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Federated learning-based AI approaches in smart healthcare: concepts, taxonomies, challenges and open issues

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Abstract

Federated Learning (FL), Artificial Intelligence (AI), and Explainable Artificial Intelligence (XAI) are the most trending and exciting technology in the intelligent healthcare field. Traditionally, the healthcare system works based on centralized agents sharing their raw data. Therefore, huge vulnerabilities and challenges are still existing in this system. However, integrating with AI, the system would be multiple agent collaborators who are capable of communicating with their desired host efficiently. Again, FL is another interesting feature, which works decentralized manner; it maintains the communication based on a model in the preferred system without transferring the raw data. The combination of FL, AI, and XAI techniques can be capable of minimizing several limitations and challenges in the healthcare system. This paper presents a complete analysis of FL using AI for smart healthcare applications. Initially, we discuss contemporary concepts of emerging technologies such as FL, AI, XAI, and the healthcare system. We integrate and classify the FL-AI with healthcare technologies in different domains. Further, we address the existing problems, including security, privacy, stability, and reliability in the healthcare field. In addition, we guide the readers to solving strategies of healthcare using FL and AI. Finally, we address extensive research areas as well as future potential prospects regarding FL-based AI research in the healthcare management system.

Keywords Artificial intelligence · Explainable AI · Federated learning · Smart healthcare · IoT · Security · Data management

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1 Introduction

The Internet-of-Medical-Things (IoMT) revolution brought comprehensive changes in the way medical facilities operate by uplifting the quality of services [1]. IoMT devices with the ability to sense and transmit health updates of an individual, are extensively used to gather healthcare data. This information is then processed using artificial intelligence [2] to materialize a variety of healthcare applications which includes distant monitoring of patient and prognosis of diseases. Deep Learning (DL) approaches, for example, have shown potential in biomedical image analysis for earlier identification of acute illnesses by managing enormous volumes of relevant data to improve healthcare efficiency [3]. Dong et al. [4] suggested a detailed analysis based on blockchain-based FL to discuss the issue of privacy concerns using datasets to identify the current state of this problem. The study suggested that blockchain-based FL has developed significantly over the last five years, and the technology is now being applied to the fields of IoT and smart healthcare applications, such as recording patient health data, medical image analysis, to study data related to analysis of cancer related illness, and relevant economic data. Smart healthcare systems have typically focused on centralized AI capabilities stored in the cloud for learning and data analytics [5–7]. Due to raw data transfer, this centralized approach is inefficient in terms of communication latency and cannot achieve high network scalability. More specifically in e-healthcare, personal data are subjected to regulations like the Health Insurance Portability and Accountability Act of the United States (HIPPA) [8]. Furthermore, a centralized AI system may be considered unacceptable in future healthcare systems, and instead must be disseminated throughout a large-scale IoMT network. As a result, switching to distributed AI approaches at the network edge for scalable and privacy-preserving intelligent healthcare applications is critical.

Federated Learning, a new distributed interactive AI concept, is especially promising for smart healthcare since it allows numerous clients (such as Hospitals) to participate on AI training whilst maintaining data privacy. As a result, the authors investigated the application of FL in smart healthcare extensively [9]. To begin, we will discuss current breakthroughs in FL, as well as the reasons and prerequisites for adopting FL in smart healthcare. The authors have presented a state-of-the-art overview of FL's developing applications in major healthcare areas such as COVID-19 detection, medical data recording, distant monitoring of patients, and biomedical image analysis. In a recent research, FL was recommended for usage in a number of IoT actions, including e-healthcare and intelligent transportation system, among others. FL, for instance, has made e-health services more accessible by allowing machine learning (ML) modeling despite the absence of health data [10]. Health data owners, such as hospitals, can avoid exchanging healthcare information by employing FL. Rather, healthcare personnel can locally train the model and then share the parameters to the accumulator for data compilation. Federated Learning has presented itself as a viable method for implementing economic, innovative healthcare systems while ensuring privacy [11–15]. FL allows training of AI models through averaging of local updates from numerous healthcare facilities and smart devices, such as IoMT, despite the lack of local data.

On the other hand, AI has been used in a wide range of disciplines, which includes the IoT, machine vision, natural language processing, and robotics, as a result of fast spreading of AI technologies. More specifically, researchers have attempted to use AI to boost scientific analysis and analyse potential remedies, hence improving the overall efficacy of the healthcare industry [16, 17]. The advantages that AI can bring to medicine have been predicted for decades. The role of AI in biomedical engineering has even been reviewed [18]. AI and its applications in healthcare have recently made considerable strides [19]. Medical facilities with an attempt towards becoming further individualized, with a predictive instinct, preventative measures, and participatory behavior, can approach AI to assist in this endeavor. Determined from the achievements so far, we predict that AI will pursue further evolution and grow as a powerful device for future healthcare.

Many studies have been undertaken to study FL based AI related issues, including healthcare, as a result of recent advancements in the field. The publications in [9], for example, provide the basic FL idea and its supporting protocols, as well as the technical hurdles of FL design and implementation. [20] covers the security and privacy challenges in FL systems, as well as potential methods for assessing harmful threats in FL networks. The authors of [21] investigates issues in FL base AI implementation like as communication expenses, resource distribution, and security concerns. In [22] researchers looks at the junction of FL-AI and the IoT by providing a review of technical challenges in FL schemes which includes sparsification, security, and extensibility, as well as a concise analysis of FL-based AI technologies in IoT [23]. Furthermore, in [24] the authors provided a review of FL applications in industrial IoT, with an emphasis on the features and basics of FL, with little mention of FL use in healthcare. Another research [25] focuses on the technological challenges and needs of adopting FL-based AI approaches in the future of digital health. The most recent advancements in FL, for instance FL aware of resources, safe and reliable FL, the potential of privacy-boosted FL, stimulus-aware FL, and tailored FL has yet to be extensively investigated.

Despite these attempts, as far as we know, no established research provides complete overview of FL-based AI uses in the sphere of smart healthcare. Furthermore, the available literature lacks a comprehensive taxonomy of FL's use in new healthcare applications. These disadvantages motivated the authors to carry out an in-depth examination regarding the usage of FL-based AI techniques in the healthcare realm. We investigate the most updated FL-AI concepts in smart healthcare. Following that, we give a splitting analysis regarding the novel FL-based AI applications in smart healthcare, including Electronic Healthcare Records (EHR) management, distant monitoring of health, biomedical image analytics, and identification of COVID-19 traits [89]. Poll results are also shared so that readers may have a better grasp of how FL can be employed in smart healthcare. Our research intends to give a bibliometric analysis of characteristics such as authors, nations, citations, and keywords to help academics and practitioners plan future research. Finally, future prospects and research problems in FL-smart healthcare are discussed. Also, we will suggest and analyze a dominating framework of variables in this topic.

1.1 Major contributions and organization of the survey

This work discusses different leading technologies–FL, AI, XAI, and intelligent healthcare. In detail, we share a state-of-the-art analysis about their concepts, taxonomies & motivations, addressing issues and solutions and further applications. We also describe some integration's of these technologies to better support applications in various areas. To this end, the survey's main contributions are outlined here:

- We provide a cutting edge outline on FL-based AI in the area of healthcare, initially with basic concepts regarding FL, AI key concepts, XAI features, and a detailed discussion of smart healthcare efficiency.
- We present the lately advanced FL-AI taxonomies and emerging AI-FL integration's and motivations applicable to intelligent healthcare applications.
- We address some technical challenges in the existing system and then directly solve the issues using vast technologies–including FL, AI, and XAI in the healthcare applications.
- Finally, we analyse the issues of different applications and direct further research towards FL-AI in innovative healthcare areas.

Table 1 List of common abbreviations with description

Keys	Description
AI	Artificial Intelligence
AUC	Area Under the ROC Curve
BC	Blockchain
COVID-19	Coronavirus Disease 2019
DT	Decision Tree
DoS	Denial of Service
DL	Deep Learning
EHR	Electronic Health Records
FL	Federated Learning
HCU	Healthcare Control Unit
HM	Healthcare Management
HPW	Healthcare Provider's Wallet
IoMT	Internet of Medical Things
IoT	Internet of Things
IIoT	Industrial Internet of Things
IP	Internet Protocol
KNN	K-nearest Neighbors
LPU	Local Processing Unit
LR	Logistic Regression
ML	Machine Learning
M2M	Machine to Machine
P2P	Peer to Peer
PCA	Patient Centric Agent
PDA	Personal Digital Assistants
PM	Patient Management
QoS	Quality of Services
SC	Smart Contact
SDP	Sensor Data Provider
SH	Smart Healthcare
SVM	Support Vector Machine
WIoT	Wireless Internet of Things
WSN	Wireless Sensor Networks
XAI	Explainable Artificial Intelligence

This study is the only potential and informative survey that integrates all the considered technologies to the best of our knowledge. Some of the notations are listed in Table 1. The rest of this survey is organized as follows: Section 2 represents a conceptual overview regarding FL, AI, and e-healthcare individually. Sections 3 offers the motivations behind the FL-AI-healthcare, FL-healthcare, and AI-healthcare integration's, also providing taxonomies of these components. Further, the addressing different issues and solutions of these issues have been presented in Sect. 4. After that, Sect. 5 focuses on the current research

Table 2 Related surveys/works regarding FL, AI and Healthcare. The works are grouped based on the related technology and reported in chronological order within each group

