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A Comprehensive Review on Federated Learning in Disease Detection

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Abstract

Healthcare data, which is frequently dispersed among various organisations, has enormous potential to improve predictive analytics and illness identification. However, there are substantial privacy & legal obstacles to sharing this private data for centralised model training. Federated Learning is a paradigm shift that allows several organisations to work together to build a global model without disclosing raw patient information. Federated Learning uses a larger dataset to provide more reliable insights while maintaining individual privacy. The use of federated learning to improve disease diagnosis and predictive health analytics' accuracy is demonstrated in this article. It investigates how, even in situations where data is localised at its source, Federated Learning architectures enable the creation of potent diagnostic and prognostic models. Federated Learning reduces the danger of data breaches and guarantees adherence to strict privacy laws such as the Health Insurance Portability and Accountability Act and the General Data Protection Regulation by encouraging collaborative learning and limiting data exposure. By overcoming the constraints imposed by the availability of data at a single site, this collaborative approach encourages the development of more accurate and generalised models. This article looks at a number of Federated Learning approaches that are relevant to the healthcare industry, including methods for managing system imbalances and data heterogeneity among participating nodes. It goes over real-world examples that show the way Federated Learning may be used to find illness biomarkers, forecast patient outcomes, and improve treatment regimens. It also discusses contemporary issues including model personalisation, communication overhead, and security flaws unique to healthcare federated learning. The article concludes by outlining potential research avenues and future directions, highlighting Federated Learning's critical role in influencing the growth of the next wave of privacy-preserving, Artificial Intelligence-driven healthcare solutions.

Keywords: Convolutional Neural Networks, disease detection, Federated Learning, logistic regression, Long Short-Term Memory Networks, predictive analytics

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INTRODUCTION

Recognizing and diagnosing illnesses early is crucial for effective treatment, improved patient outcomes, and reducing the burden on healthcare systems. In numerous conditions, early detection facilitates treatments that can greatly enhance a patient's outlook and help sustain their quality of life for extended durations. It can alleviate the financial strain on healthcare systems by decelerating disease advancement and possibly circumventing pricier late-stage interventions. In numerous cases, prompt action can avert the onset of serious and irreversible issues. Continuous advancements in technology enhance the capability to identify diseases at earlier stages. They allow for swift interventions that can impede disease progress, enhance quality of life, and frequently prevent severe complications or death [1].

Regulatory compliance, data privacy, security, and the inherent difficulties of maintaining large and varied datasets in one place are just a few of the drawbacks of traditional centralized Machine Learning (ML) in the healthcare industry. The development of scalable models is hampered by these constraints, which frequently result in data silos and ethical dilemmas [2]. Some of the issues are mentioned below.

- *Data privacy and Regulatory Issues:* The issue of data privacy and security is one of the biggest drawbacks of conventional centralized machine learning in the healthcare industry. Because of stringent privacy laws like Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR), direct sharing of medical data across institutions is frequently prohibited. By requiring data owners to upload their data to a single location, centralized models raise the danger of cyberattacks and privacy breaches by creating a single point of failure. This may result in data being stuck in "silos," which would hinder thorough study and disease prediction [3].
- *Data Scarcity and Generalizability:* For efficient training, ML and Deep Learning (DL) models frequently need large volumes of data. However, data scarcity often limits medical databases, especially for specific disorders or rare diseases. When applied to other institutions, models trained on data from a single institution may have trouble generalizing because of data heterogeneity, which is the fact that data distributions change greatly between sites [4].
- *Communication Delays and Computational Burden:* Conventional centralized cloud computing systems for disease prediction may have protracted communication delays and significant computational burdens. High latency and higher network bandwidth consumption might result from processing huge amounts of data in a central cloud. There are substantial resource requirements when large datasets must be moved to a central repository for training [5].

Federated learning (FL) is a decentralized machine learning methodology that facilitates collaborative model training across several institutions without the direct exchange of raw data, hence solving significant issues pertaining to data privacy and security in sensitive fields such as healthcare. This unique paradigm is especially advantageous for illness detection and prediction analysis, where extensive, varied datasets are essential for constructing strong models; yet, data siloing resulting from privacy constraints poses a considerable obstacle [6]. Google created this method to solve problems including ineffective communication, privacy issues, and the requirement for training results to be quickly usable due to centralized data storage [7]. In FL, only minor changes to the shared model are shared, and the training data is still stored locally on client devices. Figure 1 gives the basic workflow of FL [8].

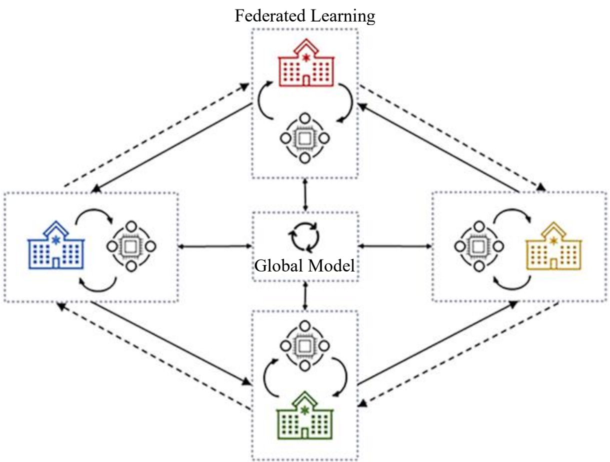

Figure 1. Basic workflow of FL.

Usually, there are several rounds to the FL process. Every round includes

- *Initialization of the Model:* A global model is initialized and distributed to participating clients by the central server.
- *Local Training:* After receiving the global model, clients train it locally using datasets of their own choosing. Several gradient descent iterations are frequently required for this.
- *Transmission of Model Updates:* Clients only communicate their calculated model updates, such as weights or gradients to the central server.
- *Global Aggregation:* To improve the global model, the central server typically uses methods like Federated Averaging (FedAvg) to aggregate these updates.
- *Redistribution:* Following refinement, the clients receive a new version of the global model for the upcoming training session [9].

FL is based on the idea of "bringing the model to the data" as opposed to gathering all the data in one specific place. By guaranteeing that sensitive or private information never leaves the client's device, this design protects data security and privacy. Based on the way data is shared among clients, FL can be broadly divided into three types: federated transfer learning (FTL), vertical federated learning (VFL), and horizontal federated learning (HFL). These categories cover various data splitting and collaboration scenarios [10].

Horizontal Federated Learning (HFL)

The most popular kind of federated learning is horizontal federated learning (HFL), sometimes referred to as sample-based FL. Clients in HFL have distinct sample spaces but the same feature and target spaces. This indicates that each client has unique data records (samples), even when the sorts of data properties are similar across clients. Google was the first to introduce HFL [11].

