Federated Learning in Healthcare: Applications, Privacy Preservation, and Data Monetization

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Abstract. Health data has immense value in advancing healthcare by enabling accurate diagnosis, early disease prediction, and informed treatment decisions, while also serving as a key resource for research and public health initiatives. However, this value is often challenged by privacy barriers, such as strict data protection regulations, which hinder access to diverse datasets and limit the accuracy of the Artificial Intelligence model. In addition, healthcare organizations face the challenge of obtaining economic value from data while maintaining patient trust .This is where Federated Learning (FL) plays a crucial role in enabling privacy-preserving collaboration of healthcare data. Against this background, this paper provides a comprehensive overview of FL applications across several healthcare contexts, disease diagnosis, prediction, classification, and medical imaging. It explores monetization through safe and fair cooperation mechanisms, internal improvement, and development of federal healthcare marketplace. Ultimately, FL emerges as a transformative approach that fosters innovation and revenue generation in healthcare while ensuring privacy and regulatory compliance.

Keywords: Federated Learning (FL), privacy-preserving, Machine learning, Deep learning, data monetization.

1 Introduction

The healthcare industry generates vast amounts of data, including patient records, clinical trial results, administrative information, and research findings. This data has enormous potential to radically transform how healthcare is delivered, managed, and improved. Most healthcare institutions, including clinical laboratories, already possess digital records and numerous data assets that can be leveraged to create additional value [1]. Although data in healthcare has a lot of potential, there are also significant challenges that organisations need to overcome if they want to maximise its benefits. Healthcare organizations face significant challenges in ensuring the privacy and security of sensitive data; they must comply with data protection laws and privacy regulations(e.g., HIPAA in the US, GDPR in the EU).which vary from country to country and impose strict requirements on the collection, storage, and sharing of personal health data [2]. Healthcare data monetization is hampered by one of the most pressing issues: patient data privacy [9] and this is because many countries enforce strict regulations Failure to legally comply with healthcare data privacy can result in hefty fines, lawsuits, loss of patient trust, reputational damage, and even and even harm to patient safety. As well, data privacy issues limit the ability to train high-quality healthcare AI models. This creates problems like bias and poor generalization. Federated Learning is emerging to balance privacy and performance. These limitations not only hinder collaboration between healthcare organizations but also limit the development and training of high-performance AI systems, which rely on large and diverse datasets to deliver accurate and unbiased results [3].

Federated Learning (FL) has recently emerged as a promising solution to this issue. By facilitating collaborative model training without the need to share raw data. FL provides security and privacy for user data. It allows collaborating participants, such as multiple hospitals from different locations in healthcare systems, to conduct training locally without sending data to a central server. This simplifies the healthcare process and improves and enhances healthcare decision-making and diagnosis [4], and offers financial benefits.

In this paper, we provide a comprehensive overview of the contributions of FL in healthcare. We review its applications in disease diagnosis, prediction, medical imaging, and classification. Furthermore, we analyze how FL contributes to healthcare data monetization.

2 Federated Learning in healthcare: foundations

In 2016, Google introduced federated learning FL, which is a collaboratively decentralized privacy-preserving technology to overcome challenges of data silos and data sensitivity [32]. First applied in Google keyboard to collaboratively learn from several Android phones [33], recently referring to multiple transitive clients (mobile devices, illustrations, organizations, etc.) aggregated in one or more central servers. FL architecture enables collaborative training models locally on private data, sharing only model updates (such as weights or gradients) with a central server for aggregation and building a robust global model. This is without the burden of local data transfer, which helps maintain data privacy and security.

There are different types of federated learning, such as Vertical Federated Learning (VFL) for clients containing datasets with other features, but from sample instances, when the opposite is Horizontal Federated Learning (HFL), and Federated Transfer Learning. The purpose of this is to add new features or samples that are not available to other clients. Additionally, Cross-Silo Federated Learning for a small number of participating entities, and Cross-Device Federated Learning that supports distributed learning across many edge devices like smartphones.

