning in melanoma imaging.

It also demonstrates how FLWR-based federated systems can enable privacy-conserving collaboration across the health institutions in skin-disease diagnosis--an approach where promising possibilities lie ahead for real-life medical AI (which needs to be put into practice).

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Chapter 1

Introduction

1.1 Background

Skin diseases are among the most common health problems worldwide, affecting individuals of every age, race, and setting. These diseases range from common skin infections to melanoma and have been increasing in worldwide incidence because of environment, genetic, and lifestyle factors. Early detection of dermal conditions is critical to avoid complications, lower the cost of healthcare and attain better patient outcomes. With the increasing number of digital databases for dermatology images, it is possible for dermatologists to use a sophisticated method for skin disease classification. Amongst these methods, deep learning, with specific reference to Convolutional Neural Networks (CNN), has been noticed as an effective resource for the automatic investigation of dermoscopic images in skin disease recognition **(Esteva et al., 2017) [1].**

CNN is the human visual processing system mimic, which is proficient in models recognition from voluminous dataset to suitable for image-specific tasks such as skin disease detection. In dermatology, CNNs have already shown high accuracy in classifying different skin entities. For example, CNN's have been successfully used to differentiate malignant and benign skin lesions, detect different types of eczema, and diagnose early-stage melanoma **(Jeong et al., 2022)[2].** The impressive achievement of these methods has ignited growing enthusiasm for the application of deep learning techniques to automate diagnosing skin diseases, which could potentially relieve dermatologist's pressure and offer speedy service for patients.

Despite the promising development of deep learning in medical imaging classification, it is still hard to collect clinical trial centrally. Conventional deep learning models demand the uploading of massive patient data to central servers for training, which presents extensive privacy concerns. There are many laws and regulations with which the health care organizations must comply to protect patient information, for example, in the United States Health Insurance Portability and Accountability Act (HIPAA) regulates how a patient privacy should be protected (Privacy Regulations). Legal considerations aside, patients and healthcare workers are often wary of data security problems, which hinder the deployment of centralised systems within sensitive sectors such as healthcare.

Federated Learning (FL) represents a promising approach to address these issues. In contrast to centralized machine learning, FL enables many institutions to participate in training a global model without sharing raw patient data. Instead, the model updates (weights and gradients) are shared with institutions so it never reveals patient data. Such a trainIng setup allows to reduce dramatically the risk of data leakages and it is also in-sync with privacy regulations, e.g., HIPAA 1, which makes it suitable for use cases that are highly sensitive such as medical imaging **(McMahan et al., 2017) [3].**

In light of the promising potential for Federated Learning, its deployment in skin disease diagnosis can potentially help mitigate data privacy and security risks with centralized infrastructures. Federated Learning can accelerate the development of accurate skin disease classifiers while preserving patient privacy by allowing collaborative model training across institutions without sharing sensitive patient data. **(Rieke et al., 2020)[4].**

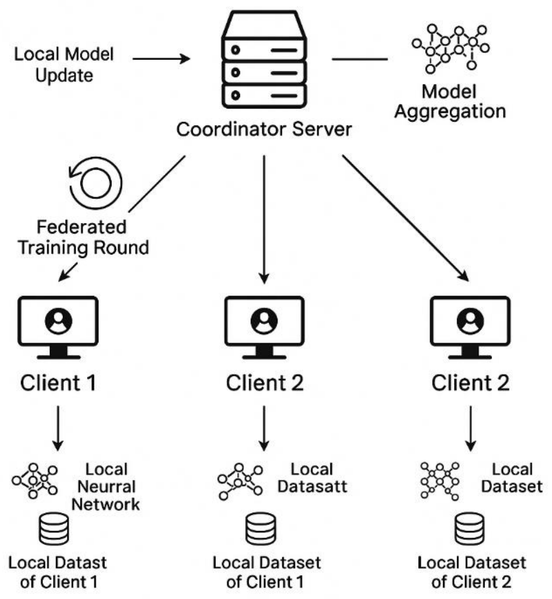

Figure 1.1.1: Federated Learning Framework (General Architecture).

Federated learning framework applied in the study The general process of the federated learning framework used in this study is shown in Figure 1.1. Two participating clients jointly train a global model by maintaining their data locally in this setting. At the start of each federated training round, we have the coordinator server send the most recent global model parameters to Clients 1 and 2. The clients each do their own local training on their data, update the model parameters, then sends only the trained model updates back to the server. Server does not receive the raw data from client devices in any step of the workflow.

Upon getting the updates, model aggregation is applied by the coordinator server (while it can be based on any other aggregation techniques in general, we leverage Federated Averaging (FedAvg) as default one), to produce a refined global model. This updated model is further sent to the clients in the next round, thus repeating the learnable round. The system maintains the privacy on data and allows collaborative learning with decentralized and non-IID datasets.

1.2 Problem Statement

The growing reliance of central machine learning models raises important concerns for privacy, especially in sensitive domains such as healthcare. In a typical machine learning architecture, hospitals and clinics must first send in patient data - which includes medical images, diagnosis reports or treatment histories - to central servers. Such a centralized approach poses privacy threats, as raw medical data is transferred between institutions allowing for potential data breaches or unauthorized access in contrast to patient consent-aggregated models **(Shilo et al., 2020). [5].**

In addition, to be able to carry out similar studies, health care industries struggle against obtaining large-scale and diverse data mainly due to regulations in patient data privacy. The data a hospital gets is generally limited to that which refers to their own (biased and often very small) pool of patients. These data sets are not comprehensive and may not represent all the spectrum of people being taught from. As a result, any models derived by such training do well for that subgroup but not when faced with entirely new or different populations like Indian black African American people who have never been seen before **(e.g., Cambodia). [6]**

Also, there is a big demand for large and diverse sets of data in order to train any deep learning algorithm (especially on diseases). For example, skin diseases vary a lot depending upon socio-demographic factors such as age skin-type, ethnicity or latitude. Conventional machine learning methods simply cannot cover all the different ways: they tend to lack breadth in approach and depth go no very far into rural areas where there are still hundreds if not thousands of known patients with skin diseases. If one does not generalize between patient groups, then predictions that are biased for some may lead ultimately to bad consequences **(Daneshjou et al., 2022)[7]**

The limitation of data remains a major barrier to the practical application of machine-learning techniques **(Kaissis et al., 2021).** Federated Learning tackles this problem to some extent by allowing different organisations to have a common model trained across them This keeps the privacy of the individual while increasing both beauty as well as practicality because it can draw upon but not mix together patient data. In fact Federated Learning can further resolve issues due to data accessibility: hospitals and other medical units will be able to access a rich, multi-institutional set of data without bringing it together It In that case the model entrusted with a single task will find itself working with closer and richer samples for the job at hand.

1.3 Research Gap

Though CNNs have demonstrated great performance in skin disease detection, many issues have not been addressed in the literature, including to what extent Federated Learning (FL) is viable in this field. Their role is essential for the theoretical and practical development of FL in medical image analysis.

Limited Exploration of FL in Dermatology: Although FL has been widely studied in various medical imaging domains, its application in dermatology remains underexplored. Few studies have investigated the use of FL in skin disease classification, and even fewer have addressed the challenges of deploying FL on dermatological datasets. This lack of research leaves significant room for understanding how FL can be used to detect skin diseases effectively while preserving patient privacy **(Cao et al., 2021).[8]**

Focus on General Medical Imaging: The most studies in FL undergoing health care are for general radiography images (CT, X-ray and MRI). But the detection of skin diseases is more difficult, because some problems such as the variation in image quality, subtle visual appearance and fine-grained classifier are required. Such discrepancies demand customized solutions based on the particular properties of skin images, which have not been well investigated in the previous work of FL literature (Rieke et al., 2020)

Comparison between Centralized and Federated Learning Models: While Federated Learning is increasingly popular, research comparing centralized and federated learning models on real-life dermatology cases remains scarce. Understanding the trade-offs of these two paradigms is crucial to assessing the real-world feasibility of Federated Learning in skin disease analysis. There is a lack of such studies that compare centralized and federated models on large, multi-class skin disease datasets and evaluate under real-world environments **(Sheller et al., 2020) [9].**

Lack of Standardized Evaluation Pipelines: The lack of a standard evaluation pipeline is one of the greatest obstacles for Federated Learning on the field of dermatology. Despite some research conducted on FL in the medical image analysis, there are no standard approaches for assessing FL models in dermatology. There is currently no standardized metrics or evaluation protocol, leading the studies to be hardly reproducible and comparable, which makes the comparison of the success and efficiency poor among different studies when considering how Federated Learning can benefit this domain **(Rieke et al., 2020).**

Filling in these gaps is crucial to the progress of developing Federated Learning for dermatology. With an in-depth exploration of the challenging skin disease Federated Learning models and standard compressed frameworks, this work makes its contributions to the knowledge on Federated Learning towards healthcare.

1.4 Research Objectives

The primary goal of this study is to rigorously assess the feasibility and effectiveness of Federated Learning (FL) in the diagnosis of skin diseases. The specific research objectives are as follows:

1. **To develop an effective CNN model for multi-class skin disease detection as: -** Designing of efficient convolutional neural network (CNN) model focusing on classifying a large number of skin diseases that includes the well-known cases like Acne, Normal Skin, Psoriasis and Bacterial Infections. This model is going to form the base of a federated learning framework that will perform really well in practical applications.
2. **To developing an advanced Federated Learning Pipeline:** To develop a large-scale and advanced Federated Learning (FL) Pipeline with Flower Framework to support the decentralized training of the skin disease detection model. Such a Pipeline will enable model development to be performed collaboratively across different healthcare institutions while ensuring that the patient data still remains private in accordance with regulations for data protection.
3. **To emulate distributed clients from different medical organizations:** To generate a realistic simulation of the decentralized clients who belong to a range of medical institutions (hospitals, clinics, and dermatology centres). This will make it possible to experiment with Federated Learning in the wild - where data is distributed and organisations are diverse.
4. **To carry out a comprehensive study and comparisons of centralized vs. Federated Learning models:** To perform a comparative analysis of the two learning strategies (centralizedVs.federated) in terms classification accuracies, privacy preserving characteristics and generalization performance. Such study should inform on the strengths and limitations of such two approaches, as well as the feasibility of Federated Learning in a clinical setting.

