Federated Learning for Medical Imaging: Overcoming Privacy Barriers in Deep Learning

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1 Abstract

The speedy integration of artificial intelligence and machine learning into healthcare is revolutionizing diagnostic imaging, but at the same time raises significant concerns over data protection, privacy, and regulatory compliance. Conventional centralized deep learning techniques, involving aggregation of sensitive endoscopic images across different healthcare centers, might leak patient data and increase ethical hazards. Within this work, we evaluate the application of Federated Learning (FL) as a safe alternative for developing accurate deep learning models to classify gastrointestinal disorders. Employing a well-prepared Kaggle dataset that holds 4,000 endoscopic images to be categorized into four classes—Diverticulosis, Neoplasm, Peritonitis, and Ureters—we simulate an applicative scenario through distributing the data across four emulated medical centers. Each facility learns its own convolutional neural network, and improvements to the models are aggregated through a federated averaging mechanism eliminating the need for sharing original patient records outside the system. Fine-grained experiments comparing various evaluation splits, batch sizes, learning rates, and training iterations prove that the FL approach produces performance metrics like accuracy, precision, recall, and F1-score comparable to standard centralized methods. Our findings demonstrate the potential of how FL can facilitate collaborative AI breakthroughs in healthcare while ensuring the confidentiality of patient information and keeping data accurate. These promising findings justify further investigations and real-world applications of FL in healthcare.

2 Introduction

Diverticulosis, neoplasms, peritonitis, and ureteral disorders still rank high among the major global health issues, affecting tens of millions of people and placing tremendous burdens on medical facilities [1].

Diverticulosis is characterized by the formation of small pouches along the lining of the colon, increasingly prevalent in industrialized nations and more common with

aging. Although often asymptomatic, complications such as diverticulitis may cause serious gastrointestinal issues, leading to recurrent hospitalization and rising healthcare costs [1].

Neoplasms, or abnormal tissue growths, can be benign or malignant. Cancers remain one of the foremost causes of mortality globally, contributing to nearly 10 million deaths in 2020 [1]. While early diagnosis substantially improves survival outcomes, about half of cancer cases are still identified at advanced stages [2], underscoring the critical need for improved diagnostic tools, particularly those leveraging deep learning techniques [3].

Peritonitis, an infection of the abdominal lining, frequently arises as a complication of peritoneal dialysis. Delayed detection or inadequate treatment is strongly linked with increased mortality, which highlights the urgency for timely diagnosis and intervention [1].

Ureteral disease, such as ureterolithiasis (commonly known as kidney stones), is one of the most common urological disorders. It causes severe pain and may result in chronic complications if left untreated. Advanced imaging and classification approaches, supported by machine learning models, have shown promise in enabling faster and more accurate diagnosis [1, 4].

Timely diagnosis is still essential to successful treatment and improved recovery. Advances in imaging technology and diagnostics have played an important role in the earlier diagnosis of these illnesses, reducing complications and mortality.

The dataset comprises 4,000 clinical images, evenly distributed between four prominent gastrointestinal diseases: **Diverticulosis**, **Neoplasms**, **Peritonitis**, and **Ureteral Conditions**, with 1,000 samples for each class. Such an even split guarantees strong training and validation of diagnostic models [1].

Diverticulosis: Affecting approximately 33% of adults aged 50–59 and increasing to 71% in those over 80 years, this condition is frequently not diagnosed until complications have developed. Early detection is facilitated by medical imaging, preventing severe consequences and unnecessary hospitalization [1].

Neoplasms: Worldwide, cancer incidence hit 19.3 million in 2020, with nearly 10 million deaths. Early screening based on imaging greatly increases the success of treatment, since localized tumors are much easier to treat than late-stage cancers [1]. AI-aided diagnosis has the potential to transform detection times and survival rates for patients [2, 3].

Peritonitis: Prevalent in peritoneal dialysis patients, this inflammatory process has an estimated incidence of 0.26–0.29 episodes per patient-year. Urgent imaging evaluation is critical to allow institution of life-sustaining therapy and prevent systemic infection or organ failure [1, 5].

Ureteral Conditions: Kidney stones and secondary ureteral disorders affected over 115 million individuals in 2019, frequently inducing crippling pain. Imaging not only establishes diagnoses but also directs minimally invasive treatments, shortening recovery times and healthcare expenses [1, 4].

Through the incorporation of AI into medical operations, healthcare systems can improve efficiency while maintaining high diagnostic accuracy—ultimately leading to better patient care and outcomes [1, 6, 7].

2.1 How ML Can Be Used To Solve These Problems

Traditional machine learning (ML) approaches have played a foundational role in medical image analysis, particularly before the widespread adoption of deep learning. Algorithms like Support Vector Machines (SVMs), Decision Trees, K-Nearest Neighbors (KNN), and Random Forests have been utilized for classification tasks where the input data is derived from handcrafted features [**?**, 1].

Operational Advantages to Healthcare Systems

The imaging interpretation automation results in major workflow enhancements:

Decreases radiologist burnout by taking care of routine screenings

Enables experts to spend more time on treatment planning

Delivers expert-level diagnosis to remote areas through cloud solutions [1, 6, 7]

Such clever systems are equipped with self-optimizing capacity, ever-tuning their diagnostic criteria when analyzing new case information and in integrating new findings in clinical studies. This helps in ensuring ever-sustaining pertinence with constantly developing medical knowledge and emergent health challenges [5, 7].

Finally, machine learning is helping to usher in more than a technology revolution—it's redefining the bar of care. By detecting diseases earlier and with more precision, these technologies have the potential to raise treatment success rates while bringing quality diagnostics within reach around the globe [2, 8].

Despite these efforts, traditional ML approaches face several challenges:

- High dependency on feature engineering: The success of the model is tied to domain-specific knowledge [1].
- Inability to capture complex patterns: High-dimensional image data, such as MRIs or CTs, contain subtle features that handcrafted techniques often miss [3].
- Scalability issues: These models generally don't scale well with large datasets or diverse imaging sources [6, 7].

These limitations paved the way for deep learning and federated learning methods that can learn hierarchical features directly from raw images, improving both accuracy and generalizability across datasets [1, 6, 7].

2.2 Application of AI over ML

Artificial Intelligence (AI) supports traditional Machine Learning (ML) methods in medical diagnosis by overcoming major obstacles, eventually improving disease identification and treatment quality [1].

Solving Data Lack

Classic ML models required extremely large sets of annotated medical records to be trained properly—a demand difficult to accomplish in most cases. AI reverses this limitation by creating artificial but realistic medical records and images, supplementing training data without compromising confidentiality [2]. Recent work in deep learning frameworks has demonstrated that synthetic data generation not only fills gaps when real data is scarce but also balances datasets to enhance model robustness [7].