Related works	Year	Technology	Main focus
Rey et al. [26]	2021	FL	N-BaIoT, modeling of network traffic of several IoT devices infected by virus attacks, has been employed to assess the proposed algorithm.
Li et al. [27]	2021		A case study that can assist the design of a Federated Learning System, including aspects and research perspectives.
Rahman et al. [28]	2021		Issues related to the design of a Federated Learning based system.
Zhang et al. [29]	2021		Survey on FL based application areas.
Pham et al. [24]	2021		Integration of FL and IIoT.
Nguyen et al. [9]	2021		Integration of FL and Blockchain technology for intelligent and secured system.
Khan et al. [22]	2021		Recent advancements include advancements in the security and privacy era. The difficulties and taxonomy of FL were then examined.
Kulkarni et al. [30]	2020		Methods of personalization for FL approaches.
Lim et al. [21]	2020		The use of FL in mobile edge networks, as well as their challenges and future directions.
Jigan et al. [31]	2020		Opportunities of Federated Learning for smart city infrastructures.
Shen et al. [32]	2020		Federated Learning for data security and privacy perspective.
Chen et al. [33]	2020		Explored the convergence time of Federated Learning when deployed across a real-world wireless network.
Shlezinger et al. [34]	2020		Attempted to tackle emerging challenges using tools from quantization theory.
Chen et al. [35]	2020		Issue to train FL model for a wireless network is detailed.
Wrabel et al. [36]	2021	AI & XAI	The use of AI algorithms to track targets using radar.
Wu et al. [37]	2021		AI for visualization of data.
Markus et al. [38]	2021		Explainable AI for the field of the health care system to create a trustworthy system.
Korica et al. [39]	2021		Opportunities, Gaps and Challenges and a Novel Way to Look at the Problem Space in healthcare.
Chakrobartty et al. [40]	2021		A systematic review of the methods and techniques of explainable AI within the medical domain.
Riboni et al. [41]	2021		Explainable AI in Pervasive Healthcare: Open Challenges and Research Directions.
Duell et al. [42]	2021		A Comparison of Explanations Given by Explainable Artificial Intelligence Methods on Analysing Electronic Health Records.
Coppola et al. [43]	2021		Utilizing AI technologies in the radiology department to reduce error rates and studying radiologist attitudes regarding AI adaption.
Hansen et al. [44]	2021		AI for IIoT (Small and Medium SMEs).
Dhuri et al. [45]	2020		Made an academy to an intelligent place.
Laird et al. [46]	2020		Highlights various applications and opportunities of SM multimodal data, latest advancements, current challenges, and future directions for the crisis informatics.
Zhang et al. [47]	2020		Assists radiologists and physicians in performing a quick diagnosis, especially when the health system is overloaded.
Cubric et al. [48]	2020		This review covered AI adoption across various business sectors–healthcare, information technology, energy, agriculture.
Rasheed et al. [49]	2020		Leveraging the techniques of artificial intelligence in order to predict the infection rate as well as the mortality rate to assist the health workers.
Tung et al. [50]	2020		AI model for the development of the quality of the river water.
Wu et al. [51]	2020		Enhancement of security of IoT by utilizing the methods of IoT.
Zhou et al. [52]	2020		Collaboration of AI and database system.
Mohanta et al. [53]	2020		Issues and solutions towards IoT security using ML, AI and blockchain methods.
Hossain et al. [54]	2020		Explainable AI and Mass Surveillance System-Based Healthcare Framework to Combat COVID-I9 Like Pandemics.

Table 2 (continued)

Related works	Year	Technology	Main focus
Amann et al. [55]	2020		A comprehensive assessment of the role of explainability in medical AI and makes an ethical evaluation.
Pawar et al. [56]	2020		XAI is discussed as a technique that can used in the analysis and diagnosis of health data by AI-based systems.
Alshqaqi et al. [57]	2022	Healthcare	Opportunities of IoT for healthcare industry.
Kashani et al. [58]	2021		This study aims to identify, compare systematically, and classify existing investigations taxonomically in the Healthcare IoT (HIoT) systems.
Kaye et al. [59]	2021		The economic impact of COVID-19 pandemic on health care facilities and systems: international perspectives.
Jaiswal et al. [60]	2021		Healthcare system by leveraging IoT associated issues, applications and threats.
Li et al. [61]	2021		ML methods for the health care data analysis.
Murthy et al. [62]	2021		Patient monitoring system by leveraging IoT methods.
Muhammad et al. [1]	2021		IoMT and related issues, types, challenges and possibilities.
Jabeen et al. [63]	2021		IoMT security in WBAN.
Philip et al. [64]	2021		Application of DL in the sphere of IoMT.
Chew et al. [65]	2020		Studied medical personnel to find the relation between psychological results and physical patterns.
Greenberge et al. [66]	2020		Managing mental health challenges faced by healthcare workers during the Covid-19 pandemic.
Amin et al. [67]	2020		The improvement of edge computing environments for the healthcare system is identified.
Hathaliya et al. [68]	2020		Security and related concerns in present healthcare 4.0 system.
Qadri et al. [69]	2020		Future healthcare systems as seen through the lens of recently developed technologies.
Alemdar et al. [70]	2010		Minimizes the complex healthcare system for nurses and assists the critically ill and elderly to lead an independent life.
Zhu et al. [71]	2021	FL-AI-XAI	The transition from FL to federated neural architecture have been discussed in this work.
Yang et al. [72]	2021		Explained several privacy preserved solutions using FL and machine learning or artificial intelligence techniques.
Truong et al. [73]	2021		Privacy ensuring methods in Federated Learning.
Zeng et al. [74]	2021		A detailed survey of FL motivational strategies.
Guberovic et al. [75]	2021		Federated Learning for intelligent system.
Tonellotto et al. [76]	2021		Recurrent NN model for FL for prediction of time series.
Xianjia et al. [77]	2021		Federated Learning for robotics and AI.
Ghassemi et al. [78]	2021		An overview of current explainability techniques and highlight how various failure cases can cause problems for decision making for individual patients.
Shaban et al. [79]	2021		Explainability and Interpretability: Keys to Deep Medicine.
Raunak et al. [80]	2021		From real-time systems to human-in-the-loop fault detection, the articles here have looked into AI explanation from varying perspectives and for multiple groups of audience.
Deshpande et al. [81]	2021		A Brief Bibliometric Survey of Explainable AI in Medical Field.
Giuste et al. [82]	2021		The use of Explainable Artificial Intelligence (XAI) during the pandemic and how it's use could overcome barriers to real-world success.
Xu et al. [83]	2021	FL-Healthcare	Provides great promise to connect the fragmented healthcare data sources with privacy preservation.
Jatain et al. [84]	2021		Aimed to reveal the technological foundation called blockchain and its usability in healthcare services.

Table 2 (continued)

Related works	Year	Technology	Main focus
Nguyen et al. [9]	2021		Improved healthcare through coordination of hospitals to execute AI training in the absence of shared local data.
Zhang et al. [29]	2021		Characteristics, challenges and application area of FL.
Blanco et al. [85]	2021		Survey on addressing security concerns using Federated Learning.
Rieke et al. [25]	2020		Discussed threats and potential remedies by leveraging FL in the healthcare sector.
Lim et al. [86]	2020		FL for intelligent healthcare system for contract design.
Grama et al. [87]	2020		Aggregation process for healthcare system to preserve privacy.
Sharma et al. [88]	2020		Intending to address the totality of Federated Learning with a complete vulnerability assessment.

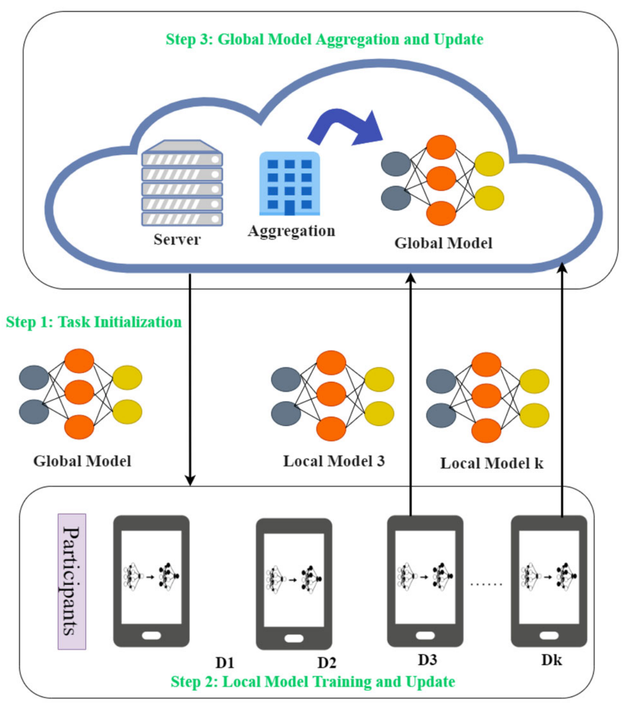

Fig. 1 Federated Learning and its Training Process

challenges and future directions of the study. Finally, we conclude the survey in Sect. 6.

2 FL, AI, and healthcare: state-of-the-art

This segment presents advanced concepts regarding Federated Learning, artificial intelligence, and e-healthcare properly. In FL segments include various aspects of developments, the necessity of FL, different features of FL in 2.1. Further, we introduce AI technology and cover the parameters of various characteristics and usefulness in 2.2. We discuss diverse concepts and issues of healthcare technology in 2.3. We also present the related works regarding Federated Learning, Artificial Intelligence, Explainable Artificial Intelligence (XAI), and Healthcare in the Table 2.

2.1 Fundamentals of federated learning

Federated Learning is essentially a machine learning (ML) algorithm which allows for collective learning of a distributed model while preserving the data composed on their devices. FL that has been shown in Fig. 1, it allows for equipping ML models with decentralized data and at the same time protects user confidential data by design. FL as a shared ML model is gaining increased popularity in situations where user's data privacy is vital [90]. In FL, local data is used to train clients using a distributed approach. The scenario involves training decentralized clients or nodes using local data and sharing system parameters. Accumulation of system or model parameters creates a global model using a server [72]. In practice, the user does not need to share their private data using FL. Rather, users drill the network locally and share the model to a central body known as the server. However, it is essential in FL for each user to effectually and feasibly transmit it's learned model through the server. The server in FL aggregates the local data into a global network through an iterative process [91]. Fig. 1 represents the training process of the federated machine learning. Following are the steps used in this figure.