FL, which offers a novel distributed AI paradigm aimed at addressing concerns related to healthcare data privacy and management [34]. In a federated learning healthcare environment, the FL clients can be hospitals, clinics, labs, or research centers, focus on institutional collaboration where each Hospitals train the model locally on their private data (e.g., Electronic Health Records (EHRs), medical images (MRI, CT scans)), then send only the model updates (gradients/weights), and server aggregates them into a global model (see Fig. 1). In addition, the devices at the edge (phones, wearables, IoT medical devices) can act as FL clients. The devices used by patients collect local health data (e.g., heart rate, blood sugar, activity levels).

FL enables collaborative model training without moving sensitive medical data, thus protecting patient privacy and adhering to data protection regulations. Collaboration can improve model accuracy and generalization by enabling training on diverse and decentralized data sources. This leads the creation of comprehensive models that leverage a wider range of patient data, improving diagnostic and predictive capabilities. FL is expected to play a key role in realizing large-scale and collaborative healthcare systems and allow for a shift from centralized health data analytics to distributed healthcare operations with privacy awareness [35].

3 Federated Learning Applications in Healthcare

In this section, we focus on machine learning (ML) and deep learning (DL) methods applied through FL across various healthcare domains: disease diagnosis, disease prediction, medical imaging, and disease classification.

Federated Learning in Disease Diagnosis. This sub section reviews federated learning approaches that integrate classical ML and DL algorithms for disease diagnosis applications while maintaining data privacy. The following Table 1 gives a summary of all FL application for disease diagnosis.

FL has shown strong potential for improving rare disease diagnosis by enabling collaboration among multiple healthcare institutions while ensuring patient data privacy. In this context, Karthik Meduri et al [5] have proposed a FL framework that permits collaborative analysis of electronic health records (EHRs) with multiple institutions to participate in rare disease research while maintaining the privacy and security of patient data. The proposed architecture allows the institutions to train ML models such as forecasting patient treatment needs, including Logistic Regression, Decision-Tree-Classifiers, Support-Vectors-Classifiers, Random-Forests, and Stacking Classifiers. Among models, Random Forest achieved the best performance (90% accuracy, F1=0.80).

FL has also been utilized for cardiac disease detection, where privacy-preserving analysis of physiological signals can enhance early diagnosis and patient monitoring. In this context, Shahazad et al [25] proposed a federated learning with an Enhanced Dragonfly Optimization Algorithm approach called FedEDFA for cardiac disease detection, using Internet of Medical Things (IoMT)) such as ECG, heart rate, blood pressure, and the ML models such KNN,DT,MLP.

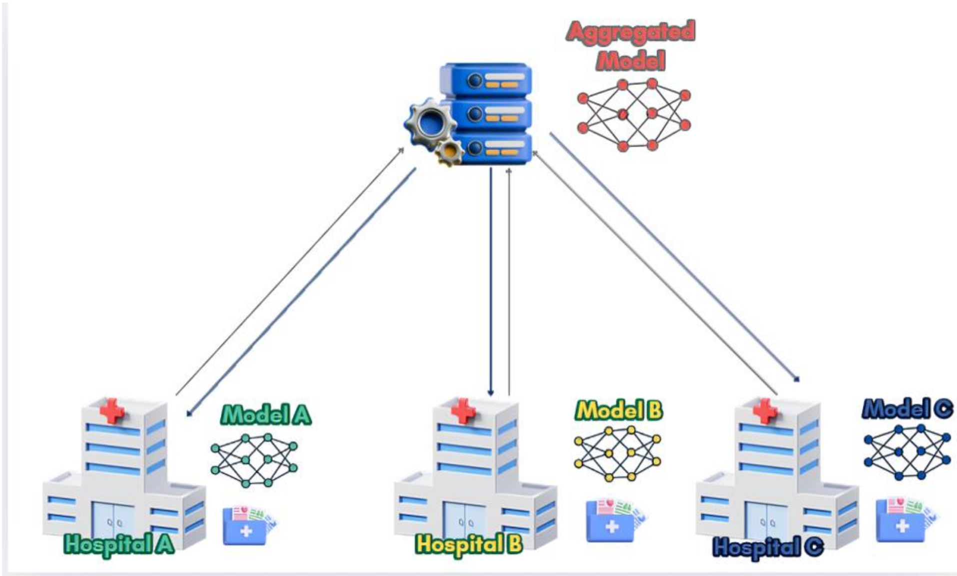

Fig. 1. Illustration overview of FL in healthcare.

