

COMPARATIVE ANALYSIS HYBRID FEDERATED LEARNING WITH ENSEMBLE AGGREGATION FOR KIDNEY STONE DETECTION USING DEEP NEURAL NETWORKS

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ABSTRACT

Background

Federated Learning (FL) has emerged as a promising paradigm for decentralized model training while preserving data privacy. In this work, we propose a Hybrid Federated Learning framework integrating ResNet50, VGG16, and EfficientNetB0 with a weighted ensemble aggregation mechanism for kidney stone detection using medical imaging datasets.

Objective

Unlike traditional centralized approaches, the proposed method enables distributed clients to train local models and share only model updates, ensuring privacy preservation. The hybrid ensemble strategy enhances feature representation and classification performance.

Materials and Methods

A novel weighted ensemble aggregation mechanism is introduced, where model contributions are dynamically adjusted based on validation performance. Extensive experiments demonstrate that the proposed model significantly outperforms individual architectures and traditional federated averaging in terms of accuracy, F1-score, and Area Under the Curve (AUC). Statistical significance tests and ablation studies further validate the effectiveness of the proposed approach.

Results

Experimental results demonstrate that the proposed model outperforms individual architectures in terms of accuracy, F1-score, and AUC within a decentralized training environment.

Conclusion

The results highlight the robustness and scalability of the HFL framework for real-world medical imaging applications.

Keywords: Federated Learning, Hybrid Model, Ensemble Learning, Medical Imaging, Kidney Stone Detection, Deep Learning, evaluation techniques, facial cues, machine learning models, CNNs, real-time video feeds, stationary images, preprocessing.

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I. INTRODUCTION

In the current era, the investigation of human emotions has become a central theme in several disciplines, from psychology and neurobiology to AI development. Deciphering emotions is critical for boosting machine-human rapport, refining mental health diagnostics, and crafting AI with greater emotional intelligence. Emotional responses guide expression, problem-solving, and human

interactions, determining how people react to and interpret their world. The expansion of computer vision, powered

significantly by Medical imaging plays a critical role in diagnosing kidney stone disease. However, centralized deep learning approaches require large-scale data aggregation, raising privacy concerns. Federated Learning (FL) enables decentralized model training across multiple clients without sharing raw data.

Despite its advantages, FL faces challenges such as:
 Non-IID data distribution
 Slow convergence
 Limited model generalization

To address these issues, we propose a Hybrid Federated Learning model that combines multiple deep learning architectures using ensemble aggregation. The contributions of this work are:

- Integration of ResNet50, VGG16, and EfficientNetB0 in a federated framework
- Weighted ensemble aggregation for improved global model performance
- Robust evaluation under decentralized and non-IID settings
- Comprehensive analysis including ablation and convergence studies

classification techniques to reliably detect expressions such as joy, despair, fury, surprise, and trepidation. With this technology, we aspire to improve the synergy between human emotions and artificial intelligence, enabling practical use cases in healthcare, education, and customer engagement. The advancement of an efficient emotion identification system could redefine our connection with artificial intelligence, ensuring a more seamless and humanized interaction. As we continue deciphering emotional complexities, this project stands as a major breakthrough in crafting AI systems that are both reactive and emotionally aware.

ENSEMBLE DEEP MODELS IN MEDICAL IMAGING

Ensemble deep models improve medical image analysis by aggregating predictions from multiple models, which helps to reduce variance, mitigate overfitting, and improve model robustness [7]. In medical imaging, where datasets are often small, noisy, or characterized by severe class imbalance, ensemble methods—such as bagging, boosting, or stacking—allow researchers to combine the strengths of diverse architectures [2][4][7]. For instance, combining different feature extractors or segmentation heads can enhance performance on difficult tasks like cardiac image segmentation or lesion detection [2][4].