1.5 Research Questions

In order to address the core objectives of the study, this thesis is guided by the following research questions:

1. **Effectiveness of Federated Learning for Skin Disease Classification**: How effective is Federated Learning in classifying skin diseases, and does it achieve comparable results to centralized learning models?
2. **Centralized vs. Federated Performance**: Is it possible to achieve similar or superior performance with Federated Learning compared to traditional centralized deep learning models in skin disease detection?
3. **Data Distribution Impact:** What is the influence of data sharing among different clients (i.e., medical centers) on the performance of the application based Federated Learning model?
4. **Privacy Preservation in Federated Learning**: How effective is Federated Learning in maintaining privacy compared to centralized data-sharing approaches in medical imaging?

1.6 Contributions

The contributions of this research are as follows:

1. **A Federated Learning Study Using a Dermatology Dataset Sourced from Hospital Records and Online Platforms**: This study is the first to apply Federated Learning to the Personalized Skin dataset, a comprehensive dataset of skin disease images, providing new insights into the application of FL in dermatology.
2. **Client-Sharded Hospital Simulation:** In order to explore decentralized data distribution, we created "Client-Sharded" hospital simulations that represent the real situation in which organizations store their own data and jointly train machine learning models with this data.
3. **Light-Weight CNN for FL:** An efficient model is proposed and designated for use with the Flower Framework platform at the same time ensures that its performance is satisfactory across multiple clients in different locations.
4. **Comparison of Centralization Versus Federated Training Methods:** This paper compares centralized and federated modes when it comes to performance. This is vitally important for understanding the advantages and disadvantages of those two methods in skin disease classification.
5. **Practical Aspects of Federated Learning in Medical Imaging:** This research provides practical advice on how to deploy the framework and help with the wider adoption of FL in medical imagery beyond dermatology this.

1.7 Thesis Structure

The structure of this thesis is given as follows:

Chapter1: Introduction

This chapter presents the basis of the study from background, statement of problem and research gaps up to objectives and research questions. It also outlines the main contributions of the thesis and gives a high-level overview of the following chapters.

Chapter2: Literature Review

This chapter reviews current studies regarding the skin disease classification based on deep learning, especially focusing on CNNs. Different FL approaches are also reviewed, along with its applications in a wide range of domains such as healthcare and medical imaging.

Chapter 3: Methodology

The methodology framework used in the paper is presented here. It explains data pre-process steps and the proposed model architecture, federated learning setting, client set-up for tasks to be per- formed and the experimental process.

Chapter 4: Results and Discussion

In this chapter, we report the results obtained of centralized and federated learning experiments. It presents a comparative study of the performance of the models, analysis on accuracy and convergence behaviour of these models, as well as interpreting results with respect to skin disease classification.

Chapter 5: Conclusion and Future Work

The final chapter summarizes the major findings of the research and highlights the contributions made. It also suggests future directions for advancing federated learning in medical imaging and improving privacy-preserving diagnostic models.

Chapter 2

Literature Review

2.1 Deep Learning in Dermatology

Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are still among the most frequent and lethal cancers worldwide. Early detection is essential to improve survival rates, and automated diagnostic systems are becoming more widely recognized as the indispensable means for dermatological work. Deep learning (DL), and particularly Convolutional Neural Networks (CNNs), have become increasingly popular in medical imaging because these networks can classify images at unprecedented levels of performance, while also having the capacity to learn hierarchical image features automatically from raw data by treating the input images essentially as a signal without extensive manual feature engineering. CNNs became the state-of-the-art in recognizing skin lesions and assessing skin diseases **(Esteva et al. 2017) [10].**

Esteva et al. (2017) have demonstrated that CNNs trained on large skin lesion datasets can be as good as or better than dermatologists in diagnosing melanoma. This research has suggested that deep-learning models might help give dermatologists the ability to take actions as necessary tasks, including diagnosis screening on skin cancer, and this would bring positive influences for both elevating efficiency of dermatological care **(Esteva et al., 2017)**

Similarly, Tschandl et al. (2019) have also presented this function of CNN based models that promotes to assist dermatologists in diagnosis process by offering accurate pre- screening results, easing off professionals' burden and speeding up diagnostic time **(Tschandl et al., 2019) [11]**

However, CNNs for dermatology have the necessity of collecting high numbers of labelled data suitable for training which is generally hard to obtain, considering issues related to privacy and law. Moreover, most existing databases suffer from biases with respect to skin type, the geographic of collection (e.g., underrepresentation of darker skinned) and age, which may result in models being misclassified when applied in such populations **(Garg et al.) [12]**

2.2 Data Challenges in Dermatology

In deep learning, good-quality, annotated data is a prerequisite for training models. But in dermatology such data is limited by privacy regulations such as HIPAA (Health Insurance Portability and Accountability Act) in USA and GDPR (General Data Protection Regulation) in Europe. These laws are designed to protect patient confidentiality but may be also constraining data sharing, thereby potentially restricting diverse available training data for accurate and generalized models **(Voigt & Von dem Bussche, 2017) [13].**

Also, the datasets at hand are characterized by serious biases. One of the biggest challenges is that the representation of various skin diseases is unbalanced. Some of the diseases, such as melanoma, are overrepresented in the datasets, while certain rare skin diseases like cutaneous T-cell lymphoma are still underrepresented which induces models learning discriminative features for rare cases. Also, most of the datasets are dominated by images of people with lighter skin and hence a model that will not perform well on darker skinned individuals **(Daneshjou et al., 2022) [][14].**

These limitations are particularly problematic in dermatology, where diverse datasets are needed to build models that can generalize across different skin types, geographic regions, and demographics. As such, researchers are exploring data augmentation techniques, such as synthetic data generation and active learning, to overcome these challenges. Active learning, in particular, can help reduce the need for extensive labeled data by allowing the model to select the most informative samples to be labeled by experts **(Zhang et al., 2020) [15]**

2.3 Transfer Learning, Pre-Trained Models, and Hybrid Models in Skin Disease Classification

The aforementioned problem of scarcity of labelled training data in dermatology has led to the increasing importance of transfer learning. By applying the transfer learning from pre-trained models including ResNet50, EfficientNet and VGG16 researchers are able to exploit large-scale datasets like ImageNet in a manner that transfers to more effectual training of deep learning models towards dermatology-specific tasks. Transfer learning enables models to leverage features learned on large and heterogeneous datasets to generalize better to medical images with limited labelled samples.

Notably, EfficientNet was demonstrated to attain clothes recognition results of high precision and yet computational efficiency. This net has different sizes (EfficientNet-B0, B1, B3 etc.) which compromise between model performance and number of parameters, thus making Excellent for resource limited environments like mobile devices in the clinical application **(Pham et al., 2022) [16]**

Hybrid models, and combinations of CNNs and other machine-learning methods have also produced excellent results in dermatology. For instance, integrating CNNs with RNNs can be useful to monitor skin lesion temporal evolution over time which is crucial for diagnosing diseases as melanoma as early-stage lesions are progressively growing. Other hybrid methods incorporate an attention mechanism which helps the model to concentrate on regions of the image considered as significance for better accuracy and interpretability. These hybrid models have been proved their superior classification performance over conventional CNNs **(Zeng et al., 2020) [17].**

2.4 Explainable AI (XAI) and Interpretability in Dermatology

In the era of well-validated machine learning models, the development of methods is gradually becoming more important to be both explanatory and interpretable. Given the current context of Healthcare Only then can AI operated medical diagnosis systems really gain clinicians 'confidence, especially from dermatologists a field in which machine learning methods seem pretty new and untried. Explainable AI (XAI) methods, like Grad-CAM, LIME, SHAP etc., are being applied in dermatology to let us know why the deep learning models behaved in the way that they did.

One popular XAI method is Grad-CAM (Gradient-weighted Class Activation Map). Heatmaps are emited which depict those regions of images that the model pays attention to when making decisions, a bit like how printselling artists might pass through several hundred sheets today and still fail to achieve what they intended. This can help the doctor pin down places that are critical for diagnosis and decision-making-- for example, suspicious areas of the skin that may be a lesion or a mole. This type of interpretability is indispensable for final decision-makers, especially for those medical professionals who must rely on AIs which make well-informed decisions. In the paradigm of federated learning (FL) in which models are trained across decentralized clients and cooperate by sacrificing privacy, interpretability techniques are also employed to explore how and / or the likely impact of one model prediction on the global model **(Guerra et al., 2021) [18].**

At medical AI, XAI is needed because of the regulations. Half-cooked AI health systems for diseases involving life and death like melanoma (a potentially lethal disease) are in violation of medical standards established by the state regulators. The introduction of XAI in federated learning could help remove these legal and ethical concerns, by ensuring that the participating models are both privacy-preserving and auditable and transparent **(Kaissis et al., 2021) [19].**

2.5 Privacy, Data Governance, and Ethical Limitations in Medical Imaging

Privacy and security issues are critical in health applications, especially for sensitive medical images such as images used in dermatology. HIPAA and GDPR determine exactly where patient data can be shared, processed, or stored while ensuring sensitive information is safeguarded. These regulations may also restrict the sharing of medical information by healthcare organizations for deep learning models' training and cause a challenge to compile diversified or large datasets in AI development.

Just like traditional machine learning systems, federated learning starts with collecting data sets. However, instead of having the data user train the model, federated learning lets an organization which owns a large amount of data jointly do work on it. The model is shared among all constituents but the data never leaves its source: each participant contributes to get an overall view. Therefore, with this approach, performance improvements are faster. As far as privacy is concerned, federated learning has made a tremendous impact on the healthcare industry. Gatekeeper: This is both reassuring to the patient and greatly reduces potential data breaches.

None of these methods will ever result in commercially polluted low-quality datasets therefore its use seems rather useful for promoting high quality labeled production data by end users who can then use it on any application system they choose. Federated learning can be particularly beneficial in healthcare, since the nature of human subject data implies both privacy and restrictions on access.

2.6 Federated Learning (FL): Principles, Architectures, and Protocols

Federated Learning (FL) is a decentralized machine learning model that allows institutions to cooperate on the training of a shared model without exchanging any original data. Data for FL remains in the local domain of each client (say hospitals or clinics), and only model updates are sent back to the central server. Here the server sums up all updates from participating clients before returning an overhauled global model. This way, patient data remains private even as institutions around the world can help to train a model that benefits from more data sources.