The proposed approach expanded healthcare access through IoMT devices and enhanced privacy.

FL has further been applied in neonatal healthcare to support early detection and intervention for critical conditions such as birth asphyxia. In this framework, Pamely et al. [26] proposed HumekaFL, a FL-based mobile application for the early detection of birth asphyxia (BA). The proposed app, Federated Support Vector Machine (FedSVM), was trained with the Baby Chillanto dataset across 10 simulated hospital clients.

Beyond traditional ML models, FL has increasingly incorporated DL techniques that have shown promising results, such as in diabetes diagnosis. In this direction, Dolo et al [6] have proposed an approach that consists of applying the Differentially Private Stochastic Gradient Descent (DP-SGD) method in the Federated Averaging (FedAvg) algorithm using the Pima Indian diabetes dataset for diabetes prediction. Results showed ANN had the highest accuracy (76.55%), followed by FedAvg (74.15%). This approach focuses on balancing privacy and utility in medical data analysis while showing that enhancing privacy can reduce the accuracy of the model. Suyel et al [22] proposed an FL framework-based healthcare approach with a designed CNN architecture, ResKNet, for client-side model training of diabetic foot ulcers (DFU) images, and the aggregation using FedAvg for Diagnosing Diabetic Foot Ulcers. This work enables training machine learning models directly on client devices, such as smartphones and tablets, without transferring sensitive patient data to a central server.

FL has also been adopted in diagnosing mental and neuro-degenerative disorders, where patient data is highly sensitive. In this context, Sun L, et al. [24] proposed a FL framework with a DNN training model for depression disorder diagnosis using mobile health data collected via the BiAffect app. The study proves FL's ability to handle heterogeneous and privacy-sensitive data for mental health diagnosis. ALAM, et al [21] proposed an FL-based framework for early autism screening using facial image datasets. The system uses deep CNNs (Xception, ResNet50V2, MobileNetV2) within a FedAvg aggregation. The FL–based model achieved better accuracy than the central model. Another neurodegenerative disorder is Parkinson's disease, where Zheng et al. [20] proposed an adaptive FL framework + ResNet-18for Parkinson's disease (PD) diagnosis using facial expression analysis.

FL has also been applied in cardiac disease diagnosis using DL techniques. In this regard, Sultan Alasmari et al [23] proposed an FL framework with an SGD-DNN training model in cardiac images, ECG signals, patient records, and nutrition data, for early detection and personalized care in cardiac disease. The accuracy results show that the proposed FL approach outperforms the current ones.

Federated Learning in Disease prediction. This sub section reviews FL approaches that integrate classical ML and DL algorithms for Disease prediction applications while maintaining data privacy. The following Table 2 gives a summary of all FL application for Disease prediction.

FL has demonstrated strong potential in predicting cardiovascular conditions and related health risks. In this direction, Abdulrahman Gaber et al [7] proposed a FL model

Approach	Application	Models Used	Dataset	Aggregation Method	Reference
ML	Disease Diagnosis (rare diseases)	LR, DT, SVM, RF, Stacking	EHRs	Cross-institution evaluation (metrics)	Karthik Meduri et al [5]
	Cardiac disease detection (IoMT)	KNN, DT, MLP + FedEDFA (Dragonfly Optimization)	IoMT signals (ECG, HR, BP)	FL aggregation with FedEDFA	Shahazad et al [25]
	Birth asphyxia detection	FedSVM	Baby Chillanto dataset	FedAvg (10 simulated hospitals)	Pamely et al [26]
DL	Diabetes prediction	ANN, FedAvg, DPSGDFedAvg	Pima Indian Diabetes dataset	FedAvg + DP-SGD	Bakary Dolo et al [6]
	Diabetic foot ulcers	ResKNet CNN	DFU image dataset	FedAvg	Suyel et al [22]
	Depression disorder diagnosis	DNN	BiAffect mobile health data	FedAvg	Sun L et al [24]
	Autism screening	Xception, ResNet50V2, MobileNetV2	Facial image datasets	FedAvg	ALAM et al [21]
	Parkinson's diagnosis	ResNet-18	Facial expression data	Adaptive FL	Zheng et al [20]
	Cardiac early detection	SGD-DNN	Cardiac images, ECG, nutrition data	FedAvg	Sultan Alasmari et al [23]