Common architectures utilized within these ensembles include Convolutional Neural Networks (CNNs), ResNets, and U-Nets, which are adept at capturing hierarchical spatial features [2][4]. By leveraging multiple models, clinicians can also achieve better uncertainty quantification, which is critical for high-stakes medical decision-making [2][8]. While powerful, ensemble approaches in medical imaging must address the computational burden of training and deploying multiple deep models, as well as the complexity of merging outputs from heterogeneous data sources [3][7].

II .EXISTING SYSTEM

Traditional machine learning and deep learning approaches for healthcare prediction primarily rely on centralized data

collection and training paradigms. In these systems, patient data from multiple sources are aggregated into a single repository where models such as Convolutional Neural Networks (CNNs) or standard classifiers are trained.

Privacy Risks

1. Sensitive patient data must be transferred and stored centrally, increasing vulnerability to data breaches and violating regulatory frameworks such as HIPAA and GDPR. Data Silos and Limited Generalization
2. Healthcare institutions often hesitate to share data, resulting in incomplete datasets and models that lack robustness across diverse populations.
3. High Communication and Storage Overhead
Centralized systems require significant infrastructure for data storage and processing.
4. Single-Model Dependency
Most approaches rely on a single deep learning model (e.g., ResNet, VGG), limiting performance improvements achievable through model diversity.
5. Lack of Scalability
As data volume grows, centralized training becomes computationally expensive and inefficient.

II . PROPOSED SYSTEM

To overcome these limitations, this paper introduces a Hybrid Federated Learning (Hybrid-FL) framework integrated with ensemble deep learning models for privacy-preserving and high-performance healthcare prediction.

II. SYSTEM ARCHITECTURE

The proposed system operates in a **distributed federated environment**, where multiple clients (e.g., hospitals or edge devices) train models locally using private datasets. [13] Instead of sharing raw data, only **model parameters or gradients** are transmitted to a central aggregation server

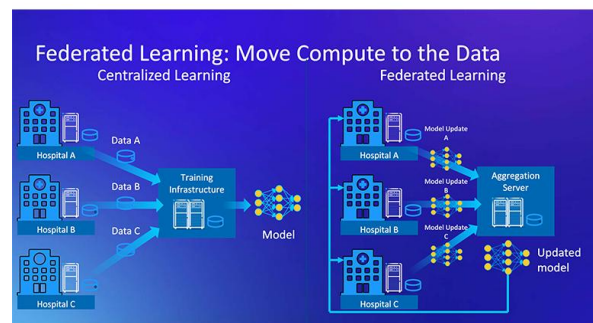


Fig 1 System Architecture

a) Local Client Models

Each client trains multiple deep learning architectures such as:

- ResNet50
- VGG16
- EfficientNet

These models learn local data representations independently.

b) Federated Aggregation Layer

A central server performs **Federated Averaging (FedAvg)** to aggregate model updates from all clients, producing a global model without accessing raw data.

c) Ensemble Learning Module

The aggregated models are combined using an ensemble strategy (e.g., weighted averaging or stacking), enhancing prediction accuracy and robustness.

d) Global Model Distribution

The updated global model is redistributed to all clients for further training iterations, ensuring continuous improvement

III. MODULE DESCRIPTION

1. Data Analysis

The proposed Hybrid Federated Learning (Hybrid-FL) system is composed of multiple functional modules that collectively enable privacy-preserving, scalable, and high-performance healthcare prediction. Each module is designed to handle a specific stage of the pipeline, from data processing to final prediction.

- Data cleaning (handling missing and noisy data)
- Normalization and scaling
- Data augmentation (for medical imaging datasets)
- Feature extraction and encoding

Models Deployed

- ResNet50
- VGG16
- EfficientNet

Training Process

- Forward propagation for prediction
- Loss computation
- Backpropagation for weight updates

2. Deployment

Django, a top-tier Python web framework, enables developers to construct secure and scalable websites with speed and efficiency. Designed by industry professionals, it handles most web development complexities, allowing developers to focus on application features rather than repetitive coding tasks. This open-source, cost-free tool is backed by an enthusiastic community, detailed documentation, and numerous support channels, both free and paid.