- Every device will have a local copy of our centralized machine learning application, which users will be able to access whenever they need it.

- The model will now gradually learn and train itself based on the data provided by the user, allowing it to become smarter over time.
- The devices then send the training results from the local copy of the machine learning program back to the central server.
- The same thing happens when you run the program on many devices, each of which has a local copy of it. The results will be compiled in a centralized server, but no user data will be included this time.
- The centralized cloud server now uses the pooled training data to update its centralized machine learning model, which is considerably superior to the prior version.
- Users update the program with the better model produced from their data while the development team upgrades the model to a newer version.

The FL is a distributed processing system built on AI, Blockchain, and machine learning algorithms at its core. The terms distributed machine learning and federated machine learning are not interchangeable. In Federated Learning, the information supplied to the server by each participant resembles no original data, rather a trained sub-model. Simultaneously, Federated Learning permits asynchronous transmission, which reduces requirements for communication purposes [92]. On this foundation, the federated machine learning formula may be revised as follows:

$$\arg\min_{w} L(x, y, w) = \sum_{k} p_k L_k(x, y, w) \tag{1}$$

where, k denotes number of clients, p_k is the weight value of the k^{th} client, and the decentralized multiuser F_1,F_2,....,F_k) scenario is used for Federated Learning. The current user's dataset (D_1,D_1,....,D_k) is available to each client user.

2.1.1 FL: Key design aspects

For constructing intelligent and privacy-enhanced IoT systems, the notion of Federated Learning has recently been presented. The major steps in the FL-smart healthcare process are as follows:

- Initialization of system and client selection: The aggregation mainframe chooses an analytic task, such as automated biomedical imaging or detection of any motion, as well as further needs like objective categorization, and learning parameters and rates. Furthermore, the endpoint chooses a number of users to engage in FL method.
- Local Training and Updates: As soon as the dataset of learning users has been identified, the network delivers an preliminary model to the clients, together with an initial global gradient, to start the distributed training. Each user teaches a local model adopting its personal data and estimates its model update. The scenario is such as, after configuring the training, the server creates a novel model, i.e., $\mathbf{w}_G^0$, and sends it to the users to begin distributed training. Employing its own data D_k, each client k drills a local model and assesses an update w_k by mitigating a loss function $\mathcal{F}(\mathbf{w}_k)$:

$$\mathrm{w}_k^* = \arg\min \mathcal{F}(\mathrm{w}_k), k \in \mathcal{K} \tag{2}$$

For various FL algorithms, the loss function might be different [93]. The loss function $\mathcal{F}$ of a linear regression Federated Learning model may be described as: $\mathcal{F}(\mathbf{w}_k) = \frac{1}{2}\left(x_i^T \mathrm{w}_k - y_i\right)^2$ with a set of input output pairings $\{x_i, y_i\}_{i=1}^K$. Then, for aggregate, each client k transmits its estimated update w_k to the server.

- Aggregation and Download of Models: Following the gathering of all updates from the specified clients, the server uses an aggregation mechanism to combine them. For example, in Google's Federated Averaging (FedAvg) technique [94], where the gradient parameters of local models are averaged element-wise with weights proportionate to the sizes of the client datasets, we may employ the model averaging strategy. The server then generates a new version of the global model and broadcasts it to all clients as the foundation for future local model updates in the next learning round. A real scenario is, the server combines all model changes from local clients and calculates a new version of the global model as follows:

$$\mathbf{w}_G = \frac{1}{\sum_{k \in \mathcal{K}} |D_k|} \sum_{k=1}^{K} |D_k| \mathbf{w}_k \tag{3}$$

by figuring out how to solve the following optimization problem:

$$(P1) : \min_{w \in K} \frac{1}{K} \sum_{k=1}^{K} \mathcal{F}(w_k) \tag{4}$$

subject to (C1): w_1= w_2=...=w_K=w_G The accuracy of the FL method, for example, the accuracy of an FL-based object classification task [35], is reflected by the loss function $\mathcal{F}$. Furthermore, the constraint (C1) assures that after each training round, all users and central server have identical training model for Federated Learning problem. Following the model's derivation, the server transmits the new global update w_G to all users, allowing them to optimize their trained models in the subsequent training round. The iteration of the process proceeds until the loss function congregates or the requisite precision is attained.

Federated Learning method can be deployed to deliver numerous appealing benefits to develop smart healthcare based on the revolutionary operating idea, as mentioned below:

– *Enhancement of Data Privacy:* In FL, local data are not required for training. This is used to train other machine learning algorithms by combining numerous local datasets and not transferring data. Local Machine Learning (ML) models are trained on local heterogeneous datasets during training. The model parameters are shared between these local data centers on a regular basis. Many models encrypt these parameters before sending them. Data samples from the local area are not shared. This increases data security and protection. In addition, a shared global model is created. As a result, risk of personal data being leaked to an external source is reduced, and privacy is ensured. FL offers security features which creates an excellent alternative for designing smart and secured IoT devices, especially in light of increasingly severe data privacy protection regulations such as the General Data Protection Regulation (GDPR) [95, 96].
– *A Reasonable Balance of Accuracy and Utility:* FL is capable of providing a suitable balance between precision and usefulness, as well as privacy enhancement, as compared to traditional centralized learning. Furthermore, FL training keeps the model generalizability while sacrificing nominal accuracy. As a result of FL's distributed learning characteristic, the smart healthcare system's scalability may be improved.
– *Health Data Training at a Low Cost:* FL can assist to mitigate communication expenses, such as data lag and power transmission, associated with transfer of raw data by avoiding the offloading of large data volumes to the server [97]. Because model gradients are typically much smaller than their actual datasets, FL can be deployed to mitigate communication expenses, such as delay and power dispatch associated with communication of local data. As a result, FL saves a significant amount of network bandwidth and reduces the risk of network congestion in large healthcare networks.

2.1.2 Why needed FL?

The ever growing number of IoT resources together with relevant applications means the requirement of processing large amount of data [98, 99]. The availability of big data analytics and computation methods such as machine learning and deep learning has enabled users to achieve effective data management. Artificial Intelligence applications is being successfully deployed to counter the issues related to optimized resource management, efficient selection of antenna in wireless systems and several other areas of communication networks. The traditional AI models usually necessitates the users to share individual information to a master network for learning purposes. A key concern with such techniques is the privacy of users sensitive information. FL is highly effective in areas where decision making is based on substantial data scattered over a wide range of training nodes at the same time addressing privacy and security concern [100]. Machine learning models are developed using data collected from several sources to allow for prediction. Regardless, as a result of bandwidth issues, security and storage facility, raw data transmission to a centralized location becomes unrealistic. FL acts a distributed learning model to ensure optimal learning, efficient utilization of collected raw data and transmission to a centralized place. FL also plays a significant role in advancement of smart cities as detailed by authors in [101]. Policy makers in urban smart cities can utilize FL to transmit the sensitive information gathered from IoT devices for effective management of priority assets. The framework in FL allows the users to access data without gaining personal information regarding other clients. Eventually, the updated global model constructed by the server is distributed to all clients [21]. The clients then download the new updated global model and utilize cloud distribution to understand interference on their individual devices.

2.1.3 Different features of FL

Federated Learning approach is a concept introduced by google to allow on-device learning and security of sensitive data [93]. FL has the benefit of distributed data processing and improved privacy factors. FL is suggested as means of training a ML model in [91] which does not require accumulation of all user's data sample. In [26], authors have investigated the deployment of FL to detect malware in IoT devices. Researchers in [34] detailed the advantages of coupling vector quantization with FL to generate an efficient decentralized training model. Federated Learning also offers a platform to allow distributed analysis in the industrial IoT sector [102]. The issues of executing FL over a wireless network is studied by authors in [35]. Another key feature of FL is the ability of the server to organize the training model and analyze the contribution of every participant [103]. FL is also being applied to the Industrial Internet of Things (IIoT) by researchers to develop efficient and robust models while preserving sensitive data. Several other features of FL include its application in healthcare and medicine sectors as discussed in [12, 83]. Electronic healthcare records from multiple data sources (several hospitals) require joint data access and uploading of data to a single database.

However, due to reasons such as privacy concerns of each institution, it is quite challenging to materialize such expectations without guaranteeing security issues. FL is a highly effective method to gather EHR data from hospitals to provide a knowledge-sharing platform without the need of sharing personal data, all while preserving the privacy [104, 105]. FL in healthcare is used to detect similarity in the patient in [106] and is used for predictive modeling as detailed in [107, 108]. Authors in [109] converted electronic health records data into readable phenotypes by using a tensor factorization model to analyze data in an FL framework. A Federated Learning framework to analyze brain structural relationships for diseases is studied in [110]. Researchers in [111] used FL based predictive modeling on EHR data to analyze the advantages of early treatment of patients. In [112], FL was deployed towards a predictive analysis to estimate prolonged stay period of patients and in-hospital mortality across a number of medical facilities. Two-stage federated Natural Language Processing (NLP) to detect patients and phenotyping from EHR data for obesity and comorbidities from several medical facilities is studied in [113]. Novel Federated Learning framework for smart wearables for activity recognition and data aggregation is studied in [114, 115]. Model-centric, cross-device, horizontal, cross-silo, vertical, data-centric, reinforcement, and other types of Federated Learning exist. The three primary forms of Federated Learning are–horizontal FL, vertical FL, and federated transfer learning. Horizontal FL uses data with the similar trait space across all devices, suggesting that Client A and Client B are using the same features. To train a global model, vertical Federated Learning incorporates multiple datasets from distinct feature areas. Finally, federated transfer learning is vertical Federated Learning that uses a pre-trained model that has been learnt on a comparable dataset to tackle a different challenge. Assume the global model is M_{FED} after an assignment is completed, and associated learning model is M_{SUM} after data aggregation. In general, the global model M_{FED} remains operational owing to parameter exchange and aggregation operations. Throughout the whole learning process of the global model's output, there will be a loss of accuracy. The performance of M_{FED} falls short of that of the aggregate model M_{SUM}. After stating the output of the global model M_{FED} on test set as V_{FED}, and the output of the aggregate model M_{SUM} on the test set as V_{SUM}, to quantify this difference. The model's loss accuracy [116] is defined as:

$$|V_{\mathrm{FED}} - V_{\mathrm{SUM}}| < \delta \tag{5}$$

where delta is a positive integer. However, because the primary criterion of FL is privacy protection, the aggregation model M_{SUM} cannot be realized in practice.