Table. 1 Summary of FL Applications in Disease Diagnosis Using Machine and Deep Learning Models.

designed for predicting cardiovascular disease (CVD) by employing logistic regression and SVM algorithms. The proposed model was experimented with using the 10-year risk of the Framingham CVD dataset from Kaggle. The FedCVD model uses logistic regression and SVM with a polynomial kernel in the Federated Averaging (FedAvg) algorithm to train global models by aggregating locally trained models from multiple hospitals. The work evaluates logistic regression and SVM between centralized and decentralized approaches. The results show Federated SVM (AUC = 0.7340) outperformed centralized SVM (AUC = 0.6962), showing better robustness.

Rabia et al [27] proposed an FL-based stroke prediction model for early stroke prediction. Risk factors include hypertension, BMI, heart disease, glucose levels, smoking habits, prior stroke history, and age, using ML models LR, DT, and KNN. It achieved with a weighted voting classifier 97% accuracy; this is highly effective for early stroke prediction and can help healthcare providers with decision-making.

Brisimi TS, et al [28] proposed a federated/distributed learning approach for predicting hospitalizations due to cardiac events using EHRs and sparse Support Vector Machine (sSVM) with Cluster Primal Dual Splitting (cPDS) Aggregation. The objective of the proposed approach is to predict which patients will be hospitalized within a year based on their medical history. In addition to traditional machine learning models, federated learning with deep learning techniques in disease prediction has shown promising results. In this direction Muhammad Amir Khan et al [8] proposed a federated deep learning approach for cardiac prediction (AFLCP), which combines a heart disease dataset and DNNs with an asynchronous FL (Async-FL) framework, for heart disease prediction using ECG data. The results show that the proposed asynchronous FL outperforms synchronous FL and FL-Avg, achieving higher accuracy, precision, and F1-score, especially with more client nodes.

BHATT, Harsh, et al. [32] proposed an FL-based ANN architecture for stroke prediction, ANN models trained on real stroke case data across multiple clients, preserving patient privacy. The proposed model, an FL-based ANN, achieved 5–10% higher accuracy than traditional centralized models.

Federated Learning in Medical images. This sub section reviews FL approaches that integrate DL algorithms for in Medical images applications while maintaining data privacy. The following Table 3 gives a summary of all FL application for medical images.

Recent research has shown increasing interest in applying FL for medical image analysis, particularly for cancer detection, due to its ability to preserve data privacy while maintaining high diagnostic performance. MD. Zahin Muntaqim El Al [10] proposed a FL framework with Explainability (Grad-CAM) for brain tumor detection using MRI images with non-IID (independent and identically distributed) data, leveraging VGG19 as the backbone model. The model achieved 98.45% accuracy using VGG19 (Scaffold), which proves FL's effectiveness for brain tumor detection with MRI. Similarly, Onaizah et al [18] proposed FL-SiCNN, a Siamese Convolutional Neural Network (SiCNN) in a peer-to-peer federated learning approach (Decentralized) for diagnosing brain tumors from MRI images. The SiCNN model achieved

Approach	Application	Models Used	Dataset	Aggregation Method	Reference
ML	Cardiovascular disease (CVD)	Logistic Regression, SVM	Framingham CVD dataset (Kaggle)	FedAvg	Abdulrahman Gaber et al [7]
	Stroke prediction	LR, DT, KNN + Weighted Voting	Risk factors (hypertension, BMI, etc.)	FedAvg + Weighted Voting	Rabia et al [27]
	Cardiac event hospitalization	Sparse SVM	EHRs	Cluster Primal Dual Splitting (cPDS)	Brisimi TS et al [28]
DL	Cardiac prediction	DNN (AFLCP framework)	Heart disease dataset + ECG data	Async-FL	Muhammad Amir Khan et al [8]
	Stroke prediction	ANN	Real stroke case data	FedAvg	Bhatt et al [32]