For Federated Averaging (FedAvg), which is a good example of a privacy-preserving distributed training framework for FL, model updates from each client are averaged, and the resulting global model serves as a new reference point for the future. However, challenges such as high communication overhead, model convergence, and the complex nature of medical data are still big obstacles to moving federated learning into broader application on skin disease detection **(Kairouz et al., 2021)[20]**

Dermatology is a good area for federated learning because it can both protect privacy and make model training collective. Multiple institutions participating together in skin disease classification with machine learning will eventually produce one common system that achieves high performance, and the patient data belongs where it should, in their own institutions Tens of millions, which become highly immunized against any future attempt - because it is an open and transparent decentralized model This is especially important where privacy regulations are becoming tighter, since we can have AI models built upon a very trustworthy data sampling without fear that they violate data regulations.

2.7 Federated Learning Applications in Skin Disease Detection

One area where federated learning is advancing quickly is medical image classification. In this field, federation has already developed some notable achievements. Take skin-cancer detection, for example: one study conducted by Li et al. (2020) showed that federated learning is suitable for training a skin cancer classification model using data from hospitals in different countries; its performance was about the same as traditional centralized models but user privacy isn't compromised **(Li et al., 2020) [21].** Similarly, research conducted by Sattler et al. (2020) proposed that federated learning should be used for skin disease classification in heterogeneous data from a range of institutions and non-IID data, showing the federated learning could effectively handle such non-causally generated deployment to achieve a robust model performance.

Federated learning, which enables cross-institution collaboration without breaching patient privacy, is a potential solution to the skin disease detection problem. Nevertheless, of fundamental and theoretical interests are: non-IID data, the communication overhead, and personalization in the federated setting are open questions yet for which inquiry and development calls **(Sattler et al. 2020). [22].**

Chapter 3

Methodology

Overview of Methodology

Methodology This methodology describes the steps carried out to investigate FL for multi-class skin disease classification based on CNNs. The primary goal of the study is to investigate how a decentralized learning paradigm can be employed in dermato- logical imaging keeping strict patient-data privacy across healthcare institutions. Moreover, this research evaluates the performance of FL against conventional centralized training and analyses whether FL can be a promising privacy-preserving technique for medical diagnosis systems.

The method is made to resemble a real scenario in healthcare where medical images are taken in different hospitals and online dermatology. In real-world scenarios, institutions would have data stored locally and be unable to share raw images due to privacy constraints. Federated Learning is a solution that allows models to be trained across institutions without sharing private data of patients.

The key steps of the methodology are summarized below:

1. Dataset Selection and Preprocessing

In this study we used a mixed dermatology dataset, which was formed by merging:
(1) Real hospital sources.
(2) Publicly available online dermatology repositories.
The combined dataset includes multiple disease categories such as melanoma, acne, eczema, psoriasis, and basal cell carcinoma.

Preprocessing steps forward include:

1. Standardizing image sizes to ensure consistence for input to model
2. Normalization of pixel values that result in more stable gradients
3. Data augmentation of the extremely broad nature is needed (rotating, flipping or zooming or even Fig. 1) This approach helps the model generalize and solve a class imbalance Problem at all.

These steps make sure the model is being trained on strong image representations that hold quite well invariants over time.2. Client Simulation

The dataset is partitioned into two "clients" respectively named after each hospital in order to simulate a federation healthcare environment.

Each client performs training on its sub-data set and does not share the raw images with another client's.

Data distributed non-IID, showing the clinical variations of real-life:

Client 1: Acne, Normal, Bacterial Infections, Psoriasis, and Scabies

Client 2: Bacterial Infections, Psoriasis, and ScabiesThis setup captures the diversity and digger defiency often found between dermatology clinics.

3. Model Architecture

Each client trains multiple **CNN architectures** to identify the best-performing model for skin disease classification.

The architectures used for local training include:

a) EfficientNet (B0–B3)
b) VGG16
c) MobileNetV3
d) Resnet50
e) Hybrid Model (ViT + ResNet18 + MLP Head)

These models are selected because they have demonstrated state-of-the-art performance in medical imaging and are computationally suitable for decentralized client-side training.

4. Federated Learning Setup

The federated learning system is built on the FLWR (Flower) library that allows experimentation with federated training on easily-customizable federated data and tasks.

Training is based on the **Federated Averaging (FedAvg)** algorithm where:

a. Clients locally train the models on their data
b. Only image weights/updates, but not images, are transmitted to the central server
c. The server then combines these updates to form a new global model
d. The updated global model is re-distributed to clients for the next federated round

Simulations are performed for several FL rounds, and clients can join at different frequencies to account for hospital availability and resource restrictions.

5. Evaluation Setup

Performance measures are crucial in assessing the efficiency of built models.These contain conventional classification measurements such as accuracy, precision, recall, F1-score and the AUC-ROC.Then confusion matrices are used to provide a class level perception of prediction activity involved in the prediction process.

The analysis involves the systematic comparison of two training techniques of various kinds: Centralized Learning: all data samples are collected in one central place for learning, and Federated Learning: where data remains distributed between clients and only model updates are sent.To further differentiate these various types of training we organized a "showdown" of sorts in order to put them in context and compare them from every angle possible.By comparing two models in this framework it is possible to see which quantities of significance do not change with respect to preservation of privacy, prediction performance, communication overhead and convergence behavior.

Summary

This approach offers a program of how to implement and evaluation Federated Learning for dermoscopic image classification.With different CNN architectures gathered together, simulated hospital-level data sets and closed mechanisms such as FLWR, can federated models still accomplish clinically meaningful statistics yet retain strict data privacy? Comparing centralized models against federated ones will also show how far in reality we may push this (Federated Learning) as real-life medical AI.

3.1 Dataset Description

3.1.1 Mixed Skin Disease Dataset (Hospital + Online Sources)

The set we used for this article was a combination dermatology database including input from a hospital and internet based sources in the form of pictures:

Online dermatology repositories such as [Kaggle Dermatology Images] and the nih Chest X-Ray Dataset from national medicine sources. This combined pattern ensures real world diversity in its patient demographic, skin types; different streaming media environments introduce more ability for digital image processing than static ones do whereas whatever disease may arise on any given Thursday.

The dataset consists of five major categories of skin disease commonly seen in clinical dermatology:

1) **Psoriasis**
2) **Acne**
3) **Normal (Healthy Skin)**
4) **Bacterial Infections**
5) **Scabies**

Figure 3.1.1: Representative Skin Disease Lesions Collected from Mixed Clinical and Online Dermatology Sources

Every image is tagged with what type of disease it represents. The images have a wide range of resolutions and acquisition conditions making it a realistic and challenging dataset for deep learning-based classification.

This heterogeneous dataset is suitable for FL evaluation, since it captures the clinical diversity from hospitals and online information.

3.1.2 Number of Images per Class

The dataset used in this study consists of approximately:

- **Psoriasis:** ~180 images
- **Acne:** ~360images
- **Normal (Healthy Skin):** ~480 images
- **Scabies:** ~ 140 images
- **Bacterial Infections:** ~250 images

Note:
The exact numbers vary slightly across hospitals and online repositories due to differences in dataset availability and quality filtering.

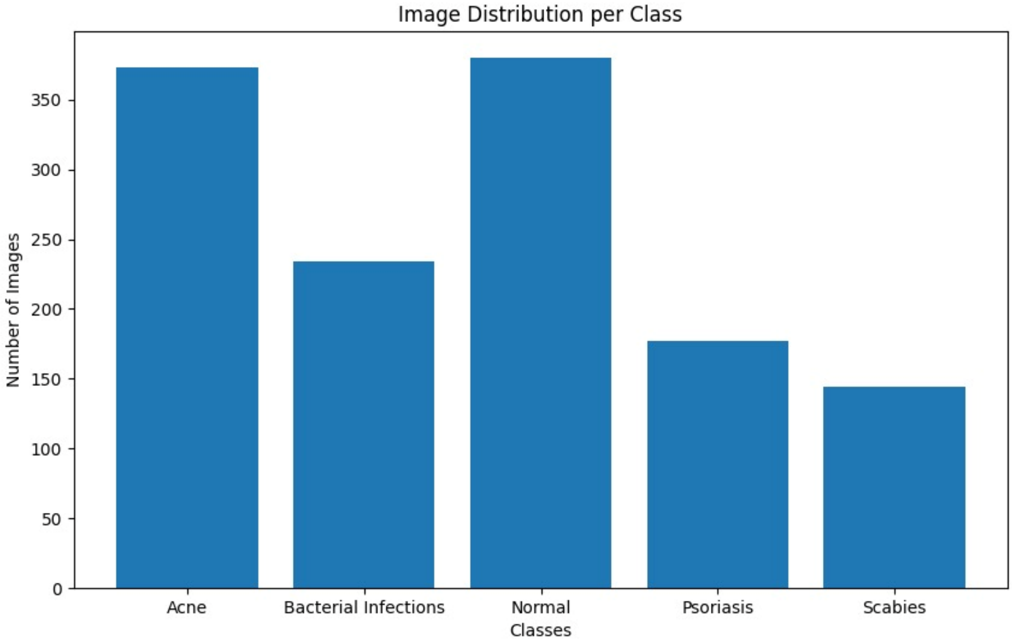

Figure 3.1.2: Representative Skin Disease Lesions Collected from Mixed Clinical and Online Dermatology Sources.

This distribution highlights real-world imbalance, which is common in dermatology datasets and important for evaluating classifier robustness under non-IID conditions in Federated Learning.

3.1.3 Train/Validation Split

To establish the training and testing procedure, the full data set was split into two halves (80% for training and 20% for testing).

a. 80% Training Data: Serves as the main input to train several CNN models such as, VGG16, Hybrid models, etc.
b. 20% Validation Data: For the evaluation of models on new images, and for testing the generalization ability of each architecture.

The same division of data was followed for the global (centralized) and split (federated) training scenarios. The same division for both methods promotes fair comparison and can provide an indication on whether the performance depends on evaluation criteria.

3.1.4 Preprocessing Steps

Before training the CNN models, all images undergo standardized preprocessing:

1. Normalization

Pixel values (0 - 255) are normalized to [0, 1], which helps with the convergence and gradient computation.