Vertical Federated Learning (VFL)

Clients that have different feature spaces but the same sample ID space are used for Vertical Federated Learning (VFL), often referred to as feature-based FL. This is a typical situation for firms that have similar users but distinct kinds of information on them. VFL enables the cooperative training of machine learning models by several parties with distinct characteristics about the same group of users without disclosing personal information [12].

Federated Transfer Learning (FTL)

A more complicated category known as Federated Transfer Learning (FTL) is used when there are insufficient shared features or samples, or when the sample ID space and feature space vary between clients. To facilitate knowledge sharing across fields with little overlap in data, FTL incorporates transfer learning strategies into the federated learning architecture [13].

FL architecture: Client, Server, Model updates

A central server manages the training process for several dispersed clients in federated learning (FL), which usually uses a client-server architecture. While maintaining the localization of raw training data on client devices, this architecture enables collaborative model training.

Client

Devices or organizations that possess their own local datasets are commonly referred to as clients in federated learning systems. These clients carry out local calculations and are the main data owners. Every client uses its own private dataset to train a machine learning model. Mini-batch stochastic gradient descent (SGD) is one iterative optimization technique used in this local training to update the model parameters. Ensuring data privacy is a fundamental component of the client's job. In contrast to conventional centralized machine learning models, raw data never leaves the client device, greatly reducing privacy concerns. Following local training, clients only compute and send the model updates, such as weights or gradients, to the central server. This preserves crucial raw data and lowers communication overhead. In each round, the server sends the clients the aggregated global model, which they utilize as a basis for the subsequent local training cycle [14].

Server

The FL process is orchestrated by the central server. Coordinating training rounds, compiling model updates, and upholding the global model are its main duties. Training sessions are started by the server, which also chooses when to start them and broadcasts the global model to specific clients. The server compiles client-provided local model modifications to create an updated global model. A popular aggregation technique called FedAvg calculates a weighted average of client updates. In situations where client data distributions differ, the server may keep track of a collection of cluster models, iteratively improving them using client models it receives, and then returning a customized model to the client [14].

Model updates

The primary data shared between clients and the server in federated learning is model changes. These updates are usually the modifications to the model parameters that the clients have learned locally. Rather than sending the actual raw data, clients typically send weight updates or gradients. This is essential for protecting privacy. Particularly for high-dimensional models or contexts with limited bandwidth, communicating model updates rather than raw data greatly lessens the communication strain. By varying the number of quantization levels during training, methods such as adaptive quantization of model updates can further improve communication efficiency. The global model's performance and convergence depend heavily on the calibre of local model updates. Performance deterioration may result from unreliable clients uploading poor-quality models. There are systems in place to penalize or commend companies according on the calibre of their local model upgrades. To create a new global model, the server combines these local updates. FedAvg, which employs a weighted average of client updates, is one of several aggregating techniques [15].

ROLE OF PREDICTIVE ANALYTICS IN HEALTHCARE

Predictive analytics is a decision science that analyses historical and current data to estimate future trends and probability using tried-and-true scientific techniques. Predictive analytics, which makes use of ML and artificial intelligence (AI) algorithms, is revolutionizing healthcare by lowering costs while also greatly enhancing early disease detection, diagnosis, and patient outcomes. It seeks to identify the best answers by using scientific principles to remove guesswork from decision-making processes. Predicting future events, probabilities, and trends using historical data is the main objective of predictive analytics. Instead of relying on reactive reactions, this forward-thinking strategy enables proactive decision-making [16]. Predictive analytics, for example, can predict future manufacturing end product rejection rates, which might affect rolling throughput yield measures. Decision-makers can take well-informed choices now to accomplish future goals by using predictive analytics, which gives them insights into possible future events. It converts unprocessed data into high-level, decision-supporting information that may be accessed instantly or very instantly. By assisting with goal-setting, competitive environment analysis, and strategic plan implementation, this competency supports strategic company management. Identifying and controlling risks before they become a reality is an important objective [17].

By evaluating and controlling the risk of patient readmissions, predictive analytics in healthcare can facilitate the development of individualized treatment plans and the best possible time for interventions. In the field of illness risk prediction, this technique is essential for determining who is at risk for different disorders. For example, it is frequently used to identify cardiac conditions and forecast the risks of hypertension using data mining technologies; two common methods are Support Vector Machines (SVMs) and Logistic Regression (LR). Predictive analytics is also becoming more popular in the early diagnosis and detection of Type 2 diabetes. It uses clinical measurements and supervised machine learning techniques to accurately forecast when the disease will manifest. As demonstrated by the Concurrent Prediction of numerous Complications (CPMC) model employing Multi-Task Learning (MTL), it also helps forecast numerous complications from chronic diseases. By using historical and current data to predict disease outbreaks, public health professionals can better allocate resources and take preventative action, improving public health responses [18, 19].

Predictive analytics plays a critical role in tracking and predicting the course of illnesses in the context of disease progression, which is essential for prompt and efficient medical intervention. More accurately than traditional approaches that rely just on initial or static clinical data, predictive models may simulate and forecast the course of chronic diseases like Alzheimer's by utilizing longitudinal data fusion. Additionally, predictive analytics has a significant impact on therapy optimization, allowing for more individualized and efficient patient care. Through the incorporation of many data sources, like as wearable technologies, genetic data, and electronic medical records, predictive models can offer important insights for customizing treatment plans to meet the needs of each patient [20]. To help with early cancer type identification and prognosis, machine learning techniques such as Artificial Neural Networks (ANNs), Bayesian Networks (BNs), SVMs, and Decision Trees (DTs) are used to create predictive models for accurate and efficient decision support systems. Predictive analytics is used to help optimize treatment strategies for cardiovascular disorders by identifying patients who are most likely to respond to specific treatments [21].

Healthcare is being disrupted by real-time analysis, which is altering how decisions are made, treatments are administered, and organizations and procedures are run. Healthcare businesses can now analyze massive datasets in real time, alerting patients to diseases, choosing the best therapies, and allocating vital resources thanks to technologies like AI, the Internet of Things (IoT), and cloud computing. This feature is particularly important in emergency medicine, where clinical decision-making and patient care are improved by real-time analytics and Clinical Decision Support Systems (CDSS). Big data analytics combined with real-time analysis is revolutionizing healthcare by supporting clinical decision-making with data-driven insights, resulting in improved patient outcomes, precision medicine, and preventive healthcare. By addressing problems or opportunities as they emerge, this combination increases productivity and enables fast, fact-based decisions through ongoing monitoring and analysis of critical data. Real-time data integration into big data analytics platforms enables predictive analytics and individualized treatment for managing chronic diseases [22, 23].