Table. 2 Summary of FL Applications in Disease prediction Using Machine and Deep Learning Models.

high accuracy, changing around (97–98%) in brain tumor diagnosis, and the P2P FL-SiCNN system also reliably detected malicious participants (93–97%). for other diseases, Md Asadur, et al [19] proposed that Lung-AttNe, a CNN model enhanced with an attention mechanism, is deployed in an FL framework for detecting lung cancer from CT scans with Avg agg. The model achieved in the FL environment an accuracy of 92% with 2 and 3 clients.

Federated Learning in Disease classification. This sub section reviews FL approaches that integrate classical ML and DL algorithms for Disease classification applications while maintaining data privacy. The following Table 4 gives a summary of all FL application for Disease classification.

RODRIGUEZ et al [11] proposed federated ML algorithms for heart disease classification using the UCI heart disease dataset. The models used are binary classification models, including LR, a fully-connected neural network (NN) with one hidden layer; SVM, KNN, NB, DT, and random forests (RF). The federated aggregation strategies used several federated aggregation algorithms, including FedAvg, FedAdam, Scaffold, and FedProx. For results, the SVM models achieved the best test accuracy of 83.3%.

Recent studies increasingly focus on utilizing FL and DL models to improve disease classification while ensuring data privacy across institutions. Divya et al [12] proposed an approach of a CNN and FL-based privacy preserving for classifying an image dataset with seven classes of skin disease. The CNN model was trained on the HAM10000, which contains a diverse range of skin lesions. The results show the proposed CNN model achieving 91.25% accuracy, outperforming AlexNet, VGG16, ResNet50, and DenseNet121.This makes CNN models the best for skin disease. Similarly, Hassan, N [29] proposed an FL framework with FedAvg aggregation method for gallbladder disease classification using ultrasonic images, and two DL models were evaluated: a custom CNN and VGG16. The accuracy results of the models were compared locally (VGG16: 94%, CNN: 81%) and with global models (VGG16 + FedAvg: 99.7%, CNN + FedAvg: 88.7%); the global models achieved better accuracy. Additionally the respiratory disease classification, where Tahmid Hasan, et al [30] proposed an FL framework with blockchain integration for multi-class respiratory disease classification (COVID-19, Pneumonia, Tuberculosis, Lung Opacity, and Uninfected), using a dataset of 5000 chest X-ray images and employing a DNN for classification. The results show that the weight-manipulated FedAvg achieved higher stability and accuracy in multi-class classification tasks.

Notably, the Federated Averaging (FedAvg) algorithm appears most frequently, reflecting its role as the standard baseline method in healthcare-related FL research due to its simplicity and effectiveness.

The studies reviewed in this section demonstrate the effectiveness of FL in enhancing data privacy, as it enables decentralized model training without transferring initial patient data across institutions. This has enabled the construction of more accurate, trained models using more diverse data. Building on these advances, the following section explores how Federated Learning extends beyond technical innovation to enable secure and fair monetization of healthcare data.

4 Federated Learning in Healthcare Data Monetization

In this section, we focus on how federated learning enables healthcare data monetization through secure collaboration, internal optimization, and marketplace-based models.

4.1 Federated Learning for Secure Monetization :

FL offers a solution that enables hospitals, research institutions, and pharmaceutical companies to collaboratively train AI models without sharing raw data, only model shared updates (e.g.,

Approach	Application	Models Used	Dataset	Aggregation Method	Reference
DL	Brain tumor detection	VGG19	MRI images (Kaggle)	Scaffold	MD. Zahin Muntaqim El Al [10]
	Brain tumor detection (P2P)	SiCNN (Siamese CNN)	MRI images	Decentralized	Onaizah et al [18]
	Lung cancer detection	Lung-AttNe CNN	CT scan images	FedAvg	Md Asadur et al [19]

Table. 3 Summary of FL Applications in Medical images Using Machine and Deep Learning Models.