2.2 Artificial intelligence concepts

2.2.1 AI–features

Smart devices with measuring sensors are on the rise [117]. All these devices mean an exponential amount of generated datasets with an intense opportunity to learn from intelligent systems. With the increased level of data, a system has the potential to increase its accuracy. Artificial Intelligence can be termed as the simulative approach by computers in a way such that it can be considered as intelligent by humans. There are several features of AI, including knowledge-gathering, problem-solving abilities, predicting, learning, and implementing with the capability to reason, manipulate and move. AI enables the ability to detect the fault and evaluate without the presence of an expert. An AI system has the ability to solve complex problems in an automated and accelerated manner. It has been generally used to optimize conventional technologies involving data-driven strategies. AI has subclasses such as machine learning, neural networks, and deep learning. ML is essentially an operation of artificial intelligence that permits a machine to train and grow without being pre-programmed based on experience.

– *Supervised Learning:* This type of machine learning employs labeled samples and applies what it has learned in the past to a fresh dataset. This will necessitate knowing the algorithm's outputs and having the information required to train the model labeled with the accurate reactions. The algorithm correlates its actual performance to the correct output depending upon these responses, and if erroneous, it trains from these response and improves its effectiveness [118].
– *Unsupervised Learning:* Such a method of learning is used with information that was not labeled previously. No correlations among input and output for the model. This particular type of learning is more complex and utilized less as compared to supervised learning. When opposed to supervised learning, unsupervised learning allows the user to accomplish more complex processing tasks. These algorithms include–clustering, anomaly detection, neural networks, etc [118].
– *Semi-supervised Learning:* This type of learning lies in between supervised and unsupervised learning. This method of training is deployed in the event of a combined issue which requires both supervised and unsupervised learning. Data with labels are used in supervised learning, while data without labels are used in unsupervised learning, but data with and without labels is used in semi-supervised learning. The model will learn from tagged data and then apply its knowledge and patterns to unlabeled data [118].

– *Reinforcement Learning:* In order to teach the algorithm, this method of learning deployed a performance - based compensation technique. The trained model will be compensated for accurate output and condemned for erroneous performance in this method of learning, so it will be trained to optimise result and at the same time minimize consequence. The primary goal of health-related AI applications is to investigate correlations between treatment or preventative strategies and patient outcomes [119]. Diagnoses of disease, to create protocol for treatment, innovation in developing medicine and potential cure, and monitoring of patient are fields in healthcare where AI is used. Even though AI's usage in healthcare is steadily rising, it is now focused on a few ailments, like cancer categorization, nervous system disease, and cardiovascular disease.

2.2.2 How does AI works?

AI can gather information from several sources and perform a task, solve critical problems or make a decision without any human instructions [120]. AI can potentially replace humans by working in wide-scale activities in the realm of industry, retail, finance, and healthcare with considerable impacts on system performance and efficiency [121] that depicted in Fig. 5. The most common AI applications in healthcare may be split into 4 groups. Among these groups, the first three classes are meant to sort large data effectively and enable rapid passage towards data to deal with challenges in healthcare facilities. These applications includes contents like assistance for the elderly and physically disabled, natural language processing methods, and basic research.

– *Artificial Intelligence for Living Assistance:* In order to assist aged and physically disabled individual, automated systems coupled with intelligent robots can significantly elevate standard of life. Recently, [122] released an outline of intelligent home with capabilities for patients with loss of autonomy, as well as smart models developed on sensory devices over wireless networks, data collection, and AI. NNs may be trained to detect human facial expressions as commands using certain image-processing processes. Furthermore, facial expression analysis-based human-machine interfaces (HMIs) enable persons with impairments to operate wheelchairs and robot support devices without the need to use a console or relevant sensors [123]. In, smart communication architecture (SCA), solutions for Ambient Aided Living (AAL) were created to permit AI to interpret data from various communication networks. Sensors capture information about the surroundings and individual activity in this scenario, which is subsequently evaluated via cloud computing or edge intelligence [124].
– *AI in biomedical information processing:* Natural language processing (NLP) used for medical applications has progressed significantly. Biological question answering (BioQA) aims to discover swift and correct responses to queries by users from a massive database. As such, NLP systems can be predicted to seek replies that are resourceful [125]. Initially, biological queries must be divided into several categories to achieve relevant information from reactions. For accuracy over 90%, ML can be categorize biological queries into 4 main kinds [126]. Then, using a smart biomedical document gathering process, parts of the details containing biomedical queries may be efficiently retrieved. AI has the ability to perform these work as accurately as an expert assessor to enhance efficiency and accuracy.
– *AI in bio-medicine:* AI offers untapped potential as a strong tool in biological research [127], in addition to acting as a eDoctor for illness diagnosis, management, and prognosis. AI has the potential to boost reviewing and indexing of research papers in biological research and development works throughout the world. Moreover, through a semantic graph-based AI technique, researchers may effectively accomplish the complex work of outlining the literature on a specific topic [128]. Furthermore, for a significantly large research article, AI can equip biomedical researchers with searching and ranking of literature. This allows researchers to enhance scientific conception, which are critical aspects in the area of biomedical research.

2.2.3 Explainable AI (XAI) concepts and features

XAI refers to approaches and techniques for using artificial intelligence in such a way that the solution's outcomes are understandable by humans. It contrasts with the "black box" concept in machine learning, when even the designers are unable to explain why an AI made a particular decision. XAI could be an example of the social right to explanation in action. Even if there is no legal right or regulatory obligation, XAI can improve a product or service's user experience by assisting end-users in trusting that the AI is making good decisions.

The goal of XAI in this manner is to explain what has been done, what is being done now, and what will be done next, as well as to reveal the knowledge on which the actions are based. These features allow you to (i) evaluate what you already know, (ii) dispute what you already know, and (iii) produce new assumptions.

Properties of XAI: Transparency, Interoperability, and Explainability all work as an interface between human and AI systems. They consist of AI systems that are both accurate and understandable by humans [129]. Although the semantic implications of these phrases are identical, they confer distinct levels of AI that are acceptable to humans. For further information, the ontology and taxonomy of XAI can be seen here at a high level:

- Transparent Model: K-nearest neighbors (kNN), decision trees, rule-based learning, Bayesian networks, and are examples of typical transparent models. Although transparency as a feature does not guarantee thet a model will be easily explainable, the decisions made by these models are frequently transparent. [130]
- Opaque Model: Random forest, neural networks, Support Vector Machine (SVMs), and other opaque models are common. These models are not transparent, despite the fact that they frequently reach excellent accuracy. [131]
- Model-agnostic: XAI techniques that are model-agnostic are created with the goal of being widely applicable. As a result, they must be flexible enough to operate purely on the basis of matching a model's input to its outputs rather than relying on the model's intrinsic architecture. [132]
- Model specific: Model-specific XAI techniques frequently take advantage of prior knowledge of a particular model and try to bring transparency to a specific type of one or more models.
- Explanation by simplification: We can identify alternatives to the original models that explain the prediction we're interested in by simplifying a model via approximation. For example, we can build a linear model or a decision tree around a model's predictions, then use the resulting model to explain the more sophisticated one.
- Explanation by feature relevance: This is analogous to the concept of simplicity. After all possible combinations have been explored, this form of XAI technique seeks to evaluate a feature based on its average expected marginal contribution to the model's choice.
- Visual explanation: This type of XAI strategy is built around visualization. As a result, the data visualization approaches can be used to interpret the prediction or judgment made based on the input data.
- Local explanation: Local explanations replicate the model in a small area, usually around a single instance of interest, and provide information about how the model works when it encounters inputs comparable to the one we're interested in describing.

Advancement of XAI: Despite the benefits of intelligent systems, the XAI research initiative raises concerns about giving them too much power without the ability to explain the decision-making process that lies beneath such complex systems to domain experts (e.g., doctors, lawyers, financial experts, etc.) in terms and in a format that they can understand. This not only aids in comprehending specific decisions made by such systems but also pushes researchers to develop more human-like (anthropomorphic) solutions, as well as encouraging further research and understanding of the brain as a natural information processing phenomena.

Because of the growing relevance of this topic, NIST published Four Rules of XAI in August 2020, which describe the following key principles [133] that an AI must follow in order to be designated a XAI:

- Explanation: According to this principle, an AI system must provide proof, support, or explanation for each decision it makes.
- Meaningful: According to this principle, the AI system's explanation must be clear and meaningful to its consumers. Because diverse groups of users may have varied wants and experiences, the AI system's explanation must be fine-tuned to fit each group's unique traits and needs.
- Accuracy: this principle states that the AI system's explanation must correctly reflect the system's processes.
- Knowledge limits: according to this theory, AI systems must recognize circumstances in which they were not designed to operate and, as a result, their answers may not be credible.