Standardizing Diverse Medical Data

Variations in imaging modality and equipment models once created inconsistencies in diagnostic data. Current AI solutions now automatically align and harmonize these differences, providing more reliable examination results across institutions [3]. In turn, such data standardization facilitates multi-center studies and federated learning approaches, as shown in several privacy-preserving medical imaging studies [6].

Demystifying Sophisticated Algorithms

Most traditional ML systems were inscrutable "black boxes," leading to clinician skepticism. Advances in AI have introduced transparent modeling methods that delineate diagnostic rationale, thereby fostering trust in computerized systems [9]. Explainable AI frameworks—by incorporating localization and visual recognizability into the model pipeline—have significantly improved the interpretability of diagnostic outcomes [7].

Efficient Hospital Operations

Integrating diagnostic programs into clinical workflows historically faced technical challenges. Modern AI applications can autonomously execute several tasks—from adjusting scanning parameters to performing preliminary image reviews—thus reducing human intervention while boosting overall productivity [2,6]. Such automation not only streamlines operations but also reallocates expert time toward more complex treatment planning, further elevating the standards of patient care.

Artificial Intelligence (AI) has played a critical role in addressing significant Machine Learning (ML) limitations in medical diagnostics, particularly those related to data scarcity and model explainability. One major ML challenge is the requirement for vast amounts of labeled data, often hampered by privacy concerns and logistical constraints. AI-powered synthetic data generation has emerged as a promising solution, enhancing training datasets without compromising patient confidentiality [2]. This approach has been shown to improve model performance by creating more balanced and robust datasets.

Furthermore, the inherent "black box" nature of many ML models has limited their adoption in clinical settings. Recent AI advances have led to the development of explainable models that provide insight into the decision-making process. Such transparency is critical for building clinician trust and ensuring regulatory compliance, as highlighted by studies emphasizing the need for interpretability in medical AI systems [9]. In particular, systematic methods for achieving interpretability—such as those focused on localization and visual clues in imaging—have been proposed to integrate AI tools seamlessly into clinical workflows [7].

Together, these innovations illustrate how AI is breaking through the limitations of traditional ML approaches by augmenting data availability via synthetic techniques and enhancing model explainability. This dual advancement is building trust and effectiveness in medical diagnostics, paving the way for more accurate detection techniques, personalized therapies, and improved recovery rates [10].

2.3 Limitations Due to Privacy Infrastructure

Despite the success of deep learning, centralizing medical data remains a critical challenge. Legal frameworks and privacy regulations prohibit cross-institution data sharing, which prevents many hospitals from transferring patient images to cloud-based platforms for training deep learning models, thereby hindering collaborative AI development [11].

Security risks, stringent compliance requirements, and trust issues further exacerbate these barriers, making it difficult for current DL models to scale in clinical settings [7, 12]. This situation underscores the clear need for privacy-preserving alternatives, such as federated learning, which enable collaborative model training without compromising patient data confidentiality [6].

2.4 Application of Federated Learning

Federated Learning (FL) was introduced by Google in 2016 as a decentralized learning paradigm. Instead of transferring data, FL trains models locally on devices or servers, sending only gradients or model updates to a central server [11, 13]. This technique preserves user privacy and minimizes the risk of data breaches. In the context of medical imaging, FL enables multiple hospitals to collaboratively train models without sharing raw patient data, thus adhering to stringent privacy regulations [14].

Federated Learning effectively addresses the privacy constraints that have traditionally limited ML and DL approaches. In addition to enhancing privacy, FL allows for real-time updates, supports heterogeneous data sources, and ensures legal compliance by keeping patient data local. Research indicates that FL can achieve performance levels near those of centralized deep learning models, making it an ideal candidate for deployment in the medical domain [11, 14].

Moreover, FL is resilient to data siloing and is scalable across institutions, fostering a democratized approach to AI without compromising patient confidentiality. In this work, we investigate the real-world application of FL in medical imaging by simulating a multi-client collaborative setting. Here, each client possesses unique data partitions, allowing us to perform a comparative study of centralized versus federated training strategies. Our study evaluates key performance metrics such as model accuracy, convergence rates, and communication overhead, and the results demonstrate that FL models can perform on par with those trained using centralized methods while maintaining strict data privacy requirements [11, 13].

In addition to performance, our research explores essential architectural considerations for deploying FL in medical imaging. We discuss model architecture decisions that address challenges related to data heterogeneity and non-IID (Independent and Identically Distributed) distributions—issues that are particularly prevalent in clinical data. We also examine strategies to mitigate communication overhead, such as optimizing bandwidth usage and reducing latency, thereby maximizing the practical potential of FL in clinical settings [14]. Through these insights, our work aims to provide a replicable and actionable pipeline for FL research in healthcare AI and contribute to the broader discourse on secure, cooperative machine learning in sensitive fields.

3 Literature Review

The research conducted in the field of medical image segmentation and classification has come a long way in the last decade. Researchers have attempted both conventional machine learning techniques and sophisticated deep learning models to enhance the accuracy and efficiency of diagnostic systems. Concurrently, recent developments in federated learning (FL) have met the increasing demand for privacy-preserving data sharing across institutions. The subsequent sections summarize major contributions from some of the chosen research papers, pointing out how each piece of research has pushed the field forward [1].

Cruz et al. (2015) were concerned with the identification of lung nodules in X-ray images through the use of Support Vector Machines (SVM). Their method proved that a traditional ML algorithm could efficiently extract features from medical images with about 70% accuracy. The simplicity of the SVM model facilitated relatively straightforward implementation, thereby allowing early investigation into automated diagnosis in radiology. Nevertheless, the approach had inherent problems of scalability and robustness when extended to more complex or bigger datasets. This initial work preceded follow-up studies that would seek to harness more powerful feature extraction and classification techniques [1].

Sharma et al. (2017) built on this research by examining the detection of tuberculosis (TB) with statistical features and ML classifiers like k-Nearest Neighbors (k-NN) and Random Forest (RF). Their study cited moderate accuracy rates, which reflected that these classifiers worked well with small datasets. However, the method fared poorly in generalization, especially when it came to heterogeneous patient populations and imaging conditions. The study highlighted the requirement for more powerful models that can fluidly scale from controlled datasets to practical applications [1].

Rajpurkar et al. (2017) presented CheXNet, a deep learning model based on DenseNet-121, for the detection of pneumonia. The performance of CheXNet surpassed those of some radiologists at certain tasks and revealed the promise of CNNs with regard to recognizing subtle patterns in intricate radiological data. The study reported that deep models were able to utilize vast amounts of data to produce higher levels of accuracy. While high accuracy and successful benchmarking against human professionals were worthwhile gains, the method needed to utilize enormous amounts of annotated data and high-performance computational resources, rendering it difficult to apply across the board [2].