Approach	Application	Models Used	Dataset	Aggregation Method	Reference
ML	Heart disease classification	LR, NN, SVM, KNN, NB, DT, RF	UCI Heart Disease dataset	FedAvg, FedAdam, Scaffold, FedProx	Rodriguez et al [11]
DL	Skin disease classification	CNN	HAM10000	FedAvg	Divya et al [12]
	Gallbladder disease classification	Custom CNN, VGG16 (transfer learning)	Ultrasound images	FedAvg	Hassan N [29]
	Respiratory disease classification (COVID-19, Pneumonia, TB, etc.)	DNN	5000 Chest X-rays	Blockchain + FedAvg (weight manipulation)	Tahmid Hasan et al [30]

Table. 4 Summary of FL Applications in Disease classification Using Machine and Deep Learning Models.

gradients or weights). This collaboration enhances the global model and, therefore, improves predictive models for disease detection and treatment optimization. Tajabadi, M et al [13] discussed the limited incentive for private sector companies to participate in collaborative learning of AI models, as they will be available to everyone regardless of their individual contributions and the amounts of data from each party. The desired goal is fair collaborative training of artificial intelligence models that enables each participant to obtain returns commensurate with the investments made. A simulation of three nodes that collaboratively train custom models with performance levels commensurate with their contributions is presented. The results showed the effectiveness of the fair scenario in achieving the best return gain for the largest data contributor. Tajabadi, M et al [13] believe that a fair framework encourages organizations to cooperate because the return will also be fair for organizations that provide fewer resources to benefit from cooperation in improving returns. HOSSEINI, S et al [14] proposed a new scheme called Federal Fair and Proportional Learning (Prop-FFL).). The proposed work is based on improving the equity model and reducing performance differences between participating hospitals, which provides more consistent performance. Pro-FFL modifies the central server's aggregation rule to balance training losses across hospitals, so all participants contribute proportionally and benefit equally. The results of the work mentioned above show that healthcare institutions can achieve secure income by participating in contributions to the Unified Learning Network and receiving financial incentives based on their contributions.

4.2 FL-Enhanced CDSS for Internal Monetization

Internal healthcare systems such as Electronic Health Records (EHRs) and Hospital Information Systems (HIS) form the foundation for advanced tools like Clinical Decision Support Systems (CDSS).CDSS is a health information technology system designed to optimise healthcare by enhancing medical decision-making, providing physicians and staff with targeted clinical knowledge and patient-specific information. It can also help with disease detection, diagnosis, and patient monitoring.

The CDSS system leverages machine learning and artificial intelligence to provide professionals with deeper insights that help them make more accurate decisions. However, these methods face significant challenges in CDSS, including maintaining patient privacy and accessing broad and diverse data sources.

To overcome these barriers, DODEVSKI et al [15] proposed an approach of integrating the horizontal cross-silo FL with CDSS with a focus on clinical workflows (e.g., diagnosis, treatment planning, antibiotic management). This system enables organizations to train models locally on their own datasets, which are compiled into a global model without sharing raw data. The study pointed out how effective FL is in ensuring privacy, security, and interoperability between institutions, enabling efficient and integrated healthcare delivery. The results show that the integration of FL with CDSS in clinical workflows can improve predictive accuracy of CDSS, provide precise Data-driven decision support, and Privacy-preserving collaboration of sensitive medical data. Importantly, this leads