2.3 e-Healthcare system

e-healthcare may be characterized as providing constant healthcare assistance to patients through technical tools and techniques such as information and communication technology, cellular technology, medical support, and wireless facilities [134]. Electronic health records, scientific journals, and similar archive on the internet, visual, and audio consultation with doctor, or internet-based process to connect with medical personal, give feedback to doctors, transfer test results, and so on are examples of e-health systems that can revolutionize the healthcare services they provide. The e-healthcare system may give general support on a larger scale, such as management assistance, healthcare service delivery, and so on, as well as specialized help, such as citizen health data [135]. The provision of health care via the internet and technology is carried out by combining existing tools and assuring the quality of the services supplied [136]. The spread of the contagious coronavirus is an issue that needs immediate attention. With the advent of new variant of coronavirus, medical personnel are facing an enormous challenge to address the health issues of the infected individual. The complexities of COVID-19 coupled with scarce resources and rising healthcare cost has encouraged many to access remote health management services using computer or similar devices [137–140]. IoT plays a fundamental act in achieving automated distant health care services. IoT and smart devices are used to transfer the health data of a patient to the cloud server to access health information of an individual [141]. The IoT and its application for healthcare management services can be divided into three steps [142]: i) gain access to the location of a patient or healthcare staff ii) to identify and authenticate an individual, and iii) to automate data collection using sensory devices. Electronic health records (EHR), decision based support systems, online consulting, and telemedicine are a wide range of components related to eHealth. Computers play a vital role to deliver therapeutic session to patients. EHR data of patients serves as the base for prescriptions originated using computers, which offer several benefits, such as linkages to software that emphasizes medication. Two key features in eHealth have ethical implications for the handling of EHRs. The first is professional, whereas the second is technical. The technical issue is promptly resolved. Assuming that there is a fiduciary physician-patient connection in eHealth, the ethical obligations for the treatment of patient data in general and EHRs in particular that arise from the fiduciary relationship in standard health care also apply in eHealth [143]. The novel coronavirus develops pneumonia like symptoms with an individual suffering from respiratory diseases. The prognosis of a patient infected with COVID-19 related illness is limited with high mortality [144, 145]. The implementation of AI in healthcare sectors [47, 146] have created an urge amongst researchers to pursue innovative methods to develop e-healthcare systems. Authors in [47], have developed an AI based system to differentiate between pneumonia of a coronavirus infected patient from that of common pneumonia traits. AI based algorithm is used in [147] for earlier detection of kidney related illness amongst diabetic individual. Researchers in [148] utilized AI to provide specific diagnosis and treatment for patients.

FL-AI is possible to deliver numerous appealing benefits to promote smart healthcare, as mentioned below, based on the innovative operational concept:

– *Improvements to Data Privacy:* Only local updates are needed by the central network for AI training in the FL-AI-based smart healthcare system, while raw data is stored at medical facilities or equipment. This approach limits the danger of personal user data being leaked to an external source, ensuring better level of client security [149].
– *A Reasonable Balance of Accuracy and Utility:* FL-AI is capable of providing a suitable balance among accuracy and usefulness, as well as privacy enhancement, as compared to traditional centralized learning. Furthermore, FL training keeps the model generalizability while sacrificing nominal accuracy. As a result of FL's distributed learning characteristic, the smart healthcare system's scalability may be improved.
– *Health Data Training at a Low Cost:* FL-AI may assist decrease communication costs, like latency and transmit power, associated with raw data transfer by evading the dumping of large data to the central network because model gradients are often considerably less in size than their real datasets [97]. As a result, FL saves a significant amount of network bandwidth and reduces the risk of network congestion in large healthcare networks.

e-Health is a broad word that encompasses the integration of healthcare and technology to serve individuals better and save healthcare expenditures. Some industrialized nations that have been adopting health-related activities have consistently prioritized eHealth [150]. However, implementing eHealth has the potential to enhance the whole health care system in both developed and developing nations. eHealth is referred to as an end-to-end method that may be used in any situation.

3 Taxonomies and motivations of integrating FL with AI in healthcare system

In this section, we make a group of unique taxonomy architectural views based on FL-AI and FL-AI-healthcare in 3.1. On the other hand, we provide the integration benefits among the FL, AI, and intelligent healthcare technologies in 3.2.

3.1 Taxonomies of FL with AI in healthcare

Federated Learning, a distributed collaborative AI model, is specifically appealing for intelligent healthcare since it allows different clients (for example, hospitals) to collaborate on AI training without the need to share local data. As a result, we have put together a detailed analysis on FL's application in advanced healthcare. To begin, we introduce the current breakthroughs in FL, as well as the reasons and prerequisites for adopting FL in smart healthcare [31, 157]. Following that, the latest FL ideas for intelligent healthcare are reviewed, which includes FL for resource management, FL aware of security concerns, incentive FL, and tailored FL. Following that, we present a cutting edge overview of

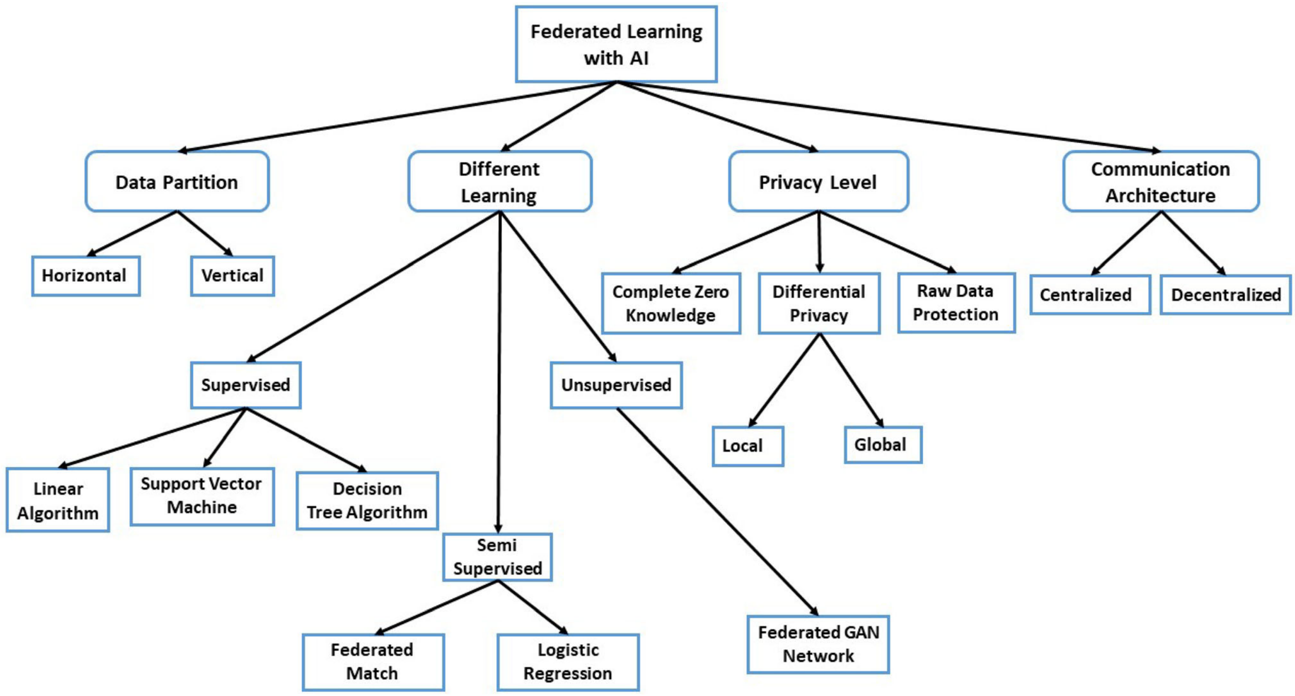

Fig. 2 Taxonomies of Federated Learning with AI

FL's developing applications in major healthcare areas such as data management, distant health monitoring, biomedical image analytics, and so on [9, 158, 159].

The proposed taxonomy for Federated Learning (FL) with Artificial Intelligence (AI) is shown in Fig. 2, and the taxonomy for FL with AI techniques in healthcare is shown in Fig. 3. We showed numerous AI and machine learning algorithms based on learning, reasoning, and discovering in these taxonomies. We divided the privacy level as well as the communication architecture. Different FL-based algorithms were also examined. Furthermore, the development of FL-AI techniques in healthcare, the applications of Smart technologies in healthcare have been systematically analyzed, and the security and privacy concerns, as well as medical issues have been portrayed. In the suggested taxonomy, we thoroughly examined the healthcare sector with the interconnection of FL-AI [4, 83, 160].

3.2 Integrating of FL with AI in healthcare

3.2.1 FL-healthcare integration

The current world is focused on data analytics, particularly in the medical sector. Healthcare data, including prescription information and supplies, patient data, healthcare professional information, and affiliated organizations responsible for insurance or other financial-related transactions, has become increasingly important for data analysis. However, the data on the healthcare sector is dispersed. They are not in the same format, and the data is susceptible in nature, as it includes information from the medical industry. The most sensitive of them are insurance sector data, which cannot be transmitted from one sector to another. Without data transfer, processing with traditional learning and training methodologies is impossible, resulting in a significant gap in data analysis.