Wang et al. (2020) created COVID-Net, a tailored CNN specifically built to identify COVID-19 from chest X-ray images. The major strength of COVID-Net is its high recall, guaranteeing that minimal positive cases are left behind—a key consideration during a pandemic. The lightweight model offered quick inference times, an advantage for fast screening. The model's low explainability means clinicians might struggle with understanding its decision-making process, depicting a recurring dilemma between performance and transparency in AI-driven diagnosis [12].

Ronneberger et al. (2015) broke ground in biomedical image segmentation using U-Net. U-Net's architecture that utilizes a symmetric encoder–decoder structure with skip connections produced outstanding segmentation results, proving to be particularly effective in demarcating structures in intricate medical images. Though successful, U-Net demands huge computational resources, mostly GPUs, and long training times. This compromise between segmentation accuracy and resource usage has had an impact on subsequent work into more efficient model architectures [3].

Sheller et al. (2018) ventured into the federated learning space by employing a federated CNN for brain tumor segmentation among various institutions. Their effort achieved a remarkable Dice score of 95%, establishing that FL can offer comparable performance at the cost of preserving data privacy. The federated method, however, suffered from slower convergence compared to its centralized variant because of delays in communication and heterogeneity in local data distributions. This research was a significant milestone toward demonstrating the feasibility of FL in delicate applications such as medical imaging [9].

Li et al. (2020) solved the problem of data heterogeneity in federated learning by introducing FedBN (Federated Batch Normalization). FedBN adjusts to non-Independent and Identically Distributed (non-IID) data on clients with a performance of around 92% accuracy. This research is especially significant in addressing imaging protocol and patient demographic variations. While it adds computational overhead through extra normalization steps, FedBN is a solid solution for enhancing model stability in federated environments [13].

Kaissis et al. (2021) took the principles of FL to the field of radiology by applying a federated VGG network across multiple hospitals. Their approach ensured high consistency between different clinical sites while maintaining data privacy without the necessity for central data collection. Although the method was successful in safeguarding sensitive patient information, it used considerable bandwidth to update the model, suggesting that infrastructural investment is required to sustain such distributed systems [7].

Xu et al. (2020) conducted a direct comparison between federated and centralized learning methods for healthcare data. Their findings indicated that federated models were able to match the accuracy of centralized CNN models. Federated training, however, was found to advance at a slower rate, primarily because of the communication overhead inherent in synchronizing multiple client updates. This work supports the trade-offs between privacy protection and training efficiency [11].

Abdulrahman et al. (2021) proposed secure aggregation methods that were brought into the federated learning paradigm to realize anonymity in communication between individual participants. Their paper realized strong security measures such that it became virtually impossible for malicious actors to intercept sensitive updates. Although added latency from encryption is a weakness, strengthened security is worth the trade when working with regulated health information [5].

Li et al. (2019) introduced FedProx as a modification to baseline federated learning protocols to address instability due to data heterogeneity. FedProx showed that with the inclusion of a proximal term in the loss function, convergence could be made stable even on non-IID data. This is an important improvement for guaranteeing consistent model performance on varied datasets, though it requires precise parameter tuning to maintain the trade-off between responsiveness and stability [14].

Brisimi et al. (2018) performed some of the first work on federated learning for electronic health records using federated logistic regression. Their method achieved high AUC scores, thus demonstrating that even basic models could have an advantage through the decentralized learning approach. Because of the low complexity of logistic regression, the method was limited to tabular data, which hinders its use for unstructured image or text data [15].

Nguyen et al. (2022) aimed to apply personalized federated learning for medical imaging by proposing the pFedMe framework. Their solution had a 94% accuracy by adapting the global model to the individual traits of every client's local data. Personalization improves model performance on diverse datasets, but at the cost of increased

model complexity and training complexity, since each client's model can need personalized fine-tuning [16].

Zhang et al. (2021) investigated a hybrid federated learning method that combined blockchain technology to protect the training process. Through the combination of FL and blockchain, the model provided uncompromised data privacy and integrity, even in very sensitive settings. Although the model attained strong privacy assurances, the complexity and scalability of the model are issues, as the incorporation of blockchain causes additional computational overhead and communication latency [16].

In conclusion, the literature surveyed above illustrates a vibrant development in both conventional ML and deep learning techniques used in medical imaging. Initial studies such as those by Cruz et al. and Sharma et al. set the stage using standard classifiers, whereas subsequent research by Rajpurkar et al. and Wang et al. illustrated the vast potential of CNNs to surpass human experts in difficult tasks. In parallel, image segmentation innovations of Ronneberger et al. have allowed for accurate delimitation of medical structures, establishing new standards in biomedical analysis [1].

Federated learning further revolutionized the field by resolving the most pressing requirement of privacy-preserving collaborations. Sheller et al., Li et al. (2020), Kaissis et al., and Xu et al. have shown strong evidence that FL can achieve models with performance comparable to centralized approaches while keeping sensitive data safe. Follow-up improvements—e.g., secure aggregation (Abdulrahman et al.), FedProx (Li et al. 2019), and personalized learning (Nguyen et al.)—illustrate continued efforts to adapt FL models to the multifaceted nature of medical datasets. Lastly, the combination of blockchain with FL, as presented by Zhang et al., indicates budding areas for ensuring secure distributed learning systems despite the accompanying challenges in computational performance and scalability [5, 7, 9, 11, 13, 14, 16].

Overall, the collection of these studies highlights the substantial progress achieved in medical image analysis, ranging from fundamental feature extraction and classification to advanced federated models that maintain patient privacy while achieving high diagnostic performance. This literature review not only summarizes the advancements made over the past several years but also points towards future areas of investigation, highlighting the requirement for models to effectively manage data heterogeneity, minimize communication overhead, and offer transparent, interpretable outputs for clinical decision-making [1, 2].