Integration of FL With Predictive Analytics

Without centralising their raw data, several entities can work together to develop a common prediction model using FL, a decentralised machine learning technique. Conversely, predictive analytics makes predictions about future events or behaviours based on historical data. Sophisticated data analysis across sensitive and dispersed datasets is made possible by the confluence of these two domains. To solve issues like data privacy, dispersed data sources, and the requirement for cooperative model creation without sharing raw data, FL is becoming more and more integrated with predictive analytics. Through this connectivity, businesses may use a variety of datasets to increase the accuracy of their prediction models while protecting the confidentiality and privacy of individual data. Merely the model upgrades or attributes are sent to a central server allowing compilation into a worldwide model in FL. Here each user trains a local copy of a model utilising its own data. By storing sensitive data on local devices, this procedure improves data security & privacy [24].

FL is an essential resource for machine learning that protects privacy, particularly when data sharing is limited for legal or commercial reasons. To adequately safeguard data throughout the training procedure, methods like secure multiparty computing & differential privacy are frequently used. By utilising a broader and more varied collection of data than any one organisation or device could supply alone, FL enables several organisations or devices to participate to the creation of a more reliable and genuine model [25].

In many fields, FL combined with predictive analytics holds great promise, especially when dealing with sensitive or widely distributed data. Without sacrificing patient privacy, FL makes it possible for healthcare organisations to securely collaborate on projects like illness forecasting, medical picture analysis, and patient monitoring. For example, in multi-modal healthcare datasets, it can improve diagnostic accuracy. FL can assist predictive analytics for individualised patient care by utilising wearables, remote monitoring, and real-time, decentralised data handling through IoT devices [26]. For a variety of clinically significant machine learning tasks, FL can be applied to multi-centre EHR datasets, providing insightful information while maintaining data confidentiality. Using data from machines, manufacturing units, and sensors, FL is essential for creating predictive maintenance and quality inspection models in Industry 4.0 while preserving data security and confidentiality across several entities. When it comes to predicting production line failures, FL-based techniques like Random Forest (RF) and Federated SVMs have demonstrated comparable efficacy to centralised alternatives. FL has demonstrated encouraging results when used to non-independent and identically distributed data when analysing the implications of various forms of data heterogeneity in machinery fault detection [27].

Using FL to forecast disease usually entails a cooperative procedure in which several clients or medical facilities train a common machine learning algorithm without explicitly sharing their private patient information. This decentralised method uses a variety of datasets to improve forecasting precision and generalisability while addressing important privacy concerns. A global machine learning model (such as a DL model like a Convolutional Neural Network or Recurrent Neural Network, or a more conventional model like Logistic Regression) is initialised on a central server at the start of the process. All contributing clients (medical establishments or data proprietors) are then given access to this starting model, together with its framework & settings. The second step comes next, in which every client has its own private dataset that is kept locally and is never shared with other clients or the central server. From the received worldwide model, consumers use their own private datasets to construct their local models. Using local computing resources, this training takes place over a predetermined number of epochs or iterations. During this stage, the model's parameters like weights and gradients are modified. Clients can use privacy-preserving strategies, such as differential privacy, throughout the local training by introducing noise into the model updates in order to further boost privacy. Updates can also be encrypted using homomorphic encryption before being sent to the server, enabling calculations on the encrypted data. Next comes the third step, in which each client shares to the centralised server just the modified model parameters (like weights and gradients). The actual raw data is never sent. All participating clients send model upgrades to the centralised server, which compiles them into a fresh global model. The most popular aggregation technique is the Federated Averaging (FedAvg) strategy, which updates the worldwide (global) model by averaging the local model parameters, which are frequently graded by the dimension of every client's dataset. It is also possible to utilise other aggregation techniques such as FedProx, FedAdagrad, or FedAdam. The worldwide model, which ideally incorporates insights from all participant datasets while maintaining the privacy of individual data, is then updated using the aggregated parameters. For a number of FL rounds, the second and third phases are repeated until a predetermined stopping criterion is satisfied. This criterion could be a target performance indicator, a maximum number of rounds, or convergence of the global model (for example, when validation loss stops getting better). To track the global model's development and decide when to halt training, its performance is routinely assessed on a different test dataset (or aggregated validation datasets from clients). Metrics including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC) are commonly utilized to assess performance. F1-Score and AUPRC (Area Under the Precision-Recall Curve) are frequently chosen for unbalanced datasets. To guarantee reliable evaluation and remove bias from data partitioning, K-fold cross-validation is frequently employed [28–30].

Logistic Regression (LR) in FL

Given its ease of use and efficacy, especially in situations where privacy preservation is required, LR is a popular statistical model for classification issues that has been frequently employed in FL contexts. Federated Logistic Regression (FLR) solves important issues with data security and privacy by allowing LR models to be trained across decentralised datasets without exchanging raw data. There are many advantages to integrating LR and FL, particularly in sensitive data domains like healthcare and finance [21]. By sharing only model parameters or encrypted coefficients instead of raw data, FL enables several parties to work together to train a centralised LR model, greatly lowering the possibility of information leakage. One important cryptographic method in FLR for safeguarding data shared between cooperative parties is homomorphic encryption (HE). It ensures privacy when combining local LR models by enabling computations on encrypted data without decrypting it. One popular semi-homomorphic encryption technique in FLR is the Paillier Cryptosystem. To further improve security and privacy, certain FLR algorithms are made to function without the assistance of a reliable third-party coordinator [31].

Convolutional Neural Networks (CNNs) in FL

For CNN training on decentralised datasets, FL offers a privacy-preserving framework, which is particularly helpful in industries where data privacy is crucial, such as healthcare. Without requiring a lot of manual feature engineering, CNNs are very good at automatically extracting hierarchical features from raw input, such photos. In FL contexts, where multiple local datasets may have different features, this capability is essential. CNNs are great for processing sensor data, medical pictures (such as X-rays, CT scans, and MRI images), and other spatial information frequently seen in FL applications since they are particularly made to analyse data having a known grid-like architecture. Recent developments in FL, like FedDCT, enable the training of high-performance CNNs on resource-constrained edge devices by breaking the model up into smaller sub-models, despite the fact that large CNNs can be parameter-heavy. This solves the memory bottlenecks that are frequently seen in FL scenarios that occur in the actual life. Strategic architectural changes to CNNs can allow them to achieve comparable or even better robustness, even if Vision Transformers (ViTs) have been proposed to perform better than CNNs in handling data heterogeneity in FL [32, 33].