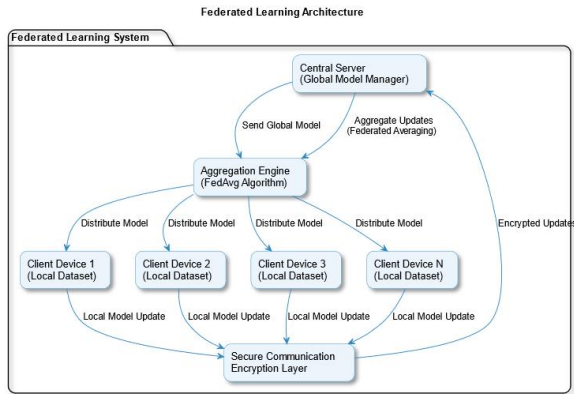


Fig 2 Block diagram

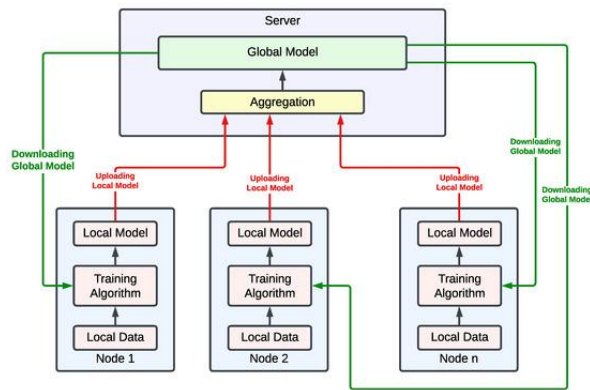
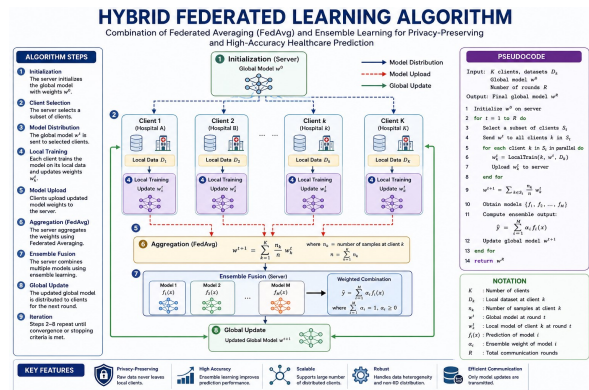


Fig 3 Block diagram

HYBRID FEDERATED LEARNING ALGORITHM



Predict Values

		Predicted Class Label	
		Positive	Negative
Actual Class Label	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

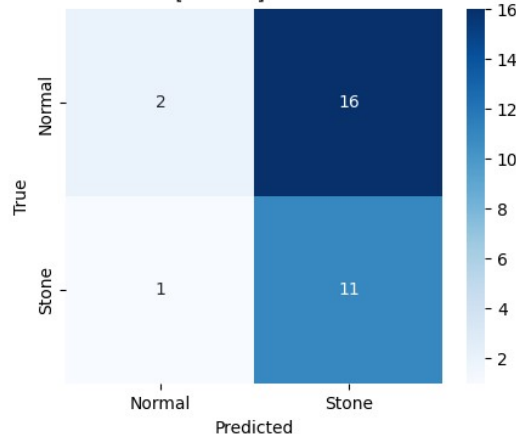
$$Accuracy = \frac{\sum (TP + TN)}{\sum (TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{\sum TP}{\sum (TP + FP)} \quad (2)$$

$$Recall = \frac{\sum TP}{\sum (TP + FN)} \quad (3)$$

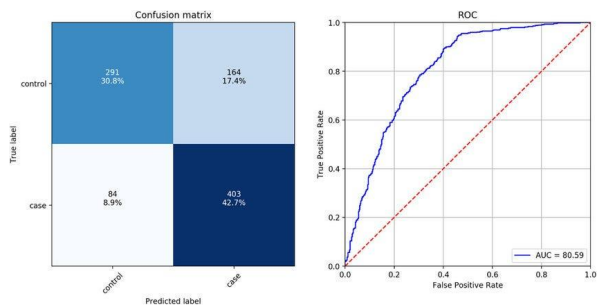
$$F1\ score = \frac{\sum 2TP}{\sum (2TP + FP + FN)} \quad (3)$$