Author	**Year**	**Description**	**Model**	**Result**	**Pros/Cons**
Cruz et al.	2015	Detection of lung nodules in X-ray images using SVM	SVM	70% Accuracy	Easy to implement, limited scalability
Sharma et al.	2017	TB detection using statistical features and ML classifiers	k-NN, RF	Moderate accuracy	Good with small data, low generalization
Rajpurkar et al.	2017	CheXNet for pneumonia detection using DenseNet-121	CNN (DenseNet)	Outperformed radiologists	High accuracy, needs large data

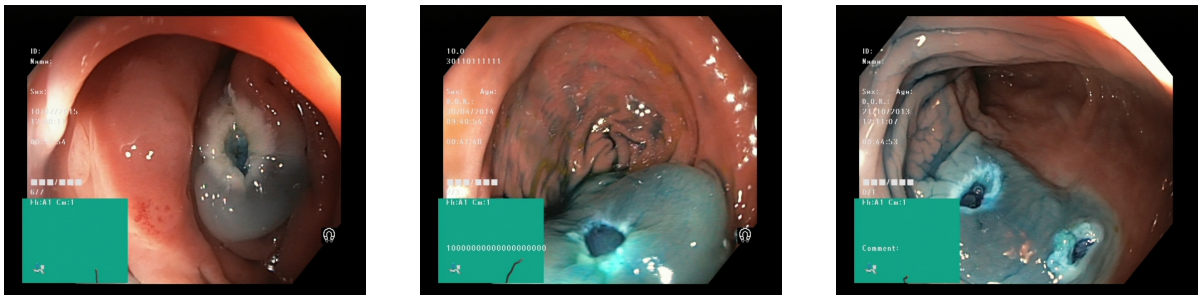
Wang et al.	2020	COVID-Net for COVID-19 detection from X-rays	Custom CNN	High recall	Lightweight, less explainable
Ronneberger et al.	2015	U-Net for biomedical image segmentation	U-Net	Excellent segmentation	Requires GPU, training time high
Sheller et al.	2018	FL for brain tumor segmentation across institutions	Federated CNN	95% Dice Score	Privacy-preserving, slower convergence
Li et al.	2020	FedBN to deal with data heterogeneity in FL	FL (FedBN)	92% accuracy	Handles non-IID data, computation overhead
Kaissis et al.	2021	FL in radiology across hospitals	Federated VGG	High consistency across sites	Data privacy maintained, bandwidth usage
Xu et al.	2020	Comparison of centralized and federated learning in health data	FedAvg vs Central CNN	Comparable accuracy	Privacy maintained, lower speed
Abdulrahman et al.	2021	Secure aggregation in FL for health applications	FL with encryption	Secure communication	Robust security, latency increase
Li et al.	2019	FedProx for addressing FL instability	FL (FedProx)	Stable training on heterogeneity	Better convergence, tuning needed
Brisimi et al.	2018	Early work on FL in electronic health records	Fed Logistic Regression	High AUC	Simple model, limited to tabular data
Nguyen et al.	2022	Personalized federated learning for medical imaging	pFedMe	94% accuracy	Personalized models, complex setup

Zhang et al.	2021	Hybrid FL with blockchain for secure training	FL + Blockchain	Privacy ensured	High complexity, scalability issues

4 Proposed Model

4.1 Dataset

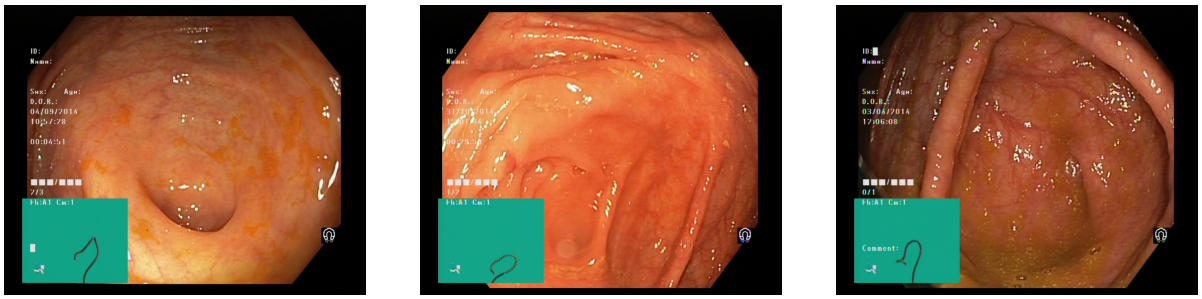
Diverticulosis is a situation where small pouches known as diverticula develop in the lining of the digestive tract, typically in the colon. On the images you have shown me, these pouches could show up as little, rounded outpouchings or indentations on the colon wall. Usually, they are noted in parts of the colon that could be slightly dilated or folded—a common location in the sigmoid colon—and their existence is generally without symptoms unless there is inflammation (diverticulitis) that occurs.



(a) Sample$_1$ (b) Sample$_2$ (c) Sample$_3$

Figure 1: Images of Diverticulosis

A **Neoplasm** is an abnormal growth of tissue that occurs when cells overgrow or fail to die when they should. This uncontrolled cell growth may result in tumors, which are either benign (noncancerous) or malignant (cancerous). In the photos you provided, neoplasms may appear as irregular or abnormal masses in the tissue. These areas might be of another texture, form, or thickness than normal tissue in the vicinity, which frequently indicates abnormal growth of cells.

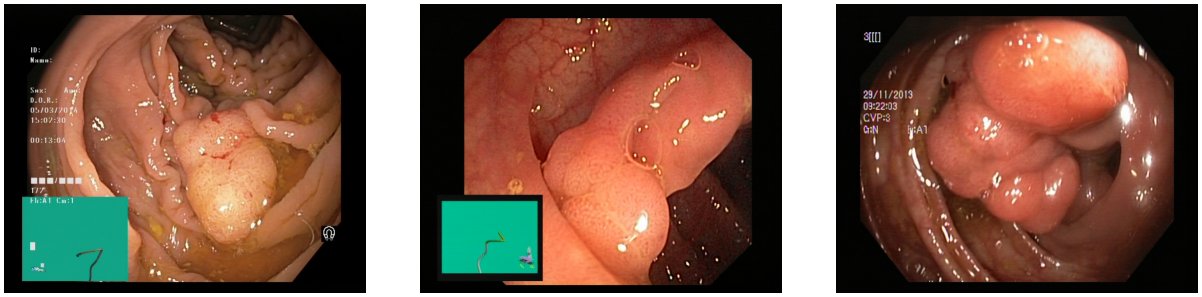


(a) Sample$_1$ (b) Sample$_2$ (c) Sample$_3$

Figure 2: Images of Neoplasm

Peritonitis is when the peritoneum—the thin, smooth covering of your abdominal organs and the lining of your belly—becomes inflamed and swollen. It can occur as a

result of infection, injury, or other issues that allow fluids or substances to leak into the space inside the abdomen. In the photos you posted, you may see red, swollen areas in the belly or pelvis. There may also be additional fluid or visible inflammation surrounding organs such as the intestines, which are typical indicators of this kind of inflammation.