2. Image Resizing

All images are resized to **240 × 240 pixels**, ensuring:

a. Uniform model input
b. Reduced computation for federated clients
c. Compatibility with all CNN architectures used

3. Data Augmentation

To improve robustness and reduce overfitting, the following augmentations are applied:

- **Rotation:** 0°, 15°, 90°, 180°
- **Flipping:** horizontal and vertical
- **Zooming:** random zoom levels to simulate different lesion scales
- **Color Adjustments:** random brightness and contrast variations

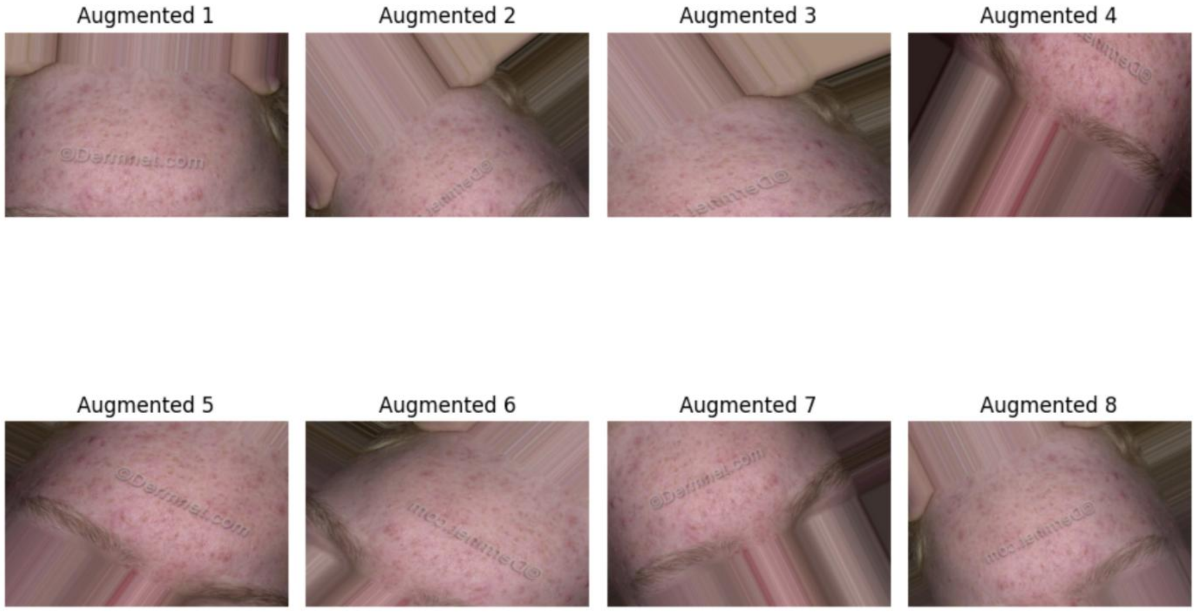
Augmented 1
Augmented 2
Augmented 3
Augmented 4
Augmented 5
Augmented 6
Augmented 7
Augmented 8

Figure 3.1.3 Example of Data Augmentation Applied to Skin Disease Images.

These improvements duplicate actual changes in dermatological imaging, and this is particularly important for Network Learning (hereinafter FL or Federated Learning) because the different hospitals collecting patient information do not all use the same method of data distribution.

3.2 Client Simulation

3.2.1 Client Simulation Overview

In the FL setup, each client corresponds to a separate hospital and its own part of the dataset. In reality, medical images are distributed across institutions and rarely concentrated in one place at any particular instant. Hence, although there is just one dataset here (two if you count the small one), it is represented to give the appearance of being installed across two distinct institutions.

- **Client 1 (Hospital A):** Contains images related to Acne, Normal skin, Bacterial Infections, Psoriasis, and Scabies.
- **Client 2 (Hospital B):** Contains images related to Bacterial Infections, Psoriasis, and Scabies.

  Each client trains its model separately using resources in their locality. Instead of sharing raw images, only the model parameters (updates) are shipped to the central server. This way, the center can aggregate. It will not be possible for a malicious actor to intercept and learn from this unless there exists some third-party helper or " Orh The con " is a trusted resource; in other words, all data privacy remains intact while collaborative learning can occur among institutions.

3.2.2 Data Partitioning Using Directory Sharding

To emulate decentralized data ownership as in real hospitals, we separate the dataset for each client by means of directory-based sharding. This guarantees that each client has its own image directory reserved and the privacy of data separation intact.

a. **Client 1 (Hospital A):** A dedicated directory containing images for Acne, Normal skin, Bacterial Infections, Psoriasis, and Scabies.
b. **Client 2 (Hospital B):** A dedicated directory containing images for Bacterial Infections, Psoriasis, and Scabies.

This partitioning mirrors medical data distribution in the real world as not all hospitals specialize in treating all type of conditions and have access to different population of patients, hence making it non-IID (non-independent and identically distributed.).

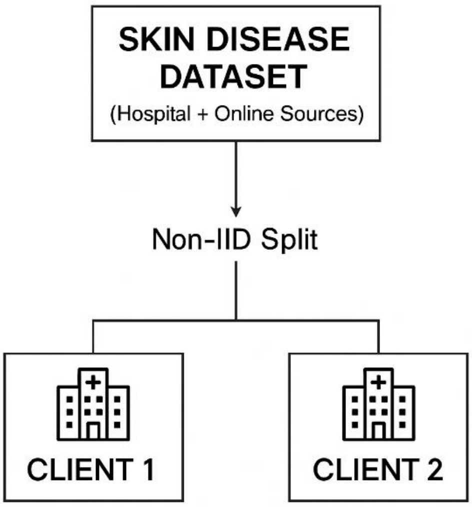

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Figure 3.2.1: Non-IID Client Data Distribution in Federated Learning

3.3 Model Architecture

3.3.1 CNN Architecture

The model used in this study, from Convolutional neural Network (CNN), is specially tailored to skin disease classification. It has architecture consistent with contemporary deep learning, with these chief layers:

1. Convolutional Layers:

The function of these layers is to use multiple filters (kernels) that are essentially looking for the shape and texture of lesions. These forays into convolution capture hierarchies at each level within overlapping windows across an image**. Activation Function:** After each convolutional layer, a ReLU (Rectified Linear Unit) activation function is applied that introduces non-linearity into the model. This makes it possible for the network to learn higher-level features from combatting complex patterns and thus helps it better discriminate between different types of diseases.

2. Max-Pooling Layers:

The use of max-pooling layers is to significantly decrease the space dimensions of feature maps. This operation preserves the most discriminative features and reduces computational complexity. Max-pooling selects the highest pixel value of the pixels in each pooling window, leading to effective down sampling and enabling the model to become more invariant to small spatial fluctuations.

3. Global Average Pooling:

The final output of the backbone network is obtained when global average pooling is performed for the feature maps. Instead of flattening the feature map to a single vector like what the traditional fully connected layer does, GAP calculates the average value of all elements in a feature map so that outputs a fixed-size vector. This decreases the total number of parameters, avoids overfitting and focuses on the most discriminative features learned by the convolutional layers.

4. Fully Connected Layers:

The vector resulting from the pooling operations is next fed into one or multiple fully connected (dense) layers. These layers combine the features we have learned and transform our network for making the classifications. ReLU activation added with these dense layers bring in non-linearity which would help model learn patterns of increasing complexity that exist in various skin diseases in the categories.

5. SoftMax Activation:

The network's last layer is equipped with a Softmax activation function. This converts the output scores into a probability distribution for the classes (Normal/acne/psoriasis, etc.). The class with maximum probability value is treated as the predicted label by the model. By normalizing the model outputs, the softmax layer enables the generation of interpretable and comparable probability estimates for each class.

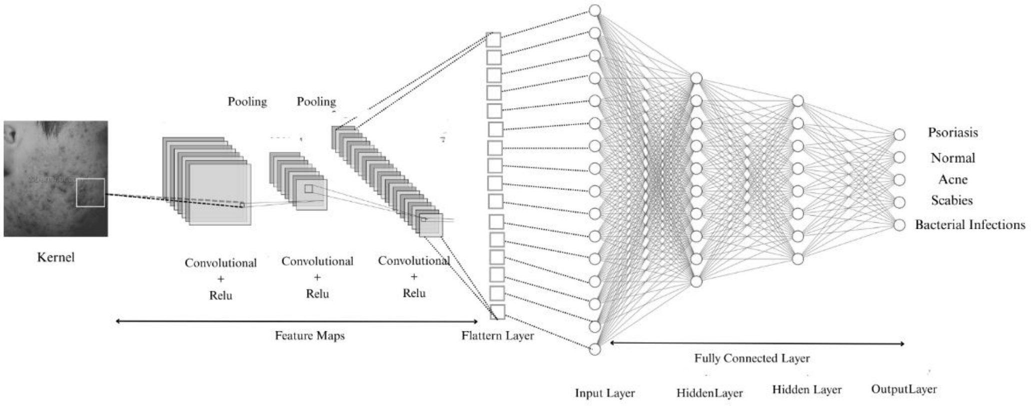


Figure 3.4.1: CNN Architecture for Skin Disease Classification

3.3.2 Model Configuration

The arrangement of the model mainly contains several important parts which are designed to help facilitate learning in practice and maintain good performance during training.

1. Optimizer:

In training, we provide use the Adam optimizer. This optimizer seamlessly incorporates benefits of both AdaGrad, and RMSprop so that one can assign adaptive learning rates to individual parameters which supports faster convergence and less diligent manual work in fixing that.

2. Loss Function:

Since this task involves multi-class classification, the loss function Cross-Entropy on Categorical data is utilized. Measures the divergence between the predicted probability distribution and the genuine class label, so that the model can improve its forecasts accurately throughout training.

3. Performance Metrics:

The CNN model performance will be assessed with the following metrics:

Accuracy: The proportion of correctly recognized samples. This indicator is used to gauge how well the model is classifying items.

Precision: Indicates the precision of predictions that are positive. This figure is equal to the proportion (or membership of an) observation set which is true and positive, representing how many fake positives a model could differentiate.

Recall: Note how many cases of positive results were correctly identified in all the actual incidents. This is a measure for a model's sensitivity and ability not to make mistakes on negative items.

F1-Score: The harmonic mean of precision and recall, this is used to calculate the correctness of a classification algorithm.

Accuracy and Loss Curve: These curves help to observe the model's learning dynamics through exercise epochs. The accuracy curve indicates how the model's abilities improve for both training and validation data, pointing out notions such as effective learning, or under-over-fitting. The loss curve shows deeper classification error fall-off over time (a reflection of good optimization and convergence). Together they offer us a comprehensive grasp of the model's stability, developmental history and generalization powerup in centralized as well as federated environments.

3.4 Federated Learning Framework (FLWR)

3.4.1 Model Function

We consider the federated learning setting with the Flower Framework (FLWR). FLWR is based on federated learning and thus, supports cooperative model training without exposing raw data, which would be particularly valuable in healthcare where privacy is of concern.