Long Short-Term Memory Networks (LSTMNs) in FL

For FL tasks that need the comprehension of long-term dependencies, LSTMNs (also known as LSTMs) are a form of recurrent neural network (RNN) that excels at processing sequential input. By using memory cells and gating mechanisms (input, forget, and output gates) that control information flow, LSTMs solve the vanishing gradient issue that plagues conventional RNNs. LSTMs can benefit from decentralised time-series data while maintaining privacy when they are incorporated into a FL framework. Because LSTMs are made especially for sequential data, they may identify intricate and non-linear patterns over time. Because of this, they are ideal for applications such as remaining usable life (RUL) estimate, traffic prediction, and load forecasting. By training locally on private data and only exchanging model parameters with a central server, FL-based LSTM models guarantee that sensitive, raw data never leaves the client's device. For applications handling proprietary or personal data, this is essential. FL-based LSTM models have outperformed conventional centralised or local learning techniques in numerous circumstances (e.g., higher accuracy, fewer false positive rates), particularly when it comes to handling sequential data and protecting privacy [34, 35].

APPLICATIONS OF FL IN DISEASE DETECTION

FL is being used more and more to diagnose chronic diabetes since it provides a private way to use dispersed medical data. For sensitive medical data, our approach makes it possible for many institutions to collaborate on model training without exchanging raw patient data. By resolving privacy issues related to centralised data collecting, FL presents a promising option for diabetes control and early detection. Chronic diabetes mellitus can cause serious organ damage if left untreated or not identified in a timely manner. Effective models for the identification of type 2 diabetes have been developed thanks in large part to machine learning; however, because these models are usually kept in a centralised repository, they frequently do not provide privacy protections for patient data. In order to solve this, FL permits models to be trained on regional datasets from different healthcare providers without requiring direct data exchange [36].

Using the Pima Indian dataset, for example, one study suggested applying Differentially Private Stochastic Gradient Descent to the Federated Averaging (DPSGDFedAvg) model for diabetes prediction. This model achieved 60% to 70% accuracy while preserving a high degree of privacy. Using actual Canadian primary care data, another study used FedAvg to predict diabetes and compared its results to those of centralised and province-based models. While federated LR fared worse than the centralised method, the federated Multi-Layer Perceptron (MLP) model was found to perform on par with or better. This implies that compared to simpler linear models, neural network parameters with more complexity, such as those in MLP, may retain more characteristics after aggregation [37, 38].

Innovative healthcare solutions are required due to the rising incidence of chronic illnesses like diabetes, and real-time monitoring is made possible in large part by the Internet of Things (IoT). Privacy concerns are raised by traditional centralised data techniques for model training. For real-time medical IoT applications, AFL-CDP (Adaptive Federated Learning for Chronic Disease Prediction) is a novel technique that improves accuracy and privacy in chronic disease surveillance, including diabetes. With the help of this framework's decentralised methodology, model training takes place across several edge devices without sending raw data to a central server. AFL-CDP incorporates Secure Private Aggregation (SPECK), a cutting-edge privacy preservation method that protects patient data throughout the FL process by using secure aggregation and encryption. In order to facilitate early diagnosis and treatment while maintaining data privacy, FL is also being thoroughly investigated for the prediction of cardiovascular disease (CVD), a major cause of death globally. Although ML techniques can help with early CVD detection, their efficacy is reliant on having access to substantial, high-quality datasets [39].

The FedCVD benchmark was created to close the gap in practical FL applications for CVD. Using naturally dispersed datasets from seven institutions, this benchmark consists of two primary tasks: echocardiography (ECHO) segmentation and electrocardiogram (ECG) classification. Real-world non-IID (non-independent and identically distributed) and long-tail data distributions provide new difficulties, as demonstrated by experiments conducted on these datasets. Non-IID data can make it difficult to train multi-label prediction models collaboratively and impede global model convergence because feature or label distributions differ greatly between institutions. Performance problems are made worse by long-tail distributions, when a small number of labels predominate and the majority are sparse, particularly at underprivileged institutions. According to studies, FL algorithms like FedInit and Scaffold, which are expressly intended to handle heterogeneity, show notable benefits over more straightforward algorithms like FedAvg. They can even beat centralised supervised models on international test sets. Mainstream FL algorithms typically retain utility and outperform non-cooperative algorithms that simply utilise unlabelled data on every client for the difficult Fed-ECHO task, wherein the data is label-incomplete. Algorithms for federated semi-supervised learning that employ unlabelled data may operate better [40, 41].

Because FL allows for cross-institutional collaborative model training while protecting patient privacy, it is being used more and more in cancer detection, especially for early diagnosis combining both medical imaging and pathology data. Without requiring the centralisation of private patient data, FL makes it easier to train strong DL models for different forms of cancer using medical images. Early identification greatly increases treatment efficacy and survival rates; therefore, this is essential. FL is extensively investigated for MRI, ultrasound, and mammography-based breast cancer detection. High accuracy has been demonstrated by FL models for breast cancer screening while protecting patient privacy. FL removes the requirement to send private patient data by allowing DL models to be trained on large datasets spread across multiple data centres. This makes it possible to use mammography images for collaborative learning from disparate data sources without jeopardising confidentiality [42].

Using CT, PET, and chest X-rays for early detection, FL is also used in the diagnosis of lung cancer. For the classification of lung cancer, histopathological image analysis is essential for identifying morphological abnormalities in tissue samples. On-site data training without transmission is made possible by this distributed data processing, which also enhances scalability and protects privacy. One important use of AI and ML is the early detection of brain tumours, with FL tackling issues like data privacy and heterogeneity. FL improves diagnostic precision while protecting patient privacy when combined with Magnetic Resonance Imaging (MRI) technology. The FL framework incorporates several CNN models for classifying brain tumours, such as VGG16, ResNet50, DenseNet121, and EfficientNet. In particular, for research-prototype algorithms, frameworks are being proposed to facilitate flexible federated learning for cross-site training, validation, and assessment of deep prostate cancer detection algorithms. By using an abstracted representation of the model architecture and data, these frameworks enable the training of unpolished prototype DL models without requiring any changes [43].

Prostate cancer diagnosis and staging from MRI is difficult for both radiologists and DL algorithms; FL helps with this. Without disclosing private patient health information (PHI), FL offers a platform for exchanging models and copious amounts of data for thorough cross-site validation and improved model training. FL is capable of managing extremely diverse patient distributions, ground truth annotations, and MRI data from several institutions. This eliminates the requirement for data transfer, pooling, or homogenisation and enables models to learn from a variety of private datasets. In order to overcome data privacy problems in healthcare settings, FL is used in the diagnosis of skin cancer. CNNs and asynchronous FL are used in privacy-conscious machine learning techniques for skin cancer detection. To improve accuracy and convergence, these techniques add temporally weighted aggregation and optimise communication rounds. One study classified skin cancer accurately and securely using VGG16 in a FL architecture that was resistant to data poisoning assaults. By aggregating models on a central server and allowing models to be trained using private patient data on local clients, FL helps solve the “Data Silo” issue by letting users to collaborate on model training without exchanging raw data [44].