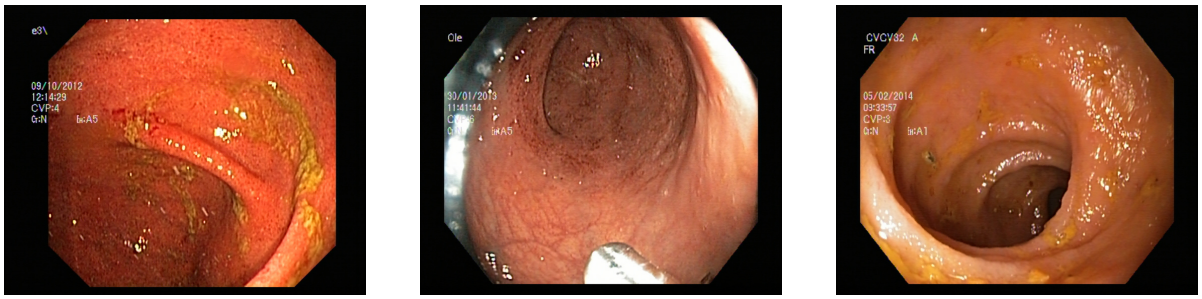


(a) Sample$_1$ (b) Sample$_2$ (c) Sample$_3$

Figure 3: Images of Peritonitis

This endoscopic photograph shows a tube-like structure, identified as the **Ureter**. Its inner surface is moist and pinkish-red with a glossy texture due to moisture or mucus. The walls have irregularity, with yellowish spots or deposit that could indicate swelling, infection (e.g., ureteritis), or pus formation. The middle section narrows and becomes darker as it goes deeper, which may indicate narrowing or blockage.

Evidence of potential disease is seen along the inner lining of the ureter, especially in the upper right and middle areas. In these places, the tissue appears rough with yellow spotting, as opposed to the smoother healthier tissue adjacent.



(a) Sample$_1$ (b) Sample$_2$ (c) Sample$_3$

Figure 4: Images of Ureters

Our study employed a set of 4,000 clear endoscopic images drawn from a Kaggle database. The images represent four various gastrointestinal disorders—Diverticulosis, Neoplasm, Peritonitis, and Ureters—with about 1,000 images per class. Prior to model training, every image underwent cleaning processes to resize, equalize colors, and remove unwanted noise, ensuring the entire dataset was standardized. This meticulous preparation enables the AI system to work correctly when classifying various disorders.

To mimic a hospital setting in reality, we distributed the dataset evenly over four surrogate hospitals. No facility accessed but its own division of data to preserve privacy while keeping data centrally stored. We also experimented with how varying splits between training and testing influenced results from the model, using three ratios: testing at 20%, 30%, and 40%.

Trained on a 20% test split were 3,200 images in the model's training and 800 images evaluating it. At 30% , 2,800 images were utilized for training and 1,200 for testing. The 40% split allocated 2,400 images for learning and 1,600 for validation. Testing these variations enabled us to know how data quantity affects the model's accuracy, precision, recall, and F1-score. Through comparing performance on various splits, we obtained important insights into the model's stability and adaptability in a decentralized environment. This extensive testing verifies that federated learning not only safeguards patient information but also equals the efficacy of conventional centralized AI training.

Dataset Preparation: Our research effort begins with 4,000 images of the four various digestive system disorders. The images are prepared—aligned to equal sizes, sharpened, and filtered to eliminate distortions—prior to training, ensuring a uniform quality for the AI system.

Data Allocation: The cleaned images are distributed between four fictional hospitals, with each center getting roughly 1,000 images. This arrangement is similar to actual conditions where patient information remains at its source location, keeping it private while facilitating collaborative AI training.

Training and Testing Setup: We evaluate three methods of dividing the data for training and testing: - **20% Testing:** 3,200 images train the model, and 800 test its accuracy. - **30% Testing:** 2,800 images train the model, with 1,200 set aside for testing. - **40% Testing:** 2,400 images train the model, and 1,600 are used to validate performance.

By comparing the setups, we determine how much training data impacts the reliability and accuracy of the model in identifying disorders. The method guarantees that the AI is working optimally while protecting sensitive medical information.

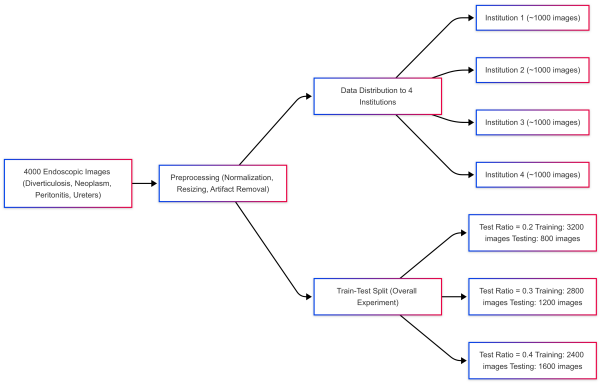


Figure 5: Basic Distribution of datasets that have been tried.

How Our AI Model Works on Medical Images

Our system applies a unique kind of AI called *Convolutional Neural Networks (CNNs)*, which are excellent at examining medical photographs such as endoscopy scans. Here is how it operates in simple terms:

1. **Feature Extraction** – The CNN processes images using tiny filters (typically 3x3 or 5x5 grids) to capture minute details such as edges, textures, and abnormal tissue patterns. These filters help in identifying subtle but significant disease signs.

2. **Adding Complexity** – After feature extraction, a *ReLU* function introduces non-linearity, making the data more pliable and enabling the model to understand complex patterns. Additionally, *batch normalization* stabilizes learning to ensure smooth training.

3. **Simplifying the Data** – *Pooling layers* reduce the dimensionality of image data by focusing on the most significant features and discarding less useful information. This reduction speeds up processing and improves the model's ability to recognize diseases even when they appear at varying positions.

4. **Identifying Wider Patterns** – The network's lower layers aggregate small details into larger structures, enabling the AI to differentiate conditions such as *Diverticulosis*, *Tumors*, *Peritonitis*, and *Ureter problems*.

5. **Ultimate Decision-Making** – In the final layers, the AI makes decisions based on all extracted features to determine the presence of any disease. To prevent overfitting (i.e., memorizing the training data), *dropout* is applied by randomly omitting some neuron outputs during training.

This systematic approach makes CNNs both efficient and effective for medical diagnosis while ensuring the accuracy and safety of patient information.