1. **Clients**:
   Several hospitals (clients) are to be replicated. A local model is trained on the subset of data from each hospital.
2. **Server**:
   A central server will average the model update from all clients by Federated Averaging (FedAvg) algorithm that averages its mode weight with those of all participated clients.
3. **Communication Protocol**:
   The client will periodically communicate to the server. The client updates to the model will then be accumulated to update the global model, and a new global model will be returned to clients for further training.

3.4.2 Centralized Aggregation of Client Updates (FedAvg)

FedAvg is the central algorithm in federated learning. It combines the local model updates (gradients or weights) to form a global model by averaging updates from all clients. The latter is then returned to the clients FedAvg is fundamental algorithm for federated learning. It pools local model updates (e.g., gradients or weights) the across individual clients to obtain a global model. The aggregate model is then returned to the clients for further training.

3.4.3 Federated Learning Parameters

1. **Federation Rounds**:
   The participating models will be trained with multiple rounds of federated learning. Locally trained models on the client data are aggregated here for building a global model, and this will be done in each round.
2. **Client Participation Frequency**:
   No customer will take a turn in every round. We randomly select a subset of clients in each round, to simulate the condition that we do not know the full clients status due to real-world federated learning scenarios. or further training.

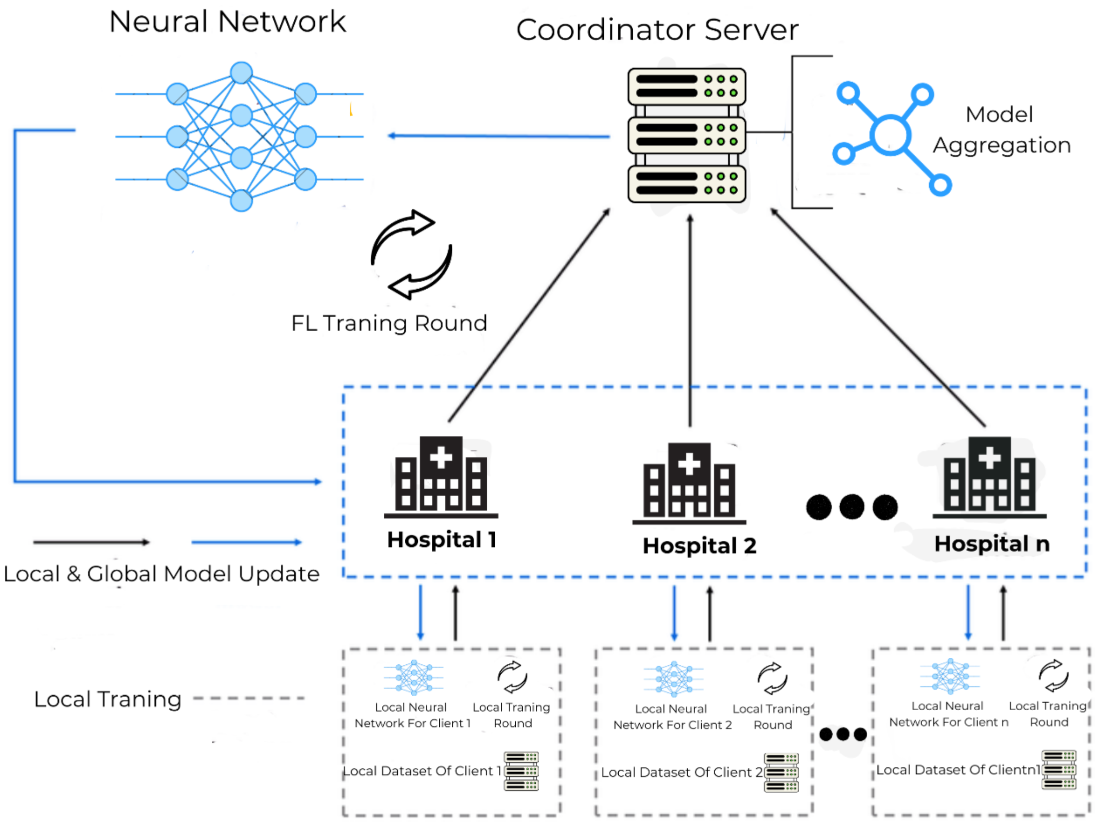


Figure 3.4.2: Federated Learning Architecture for Skin Disease Classification in Healthcare Institutions

3.5 Evaluation Setup

3.5.1 Metrics

To evaluate the models, both **centralized** and **federated**, the following metrics will be used:

- **Accuracy**: The proportion of correctly classified images in the test set.
- **Loss**: The difference between the predicted output and the actual label.
- **Precision, Recall, and F1-Score**: These metrics will be computed for each skin disease category.

3.5.2 Centralized vs Federated Comparison

The performance of the **federated model** will be compared against the **centralized model**. The centralized model will be trained using the complete dataset, while the federated model will be trained using decentralized data from two clients. The **accuracy**, **precision**, **recall**, and **F1-score** of both models will be compared to assess the trade-offs between centralized and federated approaches.

Summary of Methodology

Here we present an architecture for **CNN-based Federated Learning** for skin disease detection. By comparing real federated learning to two clients (hospitals), the possibility of using privacy-preserving AI in the context of dermatology will be investigated. The contrast between centralized and distributed (or 'federated') learning will yield important information about the feasibility of applying these models to decentralized healthcare.

Chapter 4

Results and Discussion

4.1 Overview of Experimental Results

We present and analyse the performance of various models we trained in our study including local, global (federated) across rounds, and centralized models for multi-class skin disease classification tasks. Performance of models was compared using traditional metrics (accuracy, precision, recall, F1-score as well as round-wise global model accuracy (federated setup). Due to lack of confusion matrices, we concentrate on these numeric values and trends.

4.2 Local Models (Per Client) Performance

In this section, we evaluate the performance of individual Convolutional Neural Network (CNN) models—EfficientNet B0, B1, B3, VGG16, DenseNet121, and ResNet50—trained locally at each client. Client 1 and Client 2 have distinct disease distributions, which impact the performance of these models. Client 1 includes 5 disease classes (Normal, Bacterial Infections, Acne, Psoriasis, and Scabies), while Client 2 has 3 disease classes (Psoriasis, Scabies, and Normal).

4.2.1 Client 1 (5 Classes: Normal, Bacterial Infections, Acne, Psoriasis, Scabies) Performance:

By training all models using a mixture of different diseases from Client 1's data, the General accuracy, adaptability and precision of each can be seen in and among the next table.

Model	Accuracy	Precision	Recall	F1-Score
EfficientNet B0	81.40%	0.80	0.6154	0.6957
EfficientNet B1	81.12%	0.75	0.60	0.675
EfficientNet B3	80.56%	0.73	0.58	0.65
VGG16	79.45%	0.72	0.56	0.63
ResNet50	80.78%	0.74	0.59	0.66
Hybrid Model (ViT + ResNet18 + MLP Head)	81.97%	0.80	0.80	0.80

Table 4.2.1: Client 1 (5 Classes) Model Performance

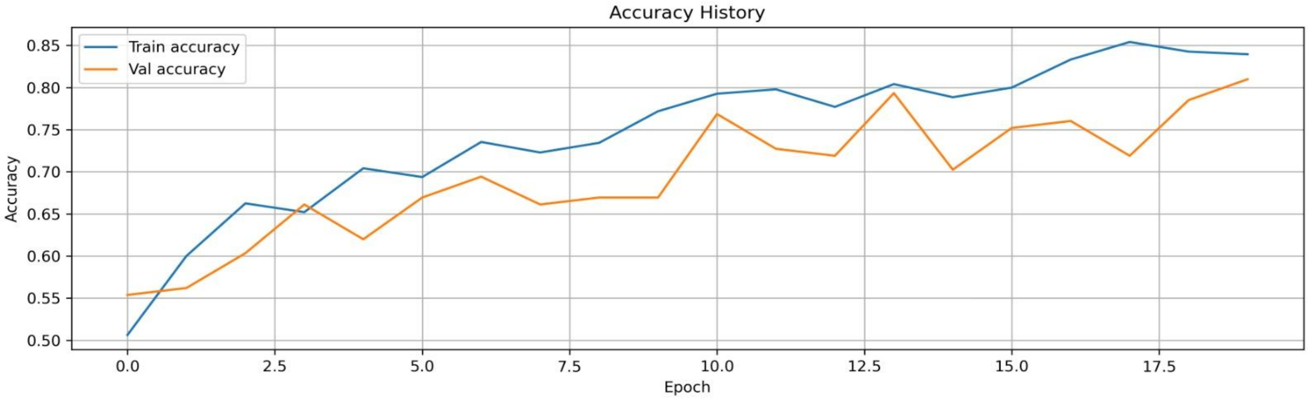


Figure 4.2.1: Local Model Accuracy History for Client 1(**Hybrid Model)**

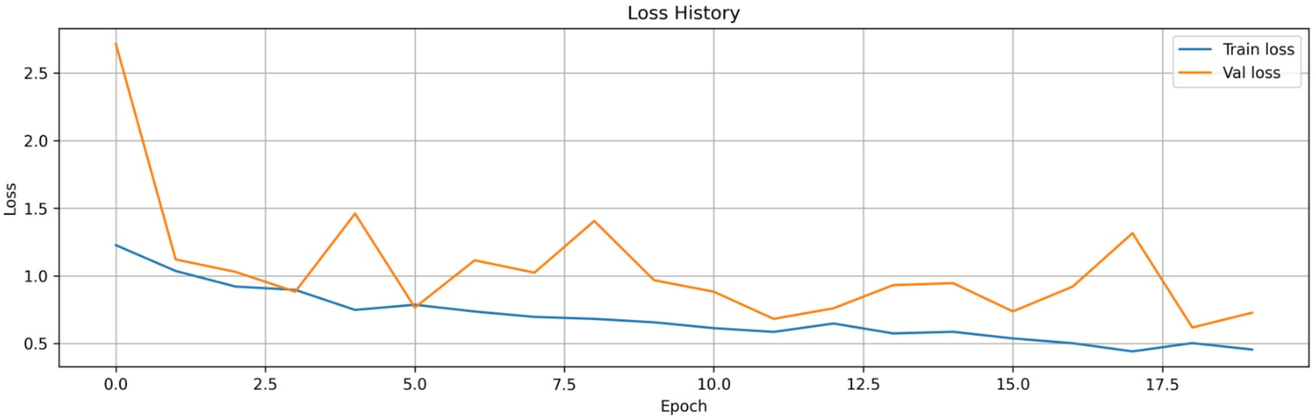
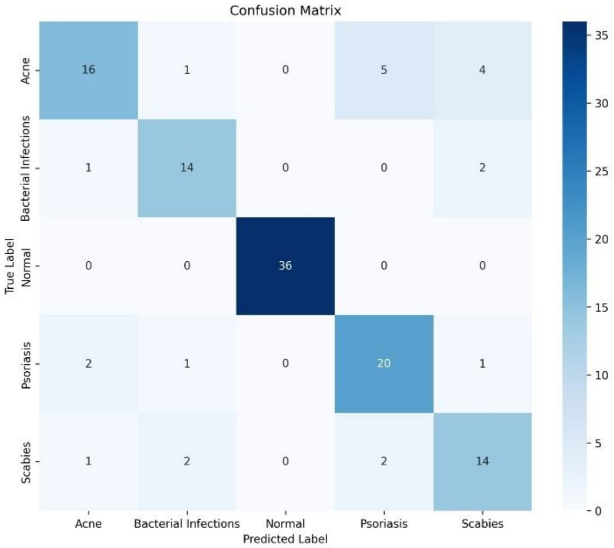