FL is used to monitor and forecast illness outbreaks, such as those caused by the flu and COVID-19. The critical need for efficient disease modelling and detection technologies was brought to light by the COVID-19 pandemic. In this context, FL has been frequently used to overcome the issues raised by data silos and privacy concerns. A mobility-based Susceptible-Exposed-Infectious-Recovered (SEIR) model has been utilised to forecast the updated COVID-19 infection rate in the USA using FL, specifically Federated Multitask Learning (FMTL). By developing customised models, this method helps address problems associated with heterogeneous local data distributions. Using real-time mobility records from several US states in 2020 and 2021, it was found that, despite varying rates of spread, COVID-19-infected cases were correlated. According to one study, Minnesota had a high root-mean-square percentage error for real COVID-19 instances compared to anticipated cases, while Colorado had a low one. Without appropriate vaccination or social separation, mobility-based SEIR simulations also predicted that extinction would occur in at least 400 days. To handle non-stationary patterns and several waves of COVID-19, hybrid models that include DL (particularly stacked-LSTM), particle swarm optimisation, and epidemic modelling have been developed. These models use data fitting and parameter optimisation to integrate the impacts of several factors and estimate parameters on a pretty consistent basis. These models have surpassed current techniques in predicting COVID-19 spread in countries like USA, India & UK and has demonstrated the capacity to manage numerous waves. Given privacy issues that forbid sharing these images between institutions, FL is often employed for COVID-19 detection from medical diagnostic images, such as chest X-rays and CT scans. For COVID-19 image classification, FL models supplemented with Generative Adversarial Networks (GANs) have been developed, enabling collaborative training while maintaining privacy in edge cloud computing environments. Federated Graph Machine Learning (FGML) systems like as Falcon have been created to forecast individual-level COVID-19 infection while maintaining privacy, particularly with respect to fine-grained user mobility trajectories [45, 46].

In addition to incorporating differential privacy techniques and pseudo-location creation to secure user information, these frameworks leverage hypergraph structures and spatiotemporal hyperedges to characterise interactions. For counteracting the performance drop caused by obfuscation, they additionally incorporate cooperative coupling methods between models at the individual and regional levels. By combining training data from several self-reporting crowdsourcing mobile and online applications, FL frameworks can be used to create fine-grained COVID-19 vulnerability prediction maps. To reduce data bias and safeguard user information, an adaptive worker selection algorithm and differential privacy strategy are implemented. The usefulness of these methods in predicting clinical outcomes has been demonstrated by the development of FL models that use Electronic Health Record (EHR) data to forecast death in hospitalised COVID-19 patients [47].

For increasing prediction accuracy & public health responses, FL is being researched for predicting flu trends across several locations by utilising distributed datasets. In USA, Centres for Disease Control and Prevention's (CDC's) had undertaken influenza prediction challenge for the 2023–2024 season. In that challenge it was found that the Flusion model, which combines ML techniques (gradient boosting for quantile regression) with Bayesian autoregressive model, had performed best. Flusion combines information from several surveillance signals, such as laboratory-confirmed influenza hospitalisations, outpatient doctor visits (ILI+), and hospital admissions recorded in the CDC's National Healthcare Safety Network (NHSN). Joint training on data from various surveillance signals and locations was the main factor in its excellent performance, underscoring the need of information sharing, particularly in situations where target surveillance systems had limited data. Metrics including mean weighted interval score (MWIS), coverage rates of central prediction intervals & mean absolute error (MAE) of the predictive median are utilized to assess flu forecasts. Forecasts that are well-calibrated show that predictions and observed data are generally in good agreement. Federated evaluation techniques are essential for tasks like client selection, incentive mechanism design, and malicious attack detection; all of which enhance FL performance in flu prediction [48].

For early detection and classification of Alzheimer's disease (AD), FL is employed in risk assessment, frequently utilising many data modalities while protecting patient privacy. To categorise the various phases of Alzheimer's disease, FL models are trained using Magnetic Resonance Images (MRI); some models have remarkable accuracy. FL uses spontaneous speech analysis to automatically diagnose AD. High accuracy is possible with this method while maintaining data privacy, and fair aggregation techniques can lessen biases brought on by client data heterogeneity. To identify multidimensional AD digital biomarkers in natural living settings, systems like ADMarker combine FL algorithms with multi-modal sensors (such as a depth camera, mmWave radar, and microphone). In FL frameworks, methods like Synthetic Minority Oversampling Technique (SMOTE) are employed to balance datasets to upgrade model learning over AD phases. To guarantee that raw data is kept secret, the procedure frequently entails local training on encrypted data, with aggregated updates transmitted to a central server [49].

FL is also being investigated for Parkinson's disease (PD) prediction and symptom evaluation, specifically in multi-omics and speech data analysis. FL uses clinico-demographic, transcriptomic, and genomic data to predict PD using several omics. Research shows that the capability of FL models substantially resembles that of centrally trained machine learning models. This suggests that FL may be a good choice for cross-institutional research including strict data rules. FL has been effective in detecting PD using speech signals from different languages, allowing institutions to work together without exchanging raw patient speech data. Although FL provides privacy benefits, performance may be impacted by statistical variability in distributed client data. According to research, FL models often follow the performance trend of central approaches, and while there may be a general decline in performance when compared to centrally trained models, it is not a significant one. To counteract domain changes, methods such as FedDis (Federated Disentanglement) separate model parameters into shape and appearance. This allows institutions to share only the shape parameters, which are more uniform [50].

CASE STUDIES OF FL IN THE HEALTHCARE SECTOR

Federated Learning (FL) is extensively being employed to overcome privacy problems and use dispersed data for model training in a variety of real-world healthcare contexts, such as hospital-specific implementations and multi-institutional partnerships. These uses highlight FL's ability to enhance medical care & diagnostic tools while protecting data privacy.