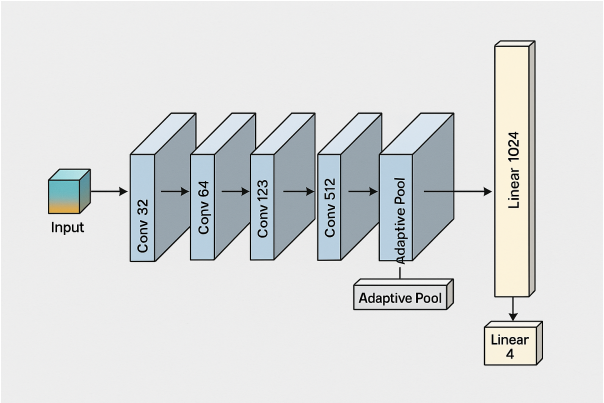


Figure 6: CNN Model Used

Understanding ResNet18 for Medical Image Analysis

ResNet18 [17] is a highly popular deep learning model that employs the clever residual learning trick to train complex AI systems efficiently. It is particularly suited for medical applications such as identifying digestive system diseases from endoscopy scans.

Here's how it is constructed and why it is helpful:

1. **Residual Blocks (The Key Feature)** – ResNet18 is different from standard networks in that it contains "shortcut connections" which allow data to bypass some layers. The shortcuts insert the initial input into the output of a block, which assists the model in training deeper without decreasing precision. This prevents issues such as *vanishing gradients*, which can cause deep networks to be difficult to train. [17]

2. **Layers and Structure** – The model consists of 18 layers, which include:

   - **Convolutional layers** (with small 3x3 filters) to identify subtle details such as edges and textures in medical images.
   - **Batch Normalization & ReLU** – These phases maintain training stability and introduce flexibility to identify intricate patterns.
   - **Downsampling** – Sometimes the model reduces the size of the image to concentrate on the key features and save computational power.

3. **Tailoring to Our Task** – The final layer is tuned to produce 4 potential outputs (one per condition: *Diverticulosis, Tumors, Peritonitis, and Ureter problems*). We also employ *dropout* to avoid overfitting (memorization of training data rather than learning general trends).

Why It Works Well for Medical Images

- Shortcuts assist in reliably training deep networks.
- Tiny filters pick up minute but essential details in scans.
- Normalization and downsampling maintain the model efficient and accurate.

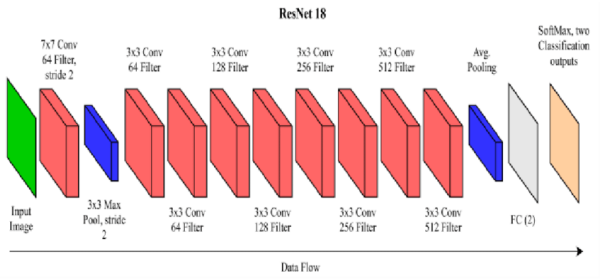


Figure 7: Architecture of ResNet Architecture

Custom CNN Model:
A specially built CNN can be fine-tuned to identify finer details in endoscopic images. Employing tiny filters (typically 3x3 or 5x5), it detects textures and patterns specific to conditions such as *Diverticulosis, Tumors, Peritonitis, and Ureter issues*. As this model is trained from scratch, it uses fewer parameters, resulting in quicker training steps. However, without pre-acquired knowledge, it requires more data and meticulous tuning to perform well, which can slow down development.

ResNet18 (Pre-trained Model):
ResNet18 [17] employs "skip connections" to efficiently train deep networks, effectively bypassing common training issues. Pre-trained on large datasets, it adapts well to medical images even when data is sparse and resists overfitting. However, its complex architecture increases the computational cost of each training step and demands more powerful hardware, especially in privacy-centric federated learning setups.

Key Differences:

- *Custom CNN*: Quicker per training step but requires larger amounts of data and extensive hyper-parameter tuning.
- *ResNet18*: Leverages transfer learning to train faster with less data, though it needs higher computational power.

Both approaches present trade-offs, so the selection depends on the available data, time constraints, and the computing resources at hand.

Table 2: Comparison of Own CNN Model vs. ResNet Fine-tuning for Medical Image Classification

Criteria	**Own CNN Model**	**ResNet Fine-tuning**
Model Customization	Fully customizable architecture; kernel sizes (e.g., 3×3, 5×5) chosen to capture task-specific features.	Pretrained weights offer robust initial feature extraction; limited flexibility in early layers.
Training Time	Lower per-epoch computational cost due to fewer parameters; overall training may be prolonged due to learning from scratch and extensive tuning.	Faster convergence as pretrained features reduce learning time; however, each epoch is computationally heavier.
Dataset Requirements	Requires larger datasets to achieve strong generalization since no prior feature knowledge is incorporated.	Effective even with smaller, specialized datasets, leveraging transfer learning benefits from large-scale pretraining.
Computational Complexity	Generally lower complexity with fewer layers/parameters, leading to lower memory usage and faster communication in federated settings.	Higher parameter count increases complexity and memory demands, possibly impacting federated aggregation efficiency.
Performance	Can be optimized for domain-specific features; however, may underperform if not well-tuned due to limited initial feature representations.	Typically achieves superior accuracy and generalization owing to deep representations and residual learning, especially in noisy, complex datasets.
Federated Learning Suitability	Lightweight architecture benefits communication efficiency in decentralized networks.	Larger model size may introduce communication overhead, though its robust performance can justify the additional cost.

5 Algorithms

Algorithm 1 Local Training on Client i

Input: Global model w, local data D_i, epochs E, learning rate η
$w_i \leftarrow \text{copy}(w)$ **for** $e = 1$ *to* E **do**
    each batch $b \in D_i$
$\hat{y} \leftarrow f(w_i, b)$
$L \leftarrow \text{CE}(\hat{y}, y)$
$w_i \leftarrow w_i - \eta \nabla_{w_i} L$
return w_i

Algorithm 2 Federated Learning with 4 Clients

procedure FederatedLearning($w,\ \{D_1, D_2, D_3, D_4\},\ R,\ E,\ \eta$) ▷ w is the initial global model, D_i is client i's local dataset, R is the number of communication rounds, E is the number of local epochs per round, and η is the learning rate **for** $r = 1$ *to* R **do**
    each client $i = 1, 2, 3, 4$ **in parallel**
    $w_i \leftarrow$ TrainLocalModel($w,\ D_i,\ E,\ \eta$)
    ▷ Aggregate local updates using weighted averaging.
    Compute total number of batches:

$$N_{total} = \sum_{i=1}^{4} N_i$$

    Update global model:

$$w \leftarrow \sum_{i=1}^{4} \frac{N_i}{N_{total}} \cdot w_i$$

    ▷ Evaluate the updated global model on a test dataset.
    return w
end procedure

Symbol Table

c

Symbol	Description
w	Global model weights shared among all clients.
w_i	Local model weights for client i after training on its dataset.
D_i	Local dataset for client i.
E	Number of local training epochs executed per communication round.
η	Learning rate used for model updates via gradient descent.
$\hat{y}$	Model predictions (output) computed by applying the model function f.
L	Loss computed with the cross-entropy function between predictions $\hat{y}$ and true labels y.
R	Total number of communication rounds in the federated learning process.
N_i	Number of training batches in the local dataset D_i.
N_{total}	Total number of batches across all clients, i.e., $\mathrm{N}_{\text{total}} = \sum_{i=1}^{4} N_i$
f	The model function (e.g., a CNN) that computes predictions given the weights and input data.