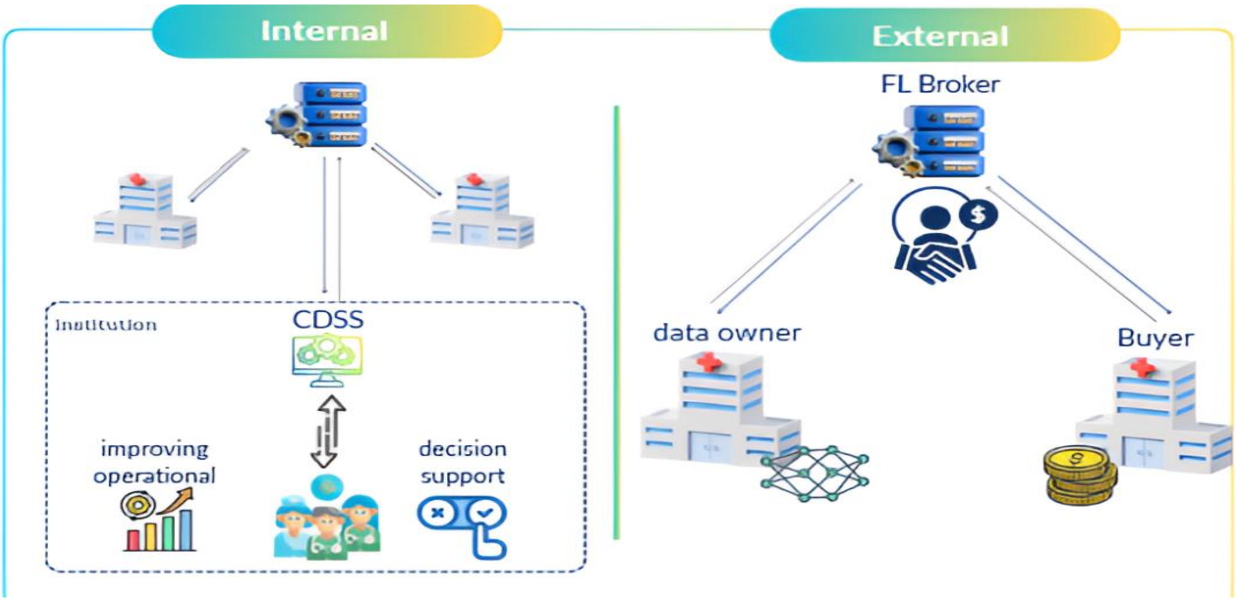

Fig. 2. Internal and External Revenue Generation Mechanisms for Healthcare Data in FL Environments

to creating internal revenue in the institution mainly through cost savings, compliance advantages, drug budget optimization, and improved staff efficiency. This is how medical data is monetized by reducing waste, avoiding penalties, and improving operational efficiency within healthcare organizations.

4.3 Federated Healthcare Data Marketplaces

Healthcare data owners are concerned about losing patient trust due to the risks of privacy breaches and the misuse of sensitive medical records. This concern has led to a decline in demand for trading medical data in the market. To address this issue, ZHENG, Shuyuan, et al [16] proposed a model market that protects privacy using federated learning called FL-Market. A typical market consists of three parties: data owners, model buyers, and an FL broker. The buyer purchases the ML model on a financial budget, and then receives special local gradations from data owners without selling or sharing raw data. While the FL-broker assigns training tasks to data subjects and aggregates their gradients into one global gradient using the aggregation mechanism OptAggr with personalized LDP parameters. FL-broker also pays the data subjects from the budget. These FL marketplaces enable collaboration among hospitals, AI developers, pharmaceutical companies, and regulatory agencies. By engaging in these platforms, organizations can monetize their contributions to AI development while ensuring compliance with privacy regulations. In addition to ensuring privacy and secure data aggregation, effective monetization also requires strong incentive mechanisms. Liu et al. [17] proposed FedCoin, a blockchain-based peer-to-peer payment system for FL that distributes rewards among participants based on Shapley Value contributions. While not originally healthcare-specific, this approach can be adapted to federated healthcare marketplaces, where hospitals and research institutions are rewarded in proportion to the value of their data and model updates. Such mechanisms ensure fairness, transparency, and sustainability in healthcare data monetization.

5 Conclusion:

Federated learning is a transformative approach to healthcare that allows machine and deep learning models to be trained collaboratively while maintaining patient privacy and complying with stringent regulatory requirements.

This paper provides a comprehensive overview of the various applications of FL in machine learning and deep learning approaches across several medical contexts, namely disease diagnosis and prediction, medical imaging and classification, in addition to its growing role in enabling organizations to monetize healthcare data through secure and equitable collaboration, internal improvement, and Federated markets.

These contributions show that FL is playing a key role in creating a new era for monetizing healthcare data while adhering to privacy regulations. FL enables value creation by improving model accuracy and generalization from distributed data while simultaneously capturing value through privacy-preserving monetization structures and collaborative markets.

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