As a result of the integration of Federated Learning with healthcare data informatics, the analysis of extremely sensitive data has become significantly more efficient, this integration scenario shown in Fig. 4. In this situation, data is not transported from source to destination in order to merge or generate a dataset for analysis; rather, the local client trains their model with their data and connects with other clients via the server bypassing only the results. As a result, the data remain secure at their origin, and the network, gains access to the server's training results. This integration will benefit both suppliers, such as the organization in charge of producing and supplying the necessary equipment to a hospital, and users of the application, such as the general public. As the linking sectors are vast in this era, and data production is also vast, it is difficult to identify malicious users among the thousands of connected clients; therefore, by leveraging the benefits of FL, the clients' data is preserved safely with their own model, and data leakage is prevented to avoid any malicious data modification in the system. Moreover, we present the overview of current analysis based on Federated Learning in healthcare in Table 3 There are various applications in

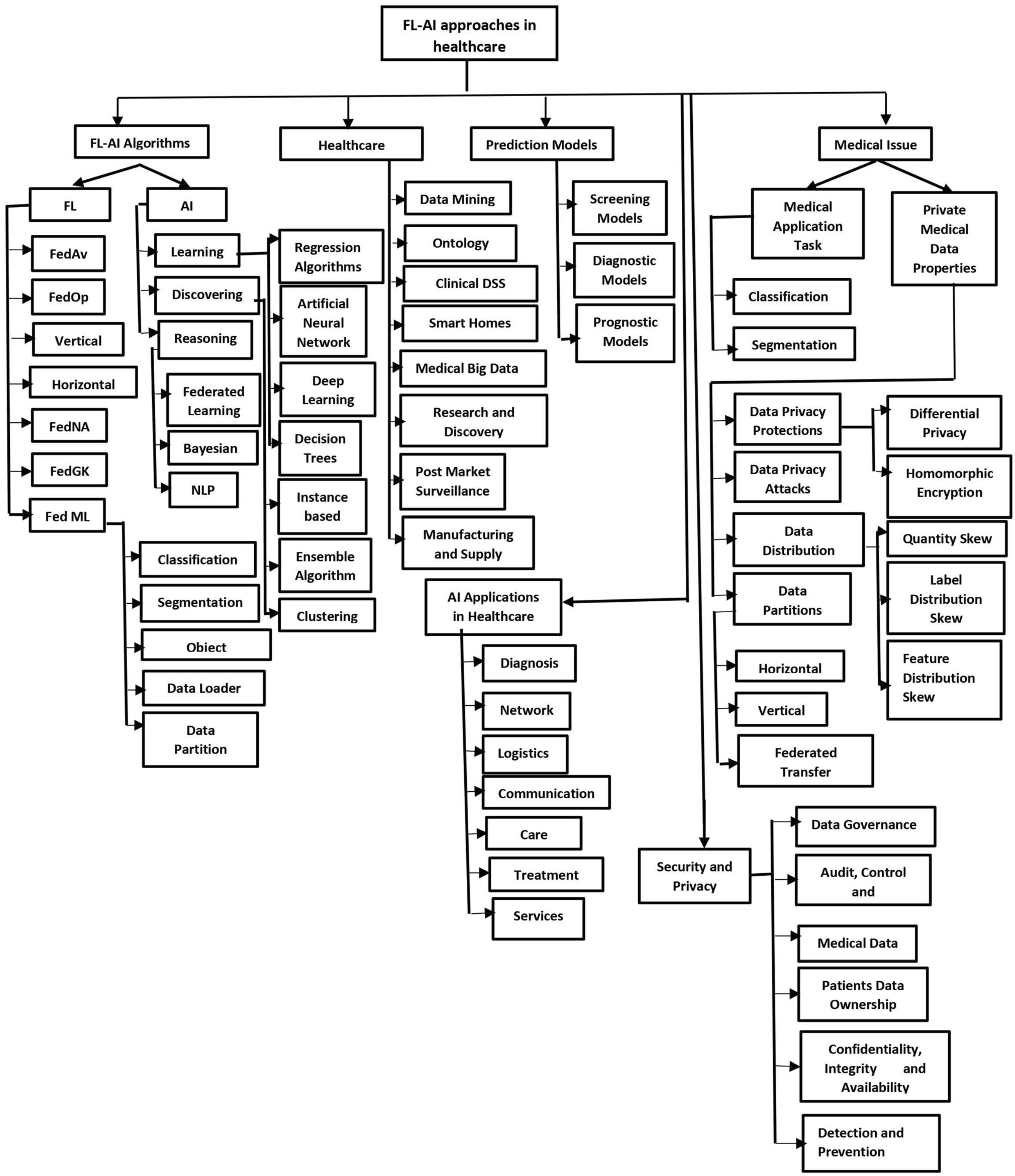

Fig. 3 FL-AI with Healthcare Overview

the healthcare sector where FL integration will increase the overall effectiveness of the process analysis:

- FL can assist to improve the security and privacy of medical industry data analysis and prediction by incorporating a data protection system [25, 161, 162] .
- FL has also allowed predictive modelling depending on several sources, from which physicians can access extra

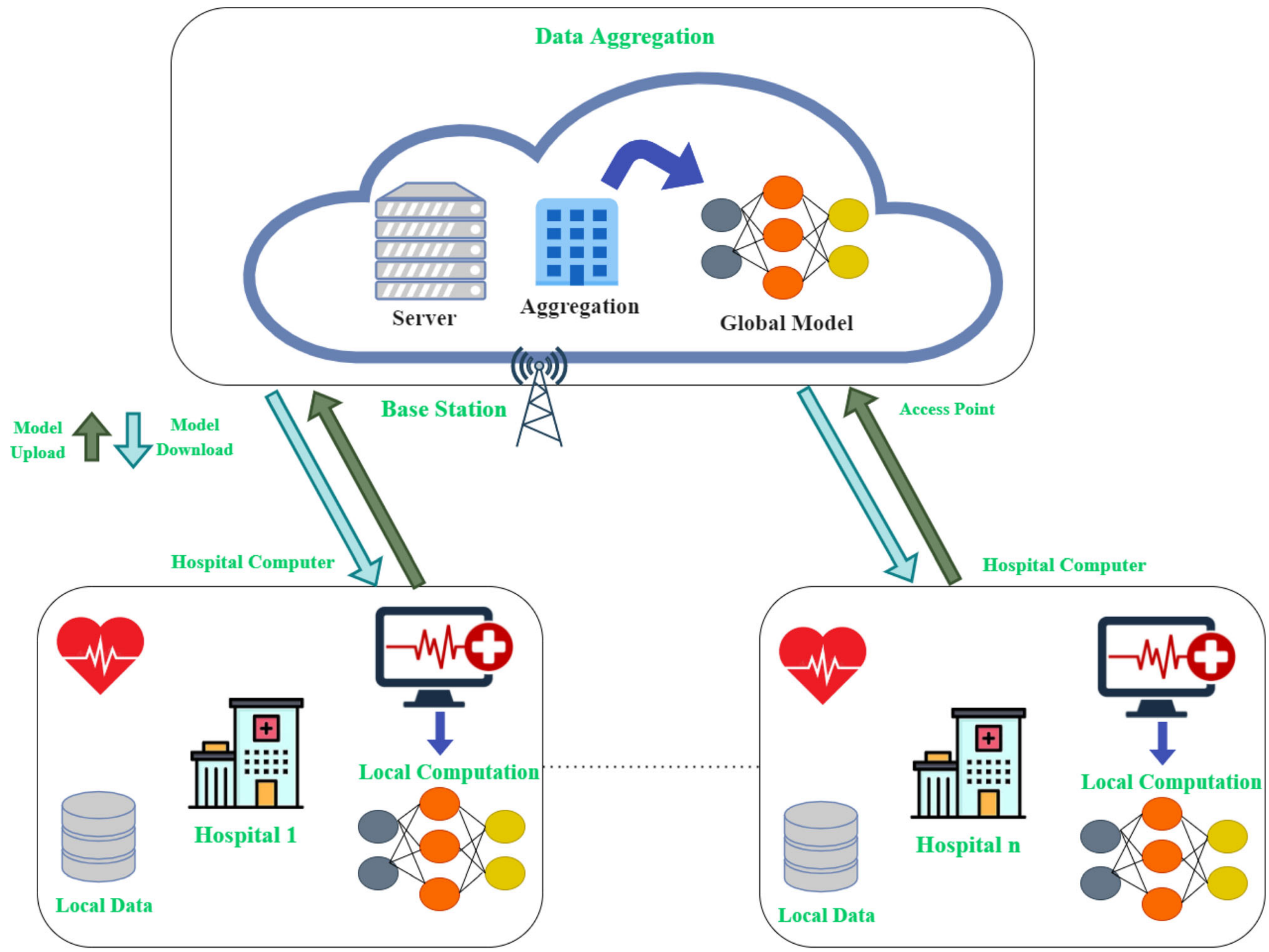

Fig. 4 Federated Learning with Healthcare

information about the potential threats and advantages of providing earlier treatment to patients [163].

- Among the many applications of FL-based healthcare models for prediction, similarity among different patients is one [164].
- Medicine resistance or therapy against various diseases, as well as survival rates or explanations, can be examined with strong privacy towards sensitive data [165].
- Hospital mortality prediction, duration of stay, or rather the rate of admission can also be examined using FL-based models for the proper management of some critical care units in the hospital while protecting the privacy of in-hospital data [161, 166].