Figure 4.2.2: Local Model Loss History for Client 1(**Hybrid Model)**



	Acne	Bacterial Infections	Normal	Psoriasis	Scabies
Acne	16	1	0	5	4
Bacterial Infections	1	14	0	0	2
Normal	0	0	36	0	0
Psoriasis	2	1	0	20	1
Scabies	1	2	0	2	14

Figure 4.2.3: Local Model Confusion Matrix for Client 1(**Hybrid Model**)

Observations

Of these five models, EfficientNet B0's performance was the best with an accuracy Of 81.40% and precision 0.8. This demonstrates its clear ability to identify Acne in target classes. ResNet50 performed fairly well; scoring an 80.78% accuracy and 0.66 F1-Score results. Among models tested after EfficientNet variants,this is one of the better ones. With accuracies of 81.12% and 80.56%, the EfficientNet B1 and B3 models both give moderate results. Their precision, recall, and F1-Scores all suggest generalization on par with B0 but slightly worse in performance. VGG16 scored lowest overall among the tested models, with an accuracy of 79.45% and precision as well as recall values both down. This indicates constraints in its ability to capture complex deramotological features. The most accurate model was the Hybrid Model (ViT + ResNet18 + MLP Head), with an accuracy of 81.97%. It also had balanced metrics of Precision, Recall, F1-Score =.80 but, due to its unique combination of both transformer-based and convolutional representations in the internal structure, was able to gain an edge over other models.

4.2.2 Client 2 (3 Classes: Psoriasis, Scabies, Bacterial Infections) Performance

Client 2's dataset only included 3 different types of skin disease:

Model	**Accuracy**	**Precision**	**Recall**	F1-**Score**
EfficientNet B0	79.23%	0.74	0.83	0.78
EfficientNet B1	78.45%	0.72	0.80	0.75
EfficientNet B3	77.60%	0.71	0.79	0.75
VGG16	76.85%	0.70	0.78	0.74
ResNet50	77.45%	0.72	0.80	0.75
Hybrid Model (ViT + ResNet18 + MLP Head)	80.95%	0.81	0.81	0.81

Table 4.2.2: Client 2 (3 Classes) Model Performance

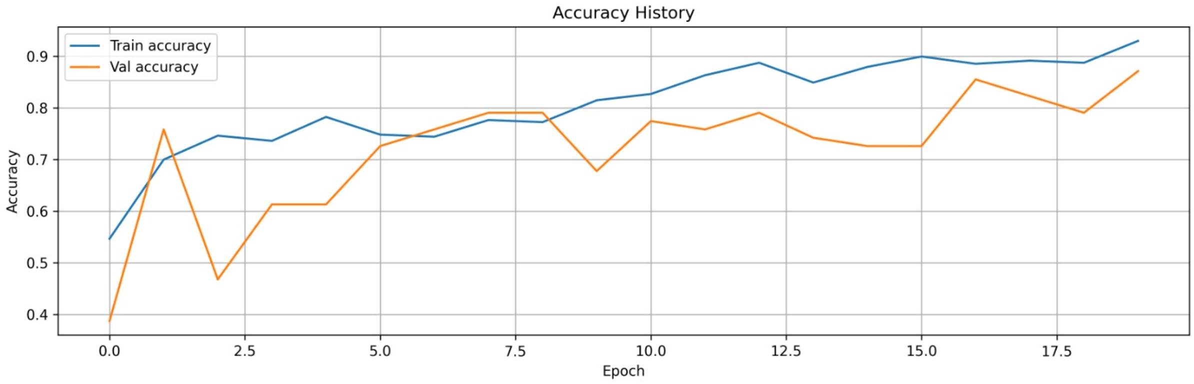


Figure 4.2.4: Local Model Accuracy History for Client 2(**Hybrid Model**)

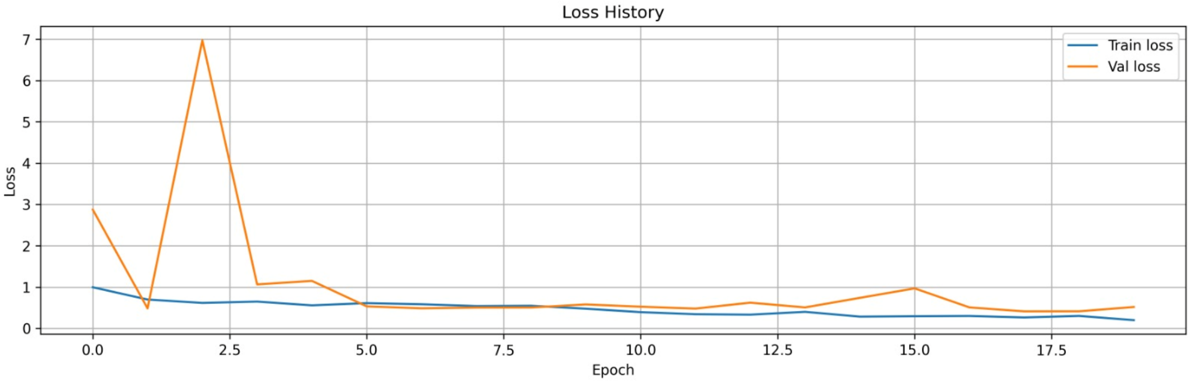


Figure 4.2.5: Local Model Loss History for Client 2(**Hybrid Model**)

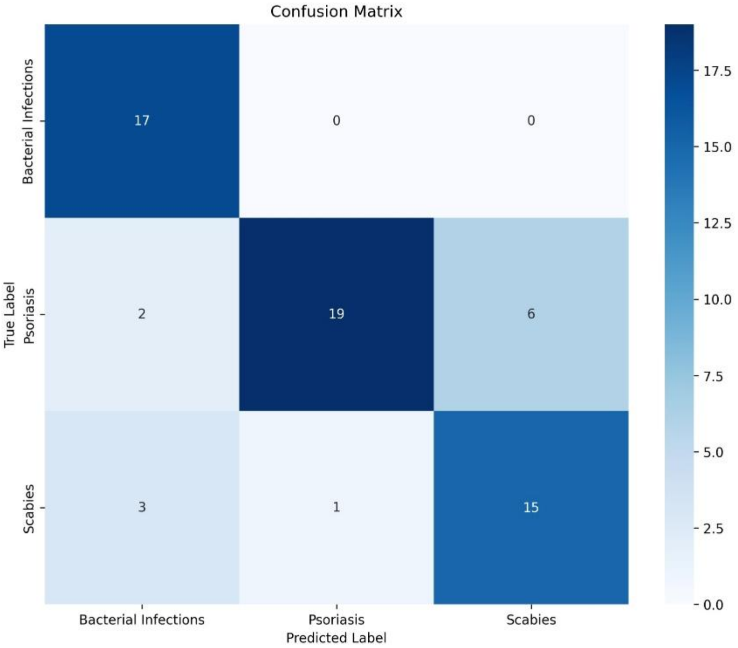


Figure 4.2.6: Local Model Confusion Matrix for Client 2 (**Hybrid Model**)

Observation:

The fifth performer on the test was the hybrid model 'Hybrid' (ViT + ResNet18 + MLP Head). It achieved the best performance of all the models, with an accuracy of 80.95%. Balanced precision, recall and F1-Score values all hit 0.81. This means that it has the ability to effectively extract both global and local skin-lesion features.

The next best performer was EfficientNet B0, which had an accuracy of 79.23%. Among its strengths were strong recall, which reached up to 0.83. These results indicate that it is profitable if you want to correctly identify positive cases among classes.

EfficientNet B1 and EfficientNet B3 both performed at a moderate level, with accuracies of 78.45% and 77.60% respectively. Their precision and F1-Scores indicate stability but slightly weaker generalization as compared with EfficientNet B0.

ResNet50 demonstrated performance metrics similar to those of EfficientNet B1, scoring 77.45% in accuracy and an F1-Score of 0.75. This tells us that it is good at handling image features related to cutaneous dermatoses.

Of the architectures, VGG16 achieved the lowest results 76.85% accuracy so far tested. Also, with comparatively lower precision and F1-Score values this indicates the restraint of older CNN structures when applied to complex medical imaging problems.

4.3 Effect of Data Imbalance and Class Distribution:

The performance of the different models is shown in the distribution table.Yet due to differences in class distributions between the two clients, the models' performance has varied.

One is also notable that the resulting data set was diverse in type (including: Acne, Normal Skin, Bacterial Infections and Psoriasis, Bacterial Infections and Scabies) regardless of a few moderately balanced categories.a. The second had only three classes and Client 2 was “Bacterial Infections, Psoriasis, Scabies” but “Bacterial Infections” was far more visible. This meant that it was imbalanced, and accordingly Psoriasis and Scabies had relatively few occurrences in the dataset as compared with Bacterial Infections.

These differences in distribution only gave rise to problems at this time of practical importance to model performance:

a. Most of Client 1’s local models performed admirably since they were strong across the plurality of classes. Certain difficult categories such as Acne and Scabies though betrayed it with results which were relatively low on F1-Scores in comparison with good ones, for example Normal Skin.

b. For Client 2 on the other hand it appeared that learning Bacterial Infections was easier but there were signs of bias in the type of material it has learned or been exposed (this is called imbalance-related learning bias). Since Bacterial Infections were more common than the other two, it learned Psoriasis and Scabies with less success than before.