Federated Tumour Segmentation Initiative

A multinational group called the Federated tumour Segmentation (FeTS) Initiative seeks to enhance brain tumour segmentation through the use of FL. By enabling artificial intelligence (AI) models to use data at participating institutions without explicitly sharing the data, this effort tackles issues with data ownership and legal considerations that arise in multi-institutional healthcare collaborations. The FeTS Initiative's main objective is to create reliable and broadly applicable AI techniques for brain tumour segmentation, which are often hampered by restrictions on the quantity and variety of training data because of privacy concerns. Through the use of FL, the project makes it possible to train AI models collaboratively, combining the expertise of geographically separated collaborators' data without transferring any data between universities. The initial use-case for FeTS focused on detecting brain tumour boundaries in MRI scans. The FeTS tool, which has been open-sourced, incorporates several

key Functionalities

- *MRI Pre-Processing:* This includes image registration and brain extraction.
- *Automatic Delineation of Tumor Sub-Regions:* This is achieved through label fusion of pre-trained top-performing BraTS methods.
- *Manual Delineation Refinements:* Tools are provided to allow for manual adjustments.
- *Model Training:* The FL training mode involves an AI model trained on local data, local model updates shared with an aggregator, combination of updates from all collaborators to develop one consensus model, and circulation of that consensus model back to all collaborators for iterative performance improvements [51].

COVID-19 Patient Outcome Prediction

Twenty institutions participated in a healthcare FL project that aimed to predict about future oxygen needs of patients infected with SARS-COV-2. The "EXAM" model was developed in this project using inputs such laboratory data, vital signs, and chest X-rays. In contrast to local models, the EXAM model demonstrated an average improvement of 16% and a 38% increase in generalisability, with an average Area Under the Curve (AUC) of over 0.92. This paved the way for FL's wider use in healthcare by demonstrating its effective use for quick data science cooperation without direct data transmission [52].

- *Prostate Segmentation:* Federated prostate segmentation has been implemented using Fed-BioMed, a Python-based FL framework. Three French hospitals from the UniCancer consortium were involved in this project: Institut Curie in Orsay; Centre Antoine Lacassagne in Nice; and Centre Henri Becquerel in Rouen. Prostate Magnetic Resonance Imaging (MRI) and related segmentation masks were provided by each institution. These were taken from publicly available databases such as ProstateX, which has information from 189 patients. After training, the model's Dice score was 0.868, and the simulated FL model's cross-validation Dice score was 0.854 ± 0.028, which was not statistically different from the centralised model's score of 0.850 ± 0.035 [53].
- *Lung Pathology Segmentation:* For developing DL segmentation models for lung pathology detection using data dispersed across six university healthcare facilities, a FL framework was created within the German Radiological Cooperative Network (RACOON). This project proved that FL functions better than simpler options in every evaluation scenario [54].
- *Cervical Cancer Detection:* CNN-based FL architectures for cervical cancer diagnosis were investigated by Joynab et al. (2024), who balanced data privacy and image classification accuracy in three experimental conditions. Test accuracies of 94.36% in an IID (independent and identically distributed) scenario and 78.4% in a non-IID context were attained by the suggested approach, which combined updates from locally trained models into a global model [55].
- *Monkeypox Classification:* Models like M-VGG16, M-ResNet50, M-ResNet101, and ViT were proposed by Ahsan et al. (2024) for image analysis-based monkeypox classification. By facilitating cooperative model training without data sharing, FL was included to enhance AI-based diagnostic models while protecting patient privacy [56].
- *Fed-BioMed:* With an emphasis on open, transparent, and trustworthy FL, this research and development project seeks to transfer FL into practical medical research applications. It targets medical research centres or university hospitals that make up research consortia. Fed-BioMed seeks to offer safe tools for federated model training and personal biomedical data governance, along with intuitive user interfaces for data suppliers and medical researchers [57].

ADVANTAGES OF FL IN HEALTHCARE

FL allows for the cooperative training of machine learning models across several institutions without exchanging sensitive patient data. This offers substantial benefits in the healthcare industry, especially for disease detection and predictive analytics. To build confidence, this decentralised strategy lowers the possibility of data breaches and guarantees patient confidentiality. FL makes it possible to train machine learning models across several decentralized datasets without directly exchanging or centralizing sensitive patient data, which greatly improves data privacy and regulatory compliance in the healthcare industry. Raw data is kept safe within each local institution, reducing the risk of data breaches and guaranteeing that sensitive health data is handled in compliance with legal requirements. This distributed approach naturally supports adherence to strict privacy regulations like HIPAA and GDPR [58]. The several benefits of FL in Smart Healthcare are given in Figure 2.

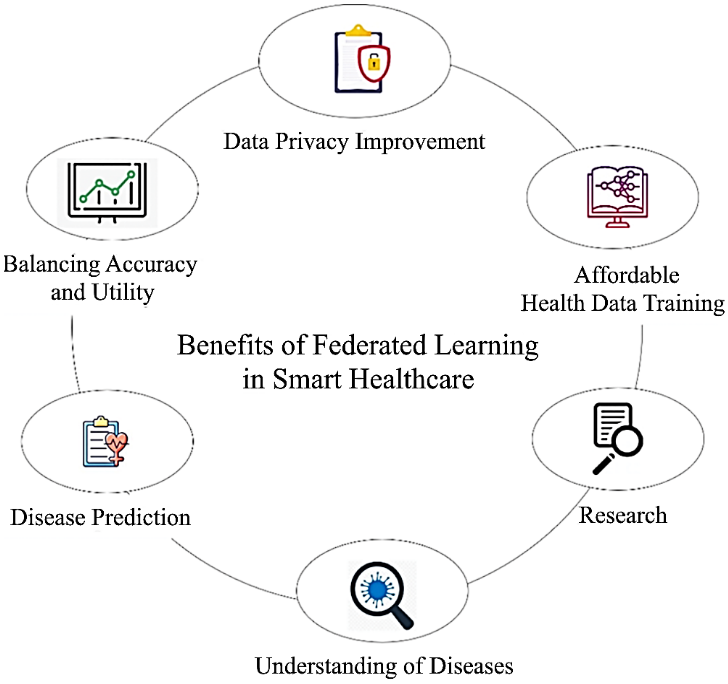

Figure 2. Benefits of FL in Smart Healthcare.

FL promotes a cooperative environment for AI development that respects individual privacy rights by sharing only model updates or insights rather than the underlying data. Collaboration without data sharing is essential in many domains, particularly in sectors like healthcare, banking, and competitive industries where data security and privacy are critical. Through this method, several parties can collaborate on common objectives, such as creating ML models or performing analyses, without having to reveal their private raw data to one another. Richer insights and more reliable models are made possible by utilising a variety of data sources that would otherwise stay isolated, in addition to addressing privacy concerns and adhering to legal requirements. FL enables effective model training across large numbers of decentralised devices while customising models to meet the demands of individual users, thereby addressing the crucial concerns of scalability and personalisation. By dividing the computational load among numerous client devices, FL achieves scalability. This lessens the strain on a central server and permits large-scale deployments with negligible communication cost [59].