3.2.2 AI-healthcare integration

As discussed in the preceding section, data from many sectors have risen considerably in the current context. Traditional or statistically based prediction for the medical sector is problematic with the expanding amount of data because it involves human data collection. There is a significant demand for automation throughout the data gathering, processing, and result creation processes. Again, a system that can receive information from multiple sources and perform a task, solve crucial problems, or make a decision without human intervention would be extremely valuable to the healthcare business. In the world of healthcare, the word artificial intelligence plays a very important and critical function in interpreting the human thinking process through the computer employing many efficient AI-based algorithms to make the difficult examination easy for healthcare professionals [167]. That is, making sensible use of machines that draw key conclusions based on data fed to them as input. The objective of integrating AI in the healthcare sector is to blend numerous aspects that may influence a specific decision and produce a proper evaluation of the result offered by the AI model using ML or DL. In general, AI models are useful for making key decisions such as ICU surveillance, mortality

Table 3 Overview of recent works analysis on FL in Healthcare

Ref.	Key Technologies	Techniques	Applications	Contributions	Drawbacks and Challenges
Chen et al. [115] (2020)	Federated Learning, homomorphic encryption	Data aggregation using FL and smart wearables	Deployment of FL framework in smartphones for activity recognition and data collection while maintaining privacy concerns	Novel framework to introduce FL with smart wearable devices for model training using transfer of information	Future applications to study specific diseases requires attention.
Sharma et al. [108] (2019)	Federated Learning, predictive model of in-hospital mortality	Distributed training and privacy-preserving framework using vital signs data	To predict in-hospital mortality while maintaining data privacy	Identification of challenges and advantages of FL in healthcare predictive modelling and addressing critical issues related to privacy and ownership are addressed	The study requires further analysis with hyper-parameters.
Huang et al. [105] (2019)	Federated machine learning	FL-based machine learning algorithm and distributed data clustering while maintaining data privacy	To predict the mortality and duration of hospital staying period using electronic health record	Improved efficiency of decentralized FL Machine learning for performing a clinical task using EHR	The work could be further extended to perform prediction for other clinical tasks for distributed data over several institutions.
Silva et al. [110] (2019)	Federated Learning, ENIGMA shape tool	Analysis of distributed biomedical data using Federated framework	Fl framework to gain secured access and meta-analysis of medical datasets concealing patient information	Successful application towards the study of subcortical brain changes in multicentric cohorts	The proposed framework requires implementation on a large scale imaging genetic datasets.
Boughorbel et al. [111] (2019)	Federated framework, Base Neural Network RETAIN	Training of the recurrent neural network model of hospital data in FL environment, data interpretation using RETAIN	EHR data analysis to predict the preterm birth	To analyze the potential threats and benefits of earlier treatment of hospitalized patient	Application on larger dataset and designation of rejection criterion needs to be addressed.
Pfohl et al. [112] (2019)	Federated averaging, differentially private stochastic gradient descent	Federated averaging technique towards distributed optimization	Use of e-ICU collaborative research datasets to gain insight towards an extended period of stay and in-hospital mortality	To present a comparison of efficacy between FL and centralized and local setting	The method used needs comparison with other approaches to understand its efficacy.
Liu et al. [113] (2019)	Federated natural language processing	NLP technologies and phenotyping for increased efficiency of reviewing clinical data	To study patient representation and EHR data for individuals with obesity and comorbidities from several hospitals	To facilitate a learning healthcare system to extract critical information for research, and improved diagnosis	The algorithm performance matrices requires further comparison with results achieved from other relevant datasets.
Lee et al. [106] (2018)	Federated Learning, MIMIC-III database, homomorphic encryption	Novel algorithm to learn context-specific codes	Similarity index for patients across several institutions	Patient identification using unique Hash codes	The work did not represent temporal effect, optimal parameter determination for decay factor and projection dimension is not considered, real-life application for ICD code requires attention.

Table 3 (continued)

Ref.	Key Technologies	Techniques	Applications	Contributions	Drawbacks and Challenges
Brisimi et al. [107] (2018)	Federated database, predictive modelling for heart disease	Federated Learning framework with iterative cluster primal-dual splitting (cPDS) algorithm for analyzing large scale sparse support vector machine issue in a distributed manner	To ensure data privacy and allow collaboration between multiple entities without exchanging sensitive user data	Faster convergence with limited communication, to gain insight to key features necessary to predict hospitalization	Real-time measurement considering time-varying graphs for cPDS analysis is not taken into account.
Kim et al. [109] (2017)	Federated Learning framework, data analysis	Federated Tensor factorization model to convert EHR data into phenotypes	Data analysis in an FL environment by converting e-medical dataset into computational phenotyping	Secured data exchange using real medical datasets while maintaining security concern	The research was limited to small scale dataset.

prediction, proper usage of hospital resources, drug inspection and reaction, and so on. By using the AI method and the vast amount of data created by the healthcare industry, such as the EHR, the remedy and conclusion may be formed efficiently for future reference of the doctors or clinicians [168]. In addition, we present the overview of recent work analysis based on Artificial Intelligence in healthcare in Table 4.

Recently, explainable AI (XAI) has been gaining popularity in cyber-physical systems such as smart healthcare. Cancer identification from MRI pictures is a critical problem in the medical field. However, with an effective cancer detection process, the chance of survival may increase because the cure is achievable at an early stage of cancer. With sophisticated XAI, the reason for the diagnosis of a certain cancer is apparent and visible to the system's user [169]. The XAI intends to reveal the internal mathematical calculations used to solve the black box known as the AI. Thus, by using this method during the diagnosis phase, clinicians can benefit from the use of XAI technologies [170]. There are several sectors where AI is integrated with healthcare like–

- The agent-based AI can interact with humans and provide comfort based on the needs of the patients. This can be useful when the patient is elderly and requires close monitoring and care. Patients with chronic diseases, in particular, require frequent monitoring of certain tests such as heart rate, blood sugar levels, and so on. All of this is simply obtained with the AI-based agent [171].
- Another significant responsibility in the medical field is assessing medication effects and forecasting how a drug will affect a human being. One essential method in this scenario is the combination of AI with computer-based medication creation and analysis [172, 173].

The benefits of AI integration in the healthcare sector are enormous which is shown in Fig. 5. Though it has various concerns, such as control over AI-based devices, it must be handled with extreme caution or it can be destructive to a nation. In this regard, the security of these systems must be powerful enough to withstand any form of intruder attack or to take appropriate steps to raise the alarm when any inappropriate data tampering occurs in the system.

3.2.3 FL-AI integration

The system with autonomous control is incorporating more and more real-time data aggregation as new technologies evolve. Intelligent systems were elevated to a new level owing to the ML and DL models. The data produced by each IoT sensor has increased exponentially with the IoT-based system, and the cloud storage system has made data storage easier in many ways. However, collecting data and feeding it to a model with advanced DL to develop an AI-based model is a very important and delicate operation. If data is altered from source to destination by an attacker, the forecast will be inaccurate, and because this method deals with highly sensitive data, the security of the data will be compromised. In the above scenario, there are a variety of methods for ensuring data security, one of which is FL integration. It produces a model and transmits a replica of the model to each local client instead of transferring data from the local machine to the central server. With their own local data, the client trains the model and transfers the new parameters or weight to the central server. During the whole process, no data must be exchanged; only the result must be transferred from clients to the central network. At

Table 4 Overview of recent works analysis on AI in Healthcare

Ref.	Key Technologies	Techniques	Applications	Contributions	Drawbacks and challenges
Sarker et al. [151] (2021)	AI, Robotics, Autonomous mechanism	AI dependent system for detecting COVID-19 using chest X-ray images	Quick verdict of COVID-19 detection using X-ray.	Assist healthcare professionals to take decision fast and provide results within short period of time	Handling sensitive data is difficult, and protecting it from hackers necessitates greater caution.
Saheb et al. [152] (2021)	AI, Robotics and ethics	Analysis (Cluster-based) of ethical difficulties in the merging of AI with healthcare	To detect deficits in existing survey to create an efficient and ethical AI-based model for tackling problems in the healthcare sector.	Identification of gaps in current academic papers in the sense of ethical sides.	The investigation of these types of ethical dilemmas requires the participation of professionals from several sectors, such as healthcare professionals, lawyers, and engineers with a background in computer science.
Kumar et al. [153]	FL, AI, Deep learning	Deep learning and FL based model to detect COVID-19	To mitigate the problem of scarcity and reliability of testing kits primary diagnosis of COVID -19 from pre-trained model.	Proposed a system that aggregates information from several sources and drills a global DL model with the help of FL based on blockchain.	The sample collection and gaining popularity of the system is challenging.
Cavasotto et al. [154] (2021)	AI, DL, ML	The use of powerful AI-based algorithms for pharmaceutical research	Discovery of new drugs from the analysis of the biomedical patterns leveraging advanced AI based methods.	Drug discovery and analysis of drugs on human	Data in this scenario is particularly sensitive, and combining data from many sources is problematic because the data might be manipulated along the route, resulting in erroneous conclusions.
Hildebrand et al. [155] (2021)	AI, DL, ML	machine learning and AI for analyzing the MSI for cancer patient	Prediction of immunotherapy response	Detection of Microsatellite Instability for patients with Colorectal cancer	Collecting samples from many sources and assembling them in a single location required extreme vigilance in order to keep them safe from intruder attack.
Zhang et al. [47] (2020)	AI, Computed Tomography database, python scikit-learn library	Using AI framework to analyze CT images of coronavirus infected patients	Quick diagnosis to differentiate between common pneumonia from coronavirus related pneumonia in overburdened healthcare facilities	To detect a critically ill patient with COVID positive traits	Improved accuracy with larger datasets for a long period is required.
Romero et al. [148] (2020)	AI framework	AI-based Clinical decision support system	To achieve an improved level of glucose control in patients with diabetes	To conduct a survey about the experience with AI-based system in medical facilities	The proposed system requires improvement in terms of providing recommendation to patients.
Rong et al. [156] (2020)	Artificial intelligence, ML algorithm, Wearable device, Digital signal processor	Patient monitoring using ML algorithm. Use of sensory device to generate electrical stimulation when necessary	Assist patients with disabled sensation to notify regarding the need to empty bladder or abnormal urinary bladder control	To develop an effective monitoring device to measure the volume and pressure of the urinary tract and send necessary feedback	Result validation using clinical trials remains unattended.

Table 4 (continued)

Ref.	Key Technologies	Techniques	Applications	Contributions	Drawbacks and challenges
Ravizza et al. [147] (2019)	AI, Roche/IBM algorithm, IBM Explorys database	Health and medical supported key features selection with data-driven strategy	Early prediction of severe kidney diseases for diabetic patients	Comparison of algorithms extracted from real-world data	The work requires additional testing with the larger dataset.
Kim et al. [109] (2017)	Federated Learning framework, data analysis	Federated Tensor factorization model to convert EHR data into phenotypes	Data analysis in an FL environment by converting e-medical data set into computational phenotype	Secured data exchange using real medical datasets while maintaining security concern	The research was limited to small scale dataset.