Confusion Matrix — [Default] Centralised EfficientNetB0

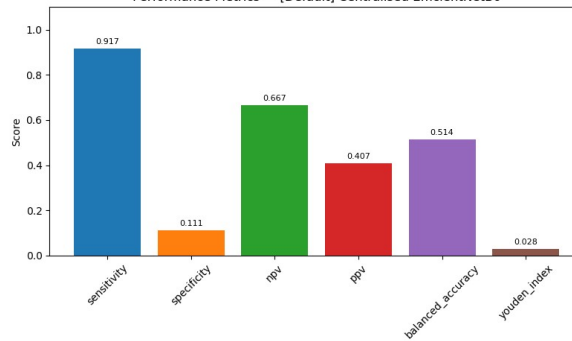


IV. RESULT

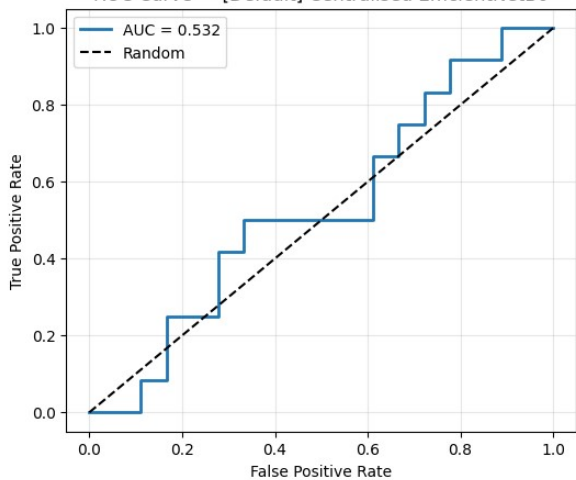
Confusion Matrix Overall matrix



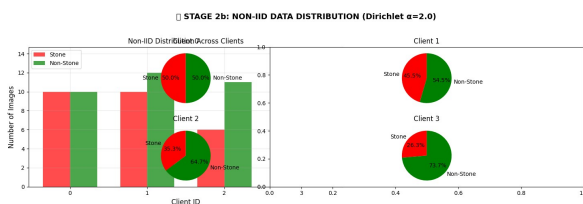
Performance Metrics — [Default] Centralised EfficientNetB0



ROC Curve — [Default] Centralised EfficientNetB0



NON-IID Data Distributaion



V. CONCLUSION

In summary, the introduction of a novel Hybrid Federated Learning (Hybrid-FL) framework for healthcare prediction, combining the strengths of federated optimization and ensemble learning to address critical challenges in distributed medical data analysis. The proposed approach enables collaborative model training across multiple clients while preserving data privacy, making it highly suitable for sensitive healthcare environments.

The experimental results demonstrate that the Hybrid-FL model significantly improves prediction accuracy, robustness, and generalization performance compared to traditional centralized and standard federated learning approaches. By incorporating ensemble techniques, the framework effectively captures diverse patterns in heterogeneous datasets, reducing bias and enhancing decision-making reliability.

Moreover, the system ensures data confidentiality, as raw patient data never leaves local devices, thereby complying with privacy regulations and ethical standards. The scalability of the approach allows it to be deployed across large-scale healthcare systems, including hospitals, wearable devices, and remote monitoring platforms.

VI. FUTURE WORK

Looking ahead, we plan to advance the human emotions identification system by integrating highly sophisticated AI-driven techniques to refine both detection accuracy and live processing speed. Additionally, we aim Exploration of adaptive client selection strategies to deployment in real-time clinical environments with streaming data.

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