Concurrently, personalisation in FL enables models to adjust to the distinct data distributions and preferences of individual clients or client groups, surpassing a single global model to provide more precise and pertinent predictions for a variety of users. FL involves optimization of the management, transport, and storage of data, which is one way to lower the costs associated with data transfer and storage, especially in cloud computing environments. Both storage and data transport are charged for by cloud providers, particularly for large data quantities. Using various cloud storage services with differing prices and performance can help cut these expenses by preventing overspending on superfluous performance [60].

CHALLENGES AND LIMITATIONS OF FL

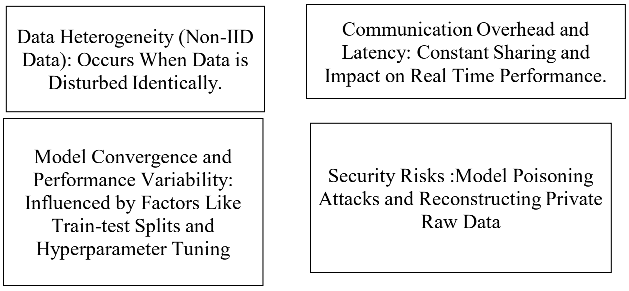

Figure 3. Challenges and limitations of FL [61].

PRIVACY AND SECURITY ENHANCEMENT OF FL

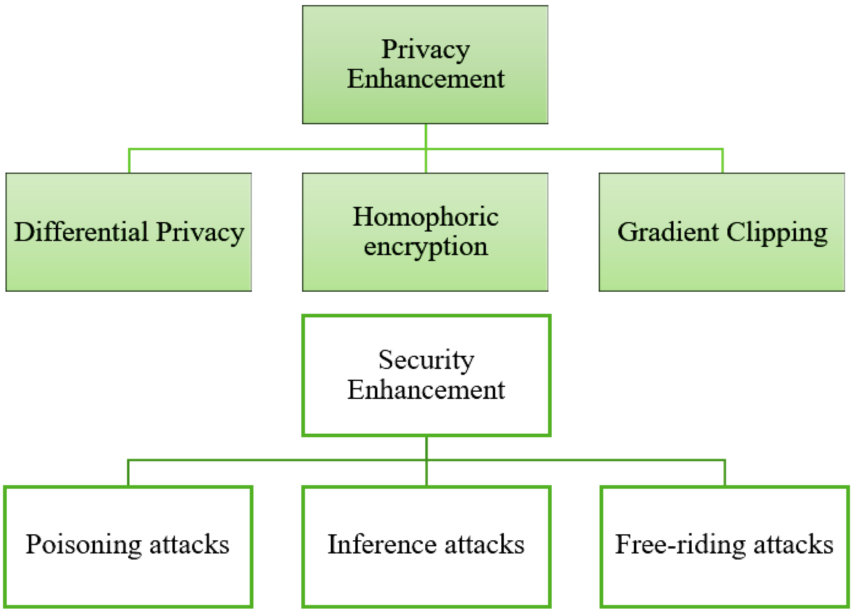

Figure 4. Security and privacy enhancements for FL [62].

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A new mathematical framework called Differential Privacy (DP) is used in FL to introduce controlled noise into model updates or parameters, hence offering robust privacy assurances. By ensuring that the addition or removal of any one data point from the training dataset does not substantially change the learning algorithm's output, DP's fundamental idea makes it nearly impossible for an adversary to deduce particular information about individual data points. DP successfully counteracts a number of privacy risks, such as membership inference attacks, in which a hacker attempts to ascertain whether a certain data record was included in the training dataset [63].

In the context of Federated Learning, Secure Multiparty Computation (SMPC), also known as Secure Multi-Party Computation (SMC), is a cryptographic technique that allows multiple parties to cooperatively compute a function over their private inputs without disclosing those inputs to one another. The main purpose of SMPC is to safely combine the local model updates or gradients that each client submits [64].

Medical institutions can perform calculations on encrypted patient data and model updates without ever decrypting them because of Homomorphic Encryption (HE), which improves privacy in Federated Learning for disease detection. This keeps sensitive health information private while training collaboratively. By encrypting the parameters of local models that are trained on confidential patient data before sending them to a central server for aggregation, it is possible to prevent the server or other participants from deducing specific patient diagnoses or traits. When used with Federated Learning, blockchain technology creates an unchangeable and transparent record of all model modifications and training procedures, which promotes trust and traceability in illness detection [65].

TOOLS AND FRAMEWORKS FOR FL

Decentralized ML is made possible while maintaining data privacy by FL frameworks such as TensorFlow Federated, PySyft, and Flower. These platforms are essential for training models on several devices without storing private information in one place. However, scalability, flexibility, and thorough benchmark support for intricate experimental settings are frequently issues with current FL frameworks.

- *TensorFlow Federated (TFF):* One popular FL framework that offers a simulation environment for FL algorithms is TensorFlow Federated. Its main purpose is to replicate the training procedure for a small group of uniform clients. The high coupling of TFF's interface may limit its flexibility and expansion. Although TFF has demonstrated exceptional performance in picture classification tasks, its scalability is limited due to its lack of support for distributed execution mode. Additionally, TFF does not offer thorough baselines or benchmarks, which may make it less useful for assessing FL algorithms [66].
- *PySyft:* Another FL framework for federated learning is PySyft, which offers a distributed computing environment. It is mainly a research platform made for differential privacy-based data science applications. PySyft performs exceptionally well in terms of text data privacy and efficiency. Some versions may not fully support complicated FL concepts because to its quick development cycles. Like TFF, PySyft lacks benchmarks and baselines, which may reduce its usefulness for performance assessment. Federated training and inference can be substantially slower than centralized methods, taking between 3 to 9 times longer for training and 15 to 40 times longer for inference, respectively, according to experiments conducted utilizing PySyft virtual and real compute nodes [67].
- *Flower:* Flower is a specialized federated learning experimental platform that facilitates extensive FL experiments and the investigation of various scenarios involving heterogeneous devices. Flower does not, however, offer alternate paradigms like asynchronous or personalized FL; instead, it only supports synchronous FL. Additionally, it lacks thorough benchmarks and provides a small number of baselines [68].
- *FedModule:* FedModule is a new modular FL framework that follows the "one code, all scenarios" approach and was created to overcome the shortcomings of previous frameworks. It provides extensive benchmark support, flexibility, and exceptional scalability. With more than

20 developed algorithms, FedModule breaks down the FL process into its component parts, enabling the smooth integration of various FL paradigms, such as synchronous, asynchronous, and personalized federated learning. To support a range of hardware conditions and experimental requirements, the framework offers different execution modes, including distributed, threaded, process-based, and linear. A DatasetPreLoad Mechanism is another feature of FedModule that loads datasets into memory, drastically lowering I/O operations and speeding up training by up to 3.6 times. It offers comprehensive testing and logging features for in-depth performance analysis, including integration and online and offline records [69].