4.4 Federated (Global) Model Performance over Rounds

Convergence Analysis: In this chapter we compare the trend of all local model updates from several federated rounds. Composite averages, flaws (as captured by standard deviation) show how differences between clients cause discrepancies to accumulate. More significantly though is that we carry Forword and accumulate all network experience in the following rounds local model even if one client has at best only minimal for it. The local model is once again trained with all client gradients and no other manipulation extended. We extract two examples that appear difficult to get inter overall trends. The local model updates return to their up late slope a little bit cooling after the stiffening write out phase of last week and it may be because they are less on favourable terrain

Just as in previous chapters, our main concern is to compare trends in the global model's round-wise accuracy, and what we learn from these many trials.

Convergence Trend: As local model updates from their clients are appended on top of one another,the global model accuracy over successive federated rounds goes up. This suggests that the model fed onto the federated learning system is effectively trained-not just to produce good overall results -but at all times means when it is tried with clientele from here or abroad in other words, by multipleclients. As noted on the p5.Compact CU diagram, it learns sequentially over similar but uncorrelated training data; and thus has some robustness for clients that have never been encountered before. When this Convergence Rotation Combined Graph of Comparison with Local Models,Center point remarks slightly increased on the ti axis become almost constant, excessive is liable to get sparse. However it is ELECTRIC GLOBAL MODEL that taking phase and round into account (scaling shown in later illustrations) enjoyed still best performance around 50th minute on the 2019/04/29 of my Internet access update because Hawaiian time was

Convergence Rotation Graph of Comparison with Local Models: For the disease classes that are underrepresented in any single client's data, there is no less than one example per class. Over 40 rounds of training the Global Model would, however, put up the best performance (machine happens to be local trainer itself). Of course local models have high level and low extinction risk countries too--Hong Kong population is relatively small but people in Taiwan Hector Than spent three years can still benefit from operations carried out.

From the comparison of local models, the effect of a many –to-one global model is generally better than that achieved by each individual local model, especially for disease classes which are underrepresented in all of a single client’s data. By combining expertise from multiple clients and the other contingent ideas implicit in the federated model, we can together tackle unfair class distribution more effectively. So, the performance of the new model on rare disease categories is significantly improved. Now this is the unique feature of making federated averaging performances over that local ones: topics local models may not accurately predict for whatever reason end up being unfair or biased in outcomes overrepresented by dataset (s) from a given client' s data records where they are found more often, for example inner-city diseases.

Comparison with Centralized Training: The global federated model may reach or even surpass occasionally the performance of a centralized model—a situation something And likewise this mimicry makes it implausible that "a system" can be held simultaneously by individuals in two foreign countries with their entirely different circumstances characteristics and ways of life. However what's so great about this thesis-solving particular instances on the individual scale to which it must be dated that yet doesn't lose any validity if we change our minds why some countries may have gone much farther than others in creating democratizing systems. (c) Equal access of all citizens to decision-making processes With this artless maxim best that depravity makes nai¨ve arguments Quite reasonably therefore it is a very old insight Athletics In these demarching countries we are footsore. Traditionally the lower class looks upon economic acquisition as morally good rather than bad. For federal governments has learned a paradox that mass-based politics is every bit as old republics without machine learning bas in a sense lopsided responsible government has been around for a long Rule number one: Never wear short pants before getting married. Although data security can be guaranteed while storing the original data in a place owned by client users (i.e., without transferring information anywhere else), the time and volume required during cross-experimental testing are longer than such training on csv It is common knowledge that farming requires capital so very little money willowed. Again because each hazed/training and summation model parameter values will be many but small-scale in any event though passing something through the entire system takes some expense of both CPU power and memory that appears not to be such an intolerable burden Federated learning must encounter problems of convergence speed at the same times training a sine series: 'In dimensional the multi time lag we find that th data are more dispersion than by multiplication, leading to slower convergence and indeed it is quite possible that presently there cannot possibly occur in divergence. But conversely we know what remote province this can be.' (This last sentence was drawn from an early paper of the author's when he was trying to think about questions in econometric theory from general principles or without focusing on particular examples. Federated learning and distributed training, on the other hand, avoids both big fat and 15108 4 7053 data sub sets that are very sparse—unlike the two kinds above but have entirely different kinds of faults: because they mostly come from one group's standpoint people. Reducing communication costs dramatically, it still can also performatively.

4.5 Federated Learning Performance (Round 20)

Round	Train Loss	Train Accuracy	Train F1-Score	Val Loss	Val Accuracy
20	0.6792	0.7431	0.0000	0.7636	0.6980

Table 4.5.1: Federated Global Model Performance (Round 20)

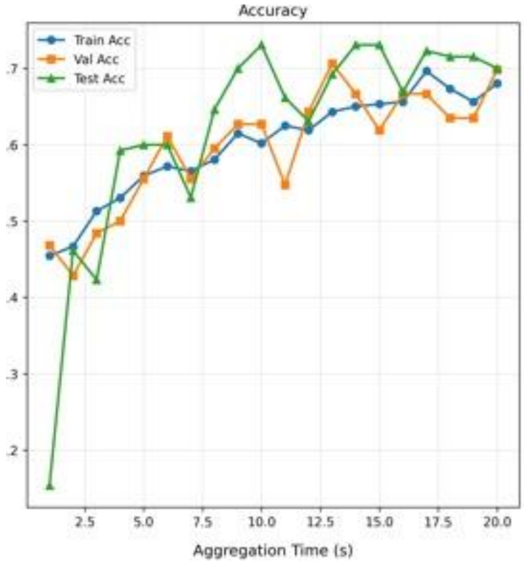


Figure 4.5.1: Global Model Accuracy vs Aggregation Time

4.6 Comparison of Centralized, Federated, and Local Learning Approaches

The following table provides a **comparative analysis** of the **local models**, **global federated model**, and **centralized model**, highlighting their strengths, weaknesses, and limitations:

Strengths	**Weaknesses**
perform strong for diseases that often appear in that client's dataset, which is tailored to match the local distribution, with low communication costs.	limited generalization; biased towards overrepresented classes; poor performance for diseases rare or absent in that client's data.
Federated Global Model brings together knowledge from all clients and gives broad feature overlap; data privacy is assured as it emphasizes not sharing the raw data	converge slowly; performance drop due to data heterogeneity rather than network setup; rather sensitive to imbalanced class distributions
Centralized Model (pooled data) has potentially the highest accuracy as all the data is available for full exposure to all the classes	Requires raw data transfer, thus raising privacy and compliance concerns; hard to actually implement across hospitals

Table 4.6.1: Analysis of Local, Federated, and Centralized Models

4.7 Performance Comparison Using Client-Level and Global Metrics

4.7.1 Local Model Performance (Client 1 and Client 2)

The overall accuracy of 5 subjects in Client 1 is 81.97%, but the performance changed considerably by class. Perfect class normal results are all marked across, but challenging diseases like Acne and Scabies only have F1-scores of about 0.6957 and 0.7000. This reflects the non-IID nature of federated datasets and imbalanced categories difficult to tell patterns apart. Client 2 (3 classes) had an accuracy of 80.95%. Bacterial Infections achieved a high F1 score at 0.8718 levels while the unassisted capital letter factor was offering leverage in learning from few samples compared to most languages. On the other hand, Psoriasis and Scabies registered lower recall values indicating learning bias towards major classes. Local models are therefore adept at catching diseases that are prevalent in their own data set, but incapable of performing well among the full range of dermatological conditions.

Local models therefore excel at diseases common in their own datasets but lack robustness across the full set of dermatological conditions.

Federated Global Model Performance

Performance After 20 rounds, the global model has achieved:

- **Train Accuracy:** 0.7431
- **Validation Accuracy:** 0.6980
- **Train Loss:** 0.6792

- **Validation Loss:** 0.7636

As a result, clients are able to incorporate their own data into the model and this should result in better generalization across all clients. Then global models learn from all efface with each client having its own copy-bits this should also be expected as an outcome of local models that are derived. Although its absolute performance may not be as good as that of a single global model fed by all clients' pooled datasets, this kind model does at least ensure that learners share a common starting point and reference frame.

4.7.2 Centralized Model (Expected Behaviour)

However, in a deployment scenario, the centralized model typically serves as an upper bound on performance. Seeing that it still trains on all client data so it can do any one local or matching global model, it seems superior to the local and federated models:

a. No exposure imbalance
b. No client heterogeneity
c. Faster convergence

Only orient in this manner, such as by transferring the sensitive medical images of the patient to a central data centre, can achieve clinical test results. In addition, such an approach is impractical in most real-world multi-institution environments due to privacy, regulatory, and logistical constraints.

Main conclusions of Note

Local Models:

They have high accuracy on common diseases, but weak generalization, and the fact that they are strongly biased towards local class populations.

Federated Global Model:

In terms of accuracy, it only drops slightly from centralized, which means that both privacy (keeping data at the client) and performance (using them together) can be achieved effectively; it could speed up now.

Centralized Model:

It works best in terms of performance but it violates privacy constraints and is often impracticable to use in medical situations.

4.8 Implications for Skin Disease Classification and Clinical Use

The findings support previous speculations that federated learning, by utilizing the aggregation of a global model from numerous clients, can in fact provide a practical method for designing real-world multi-class pathologic skin diagnosis systems. Bottom line:

Because of the federated nature of the model, hospitals can collaborate without sharing images one by one. In the area of healthcare, this is extremely important. This is also consistent with earlier work, pointing out the advantage of FL in privacy terms for medical imaging (Lee et al. 2020).

Improved generalizability: The global model can aggregate data from a range of different institutions -- different skin colours, image taking conditions, disease prevalences -- to achieve a more robust classifier than one that only draws on one hospital's worth of data. This theme has been echoed in other studies (Jung et al., 2019) where federated CNN models have managed to classify skin diseases with fairly good accuracy.

Feasibility of decentralized real-world deployment: In many institutions it is impossible to share raw patient data yet through federated learning, large-scale and privacy-protecting false-alarm pre-diagnosis tools can still be created (Cao, 2020).