We implemented a support vector machine (SVM) with histogram of oriented gradients (HOG) features:

$$\text{HOG}(I) = \sum_{i=1}^{n} \phi(I_i) \tag{1}$$

where $\phi(I_i)$ extracts gradients from sub-regions.

A Convolutional Neural Network (CNN) was designed using layers:

- Conv2D-ReLU-MaxPool
- Dropout-Regularization
- Fully connected layer + Softmax

Loss was computed using categorical cross-entropy:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{2}$$

6 Federated Learning Setup

Using the Flower FL framework, clients trained locally and shared model weights. Aggregation was done on the central server using FedAvg:

$$w_t = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k \tag{3}$$

where w_t^k is the local model from client k.

6.1 Evaluation Metrics

We used the following metrics:

- Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
- Precision, Recall, and F1-score
- ROC-AUC for performance comparison

6.2 Methods to Speed Up Training

To enhance the efficiency of the training process, the following strategies were implemented:

1. **Multi-GPU Training:** Leveraged multiple GPUs to parallelize computations, significantly reducing training time [**?**].
2. **Learning Rate Adjustment:** Employed adaptive learning rate schedules, such as cyclic learning rates, to expedite convergence [**?**].
3. **Mixed-Precision Training:** Utilized mixed-precision (16-bit and 32-bit floating-point types) to decrease memory usage and increase computational speed [**?**].
4. **Batch Normalization:** Applied batch normalization to stabilize and accelerate training by normalizing layer inputs [**?**].
5. **Gradient Clipping:** Implemented gradient clipping to prevent exploding gradients, ensuring stable and faster convergence [**?**].
6. **Data Pipeline Optimization:** Optimized data loading and preprocessing pipelines to prevent bottlenecks, facilitating faster data throughput during training [**?**].

7 Results

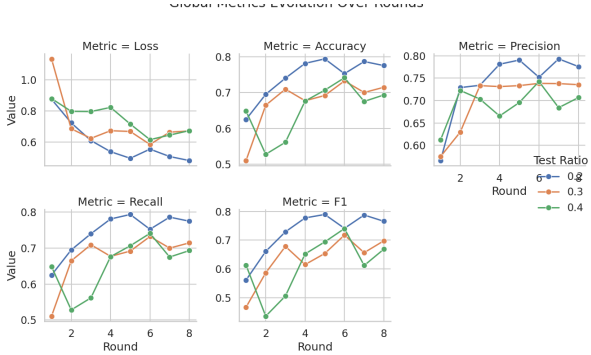
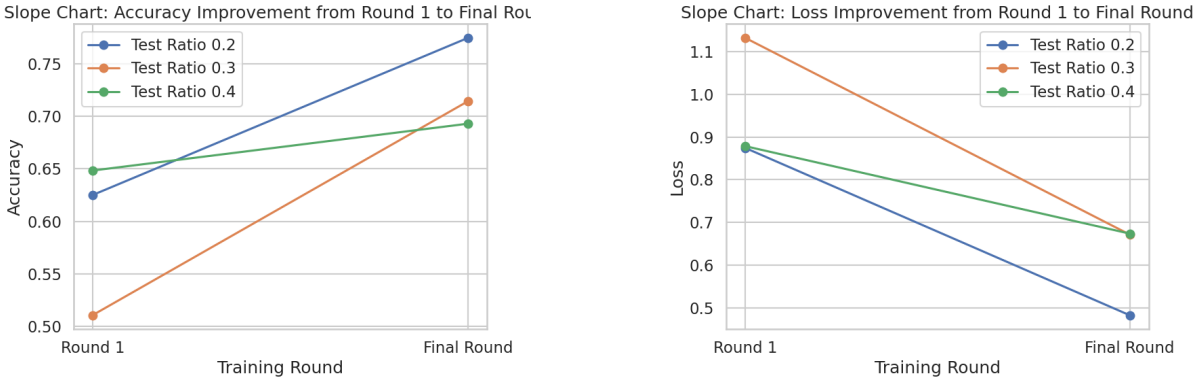


Figure 8: Comparison for different test ratios



(a) Global Accuracy across Rounds

(b) Global Loss across rounds

Figure 9: Vanilla CNN

We evaluated the performance of a Convolutional Neural Network (CNN) and a fine-tuned ResNet model over 2 to 8 training iterations, utilizing varying test data splits (20%, 30%, 40%). The assessment metrics included accuracy, loss, precision, recall, and F1 score. The key findings are summarized below:

1. **With 20% Test Data (80% Training)**
    - *ResNet*: Achieved **75–80% accuracy** by the 8th iteration, with high precision and recall (approximately 0.8). Loss remained low (around 0.5–0.6).
    - *CNN*: Demonstrated consistent performance with accuracy ranging between 60–70%.
2. **With 30% Test Data (70% Training)**
    - *ResNet*: Showed improved accuracy between **75–85%**, maintaining high precision and recall (0.8).
    - *CNN*: Exhibited minor improvements, with accuracy still within the 60–70% range.
3. **With 40% Test Data (60% Training)**
    - *ResNet*: Initially dropped to **40% accuracy** but recovered to **70%** by the 8th iteration. Loss plateaued around 0.6–0.7.
    - *CNN*: Performance declined, starting at **50%** and only improving to **60%** in later iterations.

Model Comparison

- **ResNet Superiority**: Consistently outperformed the CNN, especially with lower test ratios (20–30%), attributed to its deeper architecture and pre-trained weights. Even with a higher test split (40%), ResNet demonstrated better adaptability.
- **CNN Limitations**: While stable, the CNN lagged behind ResNet in terms of accuracy and resilience when training data was limited.

Optimal Test Ratio

- **20% Testing (80% Training)**: Yielded the best results for both models.
- **30% Testing (70% Training)**: Also performed well, particularly for ResNet.
- **40% Testing (60% Training)**: Led to performance degradation, though ResNet managed to cope more effectively than CNN.