COMMONLY USED DATASETS IN FL

Due to their applicability for privacy-sensitive applications, a number of datasets are frequently employed in federated learning research, particularly in the field of medical imaging.

MIMIC-III

The Medical Information Mart for Intensive Care-III, or MIMIC-III, is a popular and openly available critical care database. It contains physiological signals recorded from critically-ill patients during routine clinical care, including electrocardiogram (ECG), photoplethysmogram (PPG), impedance pneumography (imp/respiratory), and arterial blood pressure (abp). This dataset is often used for tasks such as predicting in-hospital mortality using neural network-based models in federated settings. Studies on MIMIC-III have shown that models trained in federated settings can achieve predictive performance comparable to those trained on centralized data, even with varying amounts of data or data distribution across computational nodes. The MIMIC-III dataset has also been used to evaluate the impact of different federation and differential privacy techniques, revealing that FedProx can resolve performance deterioration caused by extreme data distributions. Furthermore, it is utilized for enhancing ICD-9 code prediction from clinical notes [70].

NIH Chest X-rays

A lot of work has been done on automatically interpreting chest X-rays using DL techniques thanks to the NIH chest X-ray dataset, which is a sizable, open-source dataset. Although useful, this dataset's labels aren't often rich enough or descriptive enough to train sophisticated classification methods, particularly when it comes to discoveries in anterior-posterior (AP) view chest X-rays, including device placements. A new benchmark database with 73 detailed sentence-level descriptors of abnormalities in AP chest X-rays has been created in order to address this issue [71].

ADNI (Alzheimer's Disease Neuroimaging Initiative)

Through its Informatics Core, which encourages data standardization and sharing, the Alzheimer's Disease Neuroimaging Initiative (ADNI) has made tremendous progress in Alzheimer's research. Data on 190 plasma analytes from 566 people with normal cognition, AD, or mild cognitive impairment (MCI) are included in the ADNI dataset. Plasma protein signatures for pre-clinical AD have been found using this dataset, and multivariate techniques have identified 11-analyte signatures with sensitivity and specificity ranging from 65% to 86%. Classification accuracy was further increased to almost 90 by taking "meta-features" into account and utilizing longitudinal data. Over 26,000 researchers from 169 countries have been able to access and download multimodal data thanks to ADNI's open data sharing principles, which have resulted in over 5,600 publications.

FUTURE PERSPECTIVES

Healthcare frequently deals with heterogeneous data, which presents issues for the developing discipline of personalized federated learning (PFL). For applications like creating language models for mobile keyboards, where user behaviours differ greatly, PFL seeks to build individualized models that can overcome problems like client drift and offer customized predictions. New architectural designs, practical benchmarking, and reliable PFL methodologies are the direction this field is taking. For example, by securely combining multi-modal data from many expert centres, the GenoMed4All Consortium in Europe is using FL to offer tailored therapies for haematological disorders. Moreover, smart healthcare is being revolutionized by the convergence of edge AI and the Internet of Medical Things (IoMT). For real-time healthcare applications like remote patient monitoring, edge computing reduces latency and bandwidth consumption by processing data closer to its source. By bringing AI processes closer to data sources, this paradigm is particularly advantageous in smart healthcare, where it facilitates effective treatments and early disease identification. In order to improve privacy and take use of large amounts of dispersed data, federated learning divides training among edge devices close to the data source, while AI algorithms applied to IoT data enable intelligent decision-making.

Furthermore, Cross-border partnerships are essential to the advancement of AI-enabled smart healthcare, particularly in fields where safe international data sharing is essential, such as medication discovery, rare disease research, and pandemic preparedness. By enabling decentralized data processing and boosting security through immutable ledgers, federated learning, blockchain technology, and AI-driven threat detection might enable safe and moral global data collaboration. The critical need for more international cooperation to further the integration of cross-border healthcare data has been brought to light by the COVID-19 pandemic. By encouraging patient co-ownership of health data and leveraging cutting-edge technologies like blockchain and homomorphic encryption, initiatives such as the Global Patient co-Owned Cloud (GPOC) seek to support international medical research.

CONCLUSION

By facilitating collaborative machine learning and tackling important concerns like data security and privacy, federated learning (FL) has the potential to revolutionize healthcare analytics. It solves the problem of data silos that are common in the healthcare industry by enabling the training of reliable and accurate models from dispersed datasets. FL provides a number of benefits for improving healthcare analytics, including as better model generalizability, increased data privacy, and support for tailored therapy. The capacity of FL to train machine learning models on decentralized data without necessitating the sharing or transfer of raw data to a central server is among its most important advantages. This decentralized strategy lowers the possibility of data breaches or misuse while addressing strict privacy laws like HIPAA and GDPR. For example, without disclosing private patient data, FL allows hospitals to work together to train models utilizing data from their local Electronic Health Records (EHR). Data security in FL systems is further improved by methods like homomorphic encryption, safe multi-party computation, and differential privacy.

Without centralizing data, FL enables cooperative model training between various organizations, including hospitals and healthcare providers. FL can generate models with improved generalization capabilities by utilizing a variety of information from several sources, which will result in more trustworthy forecasts and healthcare decision-making. By allowing models to learn from individual patient data while maintaining privacy, FL facilitates the creation of individualized treatment regimens and improved clinical decision-making. Additionally, it enables AI training at dispersed IoT devices, which is essential for intelligent IoT applications in healthcare including real-time diagnostic feedback and remote patient monitoring. Early disease detection, medical imaging analysis (such as brain tumour segmentation, COVID-19 detection from CT scans and X-rays, and melanoma detection), disease diagnosis and prognosis, drug discovery, clinical decision support systems, and patient length of stay prediction are a few examples of FL applications in healthcare. Strong interdisciplinary collaboration and ongoing innovation are essential for the effective integration and broad acceptance of cutting-edge technologies like artificial intelligence (AI), big data analytics, and federated learning in the healthcare industry. This calls for the fusion of knowledge from a number of disciplines, including data scientists, engineers, ethicists, legal specialists, policymakers, and healthcare professionals (physicians, nurses, and clinicians).

When technologists and physicians work together, more workable and efficient solutions that fit actual healthcare requirements and processes can be produced. This entails creating scalable, effective systems that tackle issues like communication overhead and data heterogeneity. In fields like customized medicine and privacy-preserving data processing, interdisciplinary research is essential to revealing novel solutions. For example, FL and Multimodal Machine Learning (MML) together show promise for thorough medical assessments while protecting patient privacy.

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