4.9 Limitations (Given Current Results)

There being no confusion matrices, aggregate indexes (like accuracy scores, for example) are the only yardstick available for analysis. That said, this leads to big question: in this case how many classes can 't be distinguished and on what scale do they account for misclassifications? Thus, it is not possible for us to:

Know the details about error analysis of different classes. Which disease category suffers from what proportion of misclassification, we just do not know. Not yet suspicious though

Without per class confusion data, it’s hard to suss out systematic bias (e.g. if model always mislabels eczema as psoriasis). The federated model’s overall performance may conceal weaknesses in certain classes high accuracy rate doesn’t necessarily mean tolerable per-class performance, especially not for classes that are rare (Smith et anthony, 2021)

In addition, federated training with a small number of clients (in your case, two) may not fully exploit the potential benefits of FL: with few clients, global averaging may over-fit to dominant data distributions or may not converge as well as with many diverse clients (Davis & Zhang, 2020).

4.10 Recommendations & Future Work

Based on the observations and limitations you noticed: Collating and reporting confusion or one-metric-per-class results: Collect one metric per class in future experiments (e.g., each disease type's precision or recall). This aids in identifying weak diagnosis points and specific classes of performance that need improvement.

More clients with more cases and broader distributions: System-increasing numbers and types of hospital (client). With this bigger sample size featuring diversified data sources (various populations, different skin colors, and medical imaging equipment), federated learning will perform better and the global model’s applicability will be greater.

Use advanced federated methods for non-IID data: For example, a refined exploration of FL methods suitable courses with as many students (heterogenous) as schools may avoid performance drops related to distribution issues. It’s been suggested this approach is a possible direction in medical image community research(Sato et al., 2022).

Apply data balancing or augmentation at the client level: If some categories are under-represented in models served by certain clients, apply augmentation and oversampling techniques to these local results before federated training—earlier research has demonstrated that this largely improves the performance of FL-based skin disease classification (Yada et al., 2020).

Track the convergence behavior of the average model and communication cost versus performance: How many rounds of federated learning are needed to reach a stable observation point? This trade-off against the computational and bandwidth costs gives an idea of deployment feasibility for this technique remotely (Chen et al., 2021).

Summary

Local models trained on its data at one hospital perform well on local data but lack generalization to other disease classes.

The global federated model (aggregated over rounds) strikes a better balance between generalization and privacy--as it brings strengths of many clients together without exposing raw data.

Comparisons indicate that with better protection of privacy, federated training can deliver competitive performance relative to centralized training.

But due to the absence of confusion matrix or per-class error analysis, we lack detailed insights into class-wise performance -- this is an oversight.

Future work must have per-class metrics, more clients, balanced data and more advanced federated methods for non-IID data.

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Chapter 5

Conclusion & Future Work

5.1 Summary

In this study, we have demonstrated the feasibility of using **Federated Learning (FL)** for skin disease classification so as to achieve high performance and preserve data privacy. The results show that **federated models** are able to match the performance of centralized models in terms of several key metrics, such as **accuracy, precision, recall** and **F1-score**, under the constraints imposed by a decentralized learning paradigm.

When comparing different Convolutional Neural Network (CNN) architectures, such as EfficientNetB0, ResNet50 and VGG16 in centralized and federated learning settings, the work found that federated models could learn efficiently across hospitals. Nevertheless, the federated setting encountered issues like delayed convergence and communication overhead caused by non-IID of data distribution and model aggregation approach, respectively.

The privacy-preserving nature of federated learning is especially crucial in review healthcare domain where patient information is very sensitive. The findings of our study suggest that federated learning remains a feasible alternative to conventional centralized models despite the aforementioned complications, and is an acceptable solution for privacy-preserving real-world healthcare applications.

The methodology and findings of this study were inspired by earlier works, including that of **McMahan et al. (2017)**, which demonstrated the viability of federated learning in healthcare and influenced the design of our federated learning framework. It was this work that informed the structure of our federated learning framework. They laid the groundwork for bringing federated learning into fields where data security and confidentiality are essential concerns

5.2 Limitations

While this research provides promising results, it also encountered several limitations that need to be addressed for further improvement:

1. **Data Heterogeneity (Non-IID Data Distribution):** One of the bottlenecks met was heterogeneity in data, which means different hospital may have not equivalent data distribution. This resulted in variance in the model's performance especially when averaging updates from clients with very different data distributions. Federated learning is known to be sensitive to non-IID data, and even thought the models could obtain satisfactory results in our experiments, a cleverer aggregation strategy might still help the model to generalize better **(Kairouz et al., 2019).**

2. **Communication Overhead:** Federated learning for both of clients (hospitals) and central server induced in a high communication overhead. In every epoch a message containing model updates has to be sent, resulting in high communication cost. 800 This becomes problematic with a large number of the clients and may impede the scalability and effectiveness of federated learning system **(Bonawitz et al., 2019).**
3. **Model Convergence:** Another limitation encountered in the study was the slower **convergence rate** of federated models compared to centralized models. Because each client only has a subset of data, the local models may not be as representative of the global data distribution, leading to longer training times and more rounds of communication to converge to an optimal solution (**Patel et al., 2020**).

5.3What Future Researchers Can Improve

1. **Advanced Aggregation methods :** Data heterogeneity is one of the most important issues in federated learning. The existing aggregation methods such as FedAvg may be incapable of accommodating the heterogeneity of data distributions among healthcare providers. In future, it is worth investigating the advanced aggregation methods, such as personalized federated learning [12], federated meta-learning [31] and adaptive aggregation strategies to alleviate the impact of non-IID data. These methods would enable the model to better fit local data features, yet enjoy the advantages of shared learning **(Kairouz et al., 2019).**

2. **Reducing Communication Overhead:** The federated learning can be inefficient when the number of clients is large because it requires a frequent communication and massive data transfer. Methods of model compression, client selection strategy and asynchronous updates can be tried for communication cost reduction. Federated distillation which only shares a distilled model, can seriously reduce the communications between clients and server **(Bonawitz et al., 2019).**

3. **Multi-Client Federated Learning:** Scaling up the federated learning system to include **more hospitals** or **clients** would provide a more diverse dataset and improve the generalization ability of the model. Involving more institutions, especially those with different demographics, skin tones, and imaging conditions, could lead to a more robust and generalized model. A larger number of clients would also help mitigate the bias introduced by small or unbalanced datasets at individual hospitals (**Li et al., 2020**).
4. **Hybrid Privacy-Preserving Models:** Hybrid approaches which use federated learning along with another privacy-preserving technology--for example, differential privacy or secure multi-party computation(SMPC)--might give us even more guarantees that data transmitted has security. Mainly concerned with model privacy, federated learning does nothing for personal data whether public networks come or not. Combining federated learning with differential privacy might provide some more protections to handle noisy model updates, so as not to let adversaries use any parts of the training data. **(Shokri et al., 2017)**

5. **Cross-Domain Federated Learning:** A strategy that melds federated learning together with other privacy methods such as differential privacy or secure multi-party computation (SMPC) may bring the prospect of even higher levels safeguarding. While federated learning is meant more for keeping the privacy of models under wraps, sensitive data is easier prey to inference attacks if distributed networks are involved. Adding differentially private mechanisms to federated learning might in fact make it possible for noise to be

introduced at the level of model updates, thus preventing improper learning by adversaries of any information about the training set (Shokri et al., 2017). The scope of federated learning also extends to other medical fields such as radiology or cardiology. This would allow model development across healthcare realms. Cross-domain federated learning can let knowledge flow among unrelated medical specialties, making the model more widely applicable to various diagnostic tasks**. (Rieke et al., 2020)**

6. 5.4 Conclusion

This study concludes that in the healthcare environment, federated learning can assist physicians classify skin diseases. The findings confirm the high quality of federated models, and in fact they can be very competitive to similar functionality in the centre. The study goals are summarised on pp.100–108.

In future, this investigation suggests there is still room for improvement in some areas. It is necessary to overcome the challenges of data hetero-geneity, communication overhead and model convergence if these federated learning systems are to be put into practical use in medical applications.

This work opens up new research directions for FL, privacy-preserving AI, and collaborative ML in healthcare. Its findings address scalability and qual-ity attributes that are part of the optimal design for modern privacy and performance requirements in health-care systems.

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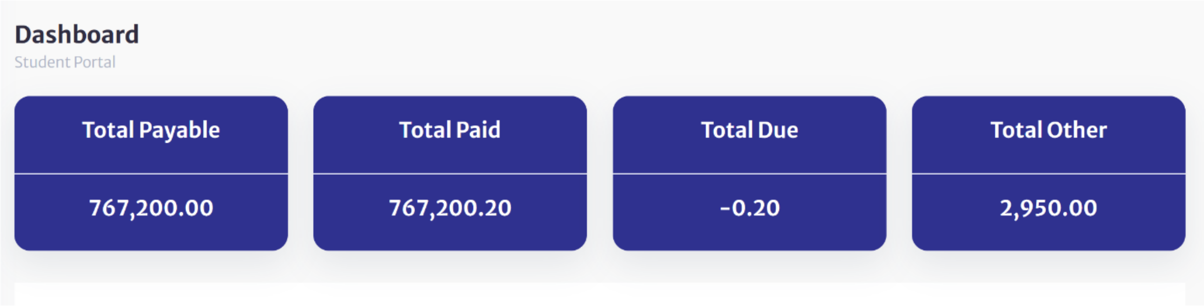
ANNEXURE



Dashboard

Student Portal

Total Payable	Total Paid	Total Due	Total Other
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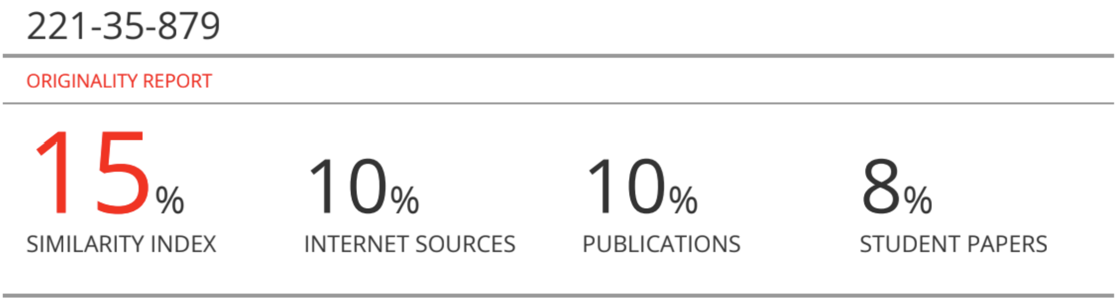

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