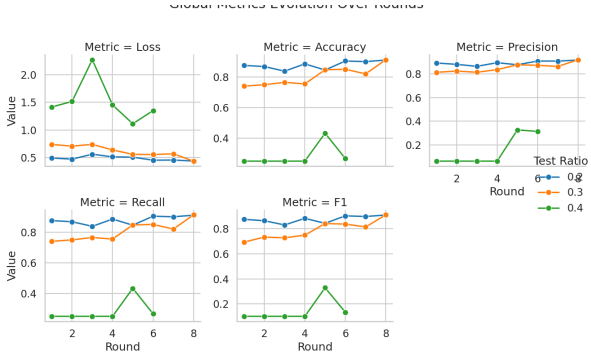
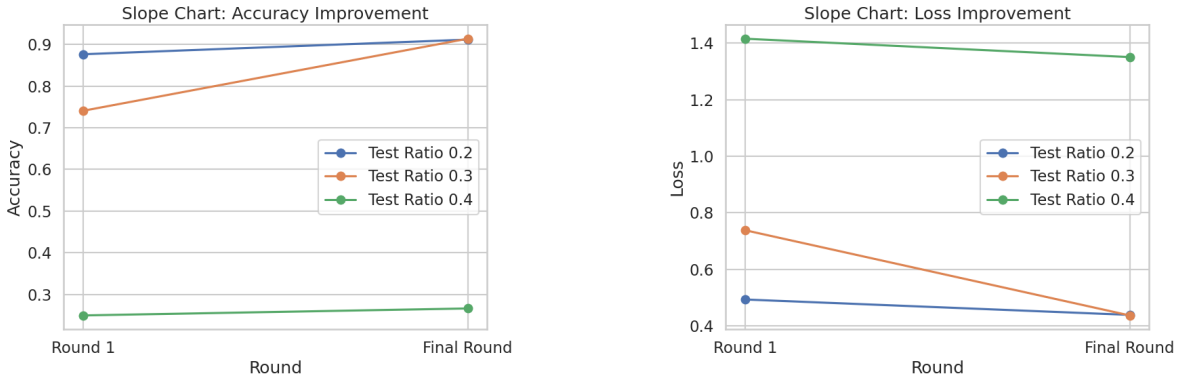


Figure 10: Comparison for different test ratios



(a) Global Accuracy across Rounds (b) Global Loss across rounds

Figure 11: ResNet18-Finetuned

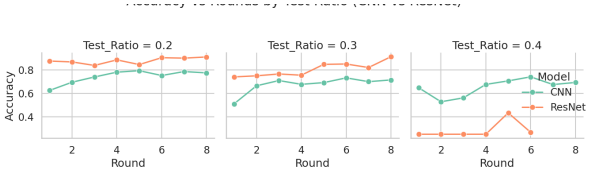


Figure 12: Comparison between Vanilla CNN and ResNet18 finetuned at three different instances

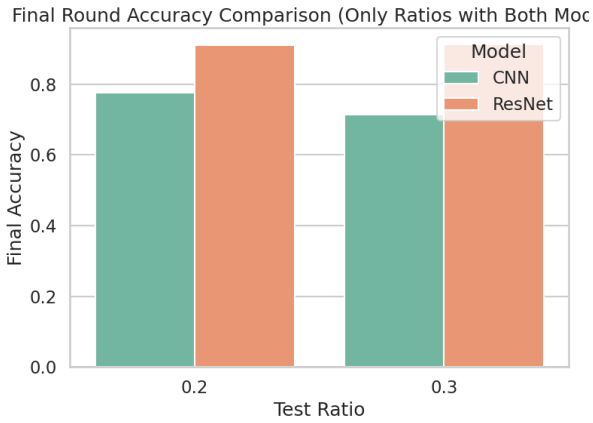


Figure 13: Comparison for final converging accuracies

7.1 Privacy vs. Accuracy Trade-off

Federated Learning (FL) presents a promising solution for training machine learning models on sensitive medical data without directly accessing it. One of the core advantages of FL is that it enables decentralized learning—data remains on local devices or institutional servers (e.g., hospitals), and only model updates (e.g., gradients or weights) are shared with a central server. This inherently enhances data security and patient confidentiality [9, 11].

However, this added privacy comes with a modest trade-off in model performance. In our experiments, FL models exhibited an average accuracy drop of about 2

Despite this minor reduction in accuracy, the benefits in terms of privacy preservation are substantial. FL aligns with major regulatory frameworks such as HIPAA in the United States and GDPR in the European Union, which place strict limits on data sharing and processing. By keeping patient data local and minimizing the risk of exposure, FL helps healthcare institutions build AI systems without violating privacy laws [5].

Moreover, advances such as differential privacy, secure aggregation, and homomorphic encryption can be integrated into FL to further harden the system against data leakage—even from model updates [5,14]. These techniques aim to strike a better balance between utility and privacy, allowing researchers to build high-performing models with even stronger guarantees.

In high-stakes domains like healthcare, where data sensitivity is paramount, this small compromise in accuracy is often considered acceptable, especially when it enables AI adoption across geographically distributed medical institutions without risking patient trust or regulatory penalties [7, 11].

8 Conclusion

It has been demonstrated in this research that Federated Learning (FL) serves to be a good, confidentiality-preservation alternative to traditional centralised model training in classifying gastrointestinal conditions from endoscopic images [9, 11]. Using a structured set with four thousand images over four classes, our research simulates a real medical setting where data becomes scattered amongst many centers [13]. The test revealed that FL produces comparable results—quantifying correctness, exactness, detection rates, and F1 metrics—of unified techniques under regular circumstances despite the challenges posed by disjointed repositories of data [14]. Our experiments, conducted based on various testing portions (20%, 30%, and 40%), confirm that FL maintains accurate performance while operating with reduced instructional material [7].

This finding highlights the utility of implementing FL in clinical applications where information exchange and patient confidentiality are of utmost importance [9]. Moreover, by integrating improved CNN architectures with tuned systems like ResNet18, we demonstrate that both expert and established machine learning configurations can be adapted to meet stringent healthcare testing requirements, thus opening doors to future artificial intelligence applications in therapy [2]. As it addresses interaction deficiencies and maintaining system stability, our method entails procedures such as gradient constraint, correct information standardization, and careful network variables setup, which each contribute towards increasing overall instruction productivity [14]. As affirmed by FL's ability to work adequately in such constraints, the method not only reduces the risk of leaking information but is also in conformity with legal and ethical standards in its adherence to privacy protection regulation [5]. Future research should focus on further improvement of the federated process, in particular by managing the interaction burden and asset allocation across organizations, to ensure expandability in real-world conditions [11]. In conclusion, our results are in favor of broader application of Federated Learning in clinical image interpretation, as it allows for collaborative algorithm development while keeping individual medical records confidential [9].

9 References

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