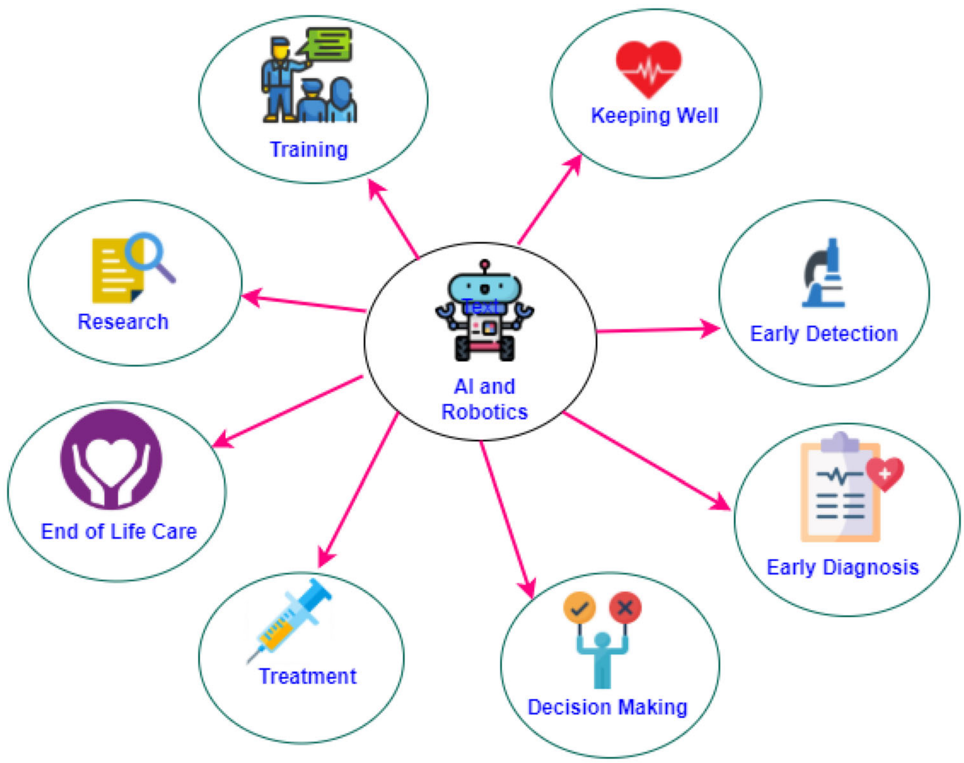

Fig. 5 Use case of Artificial Intelligence in Healthcare System

the server, the local training outcomes are averaged, and the revised weights are then relayed back to all clients connected to the server. There is no need to transfer data because the raw data is kept in the local area, and thus data security may be assured. The integration benefits of FL and AI covers a huge area. For example;

- FL-based mechanism aggregation at the edge may be beneficial because the volumes of information gained from nodes are quite high in rate using such approaches [174].
- Device heterogeneity can be preserved in a safe data training and evaluation environment [175].
- The FL with AI is more powerful thanks to its raw data protection method and local and global privacy levels [176].
- Integration of an FL-based AI model can result in a more energy-efficient solution [177, 178].

4 Addressing and defending challenges on FL with AI in healthcare system

This section is the most strong side compared to the other survey. However, firstly, we discuss the existing problems and issues–security, privacy, reliability, confidentiality,

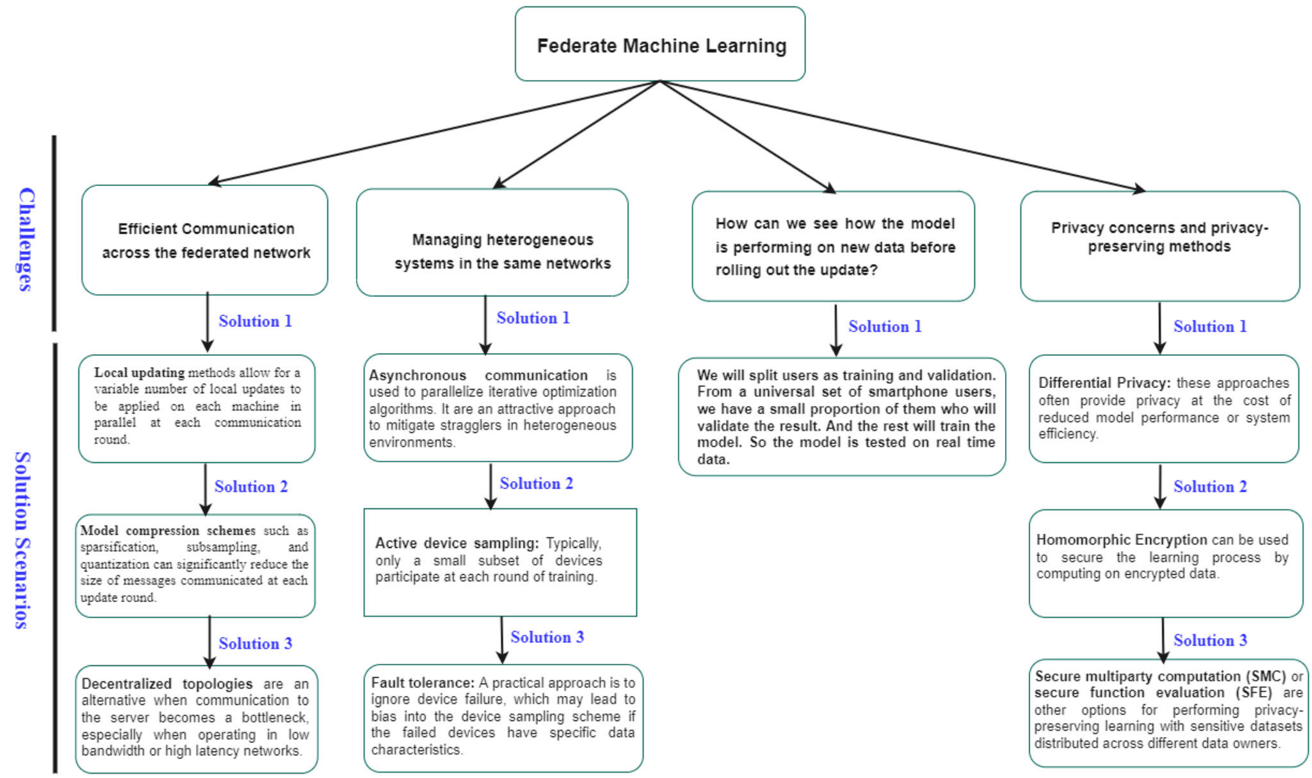

Fig. 6 Challenges and Solution Scenarios of Federated Learning

scalability, etc. in 4.1. In addition, we present the different solutions strategies that have been shown in Fig. 6 based on the proposed techniques–FL, AI, healthcare in 4.2. Furthermore, we summarize the overview of Federated Learning with AI in Healthcare as well as the key applications area, challenges, and solution in Table 5.

4.1 Existing challenges in healthcare system

4.1.1 Security and privacy concern

The current healthcare system relies on the internet to transfer data and other sensitive information. The Internet of Medical Things, or IoMT, is this term. It has drawn significant attention in the twenty-first century since it can carry information from one portion to another in a concise period of time and at a very low cost. However, along with the benefits, there are also drawbacks. One of the most serious topics is security, and privacy [197]. This type of healthcare solution includes data transfer, mobile application usage, telemedicine, and accessing the information of the healthcare remotely. In the IoT-based healthcare system, several attacks can hamper the total loss of the system. Preference, side-channel attack [198], data duplication using the tag, physical hampering of the sensor devices, or sensor tracking are some of the attacks that may cause issues in the perception layer [199]. Then, some attacks from the intruder can access the information sent from the hardware system by directly attacking at the decryption point or by weakening the authentication procedure such as Eavesdropping attack, reply attack, MITM attack, rouge attack, DoS attack, DDoS attack and these type of attack causes to hamper the network layer of the IoMT [200].

4.1.2 Reliability problem

Following the aforementioned security concerns, the current healthcare system's reliability has also become a source of concern. By embracing session hijacking in the existing smart healthcare system, an attacker can take control of the session as well as the data being transferred in that session, potentially causing a major problem for the entire system. The intruder can then gain access to the IoT network using a side script. When a faulty SQL code is injected into the database, it can jeopardize the system's vital information [201]. Packet interception can also impact the loss of information which is in the form of identity while a user tries to authenticate or log in. An intruder can encrypt the personal data of a healthcare system user via a ransomware assault. As a result, these attack possibilities

Table 5 Overview of Federated Learning with AI in Healthcare Research covered with key applications area, challenges, and solution

Works	Applications fields	Addressing challenges	Proposed solution
Xu et al. [83]	EHR, prediction mortality, Biomedical	- Statistical	Review of several present solution leveraging Federated Learning.
		- System	
		- Privacy issues	
Brisimi et al. [107]	Heart disease related learning mechanism	- Sparse SVM issue	Proposed an architecture cPDS that can differentiate the mentality of patient those who wanted to be hospitalized and those who don't.
		- Issue of raw data exchange	
Passerat et al. [179]	Privacy preserved audit section	- Privacy issue	Blockchain and Federated Learning-based solution to preserve privacy in the network without knowing the identities.
		- Data access policy issue	
		- Security issue	
Silva et al. [180]	Federated Learning method for brain image data	- There is no FL based production ready approach	A software base client and central module for learning process for the real-world scenario.
Chen et al. [115]	FL based healthcare system for Parkinson's disease	- User data aggregation from different sources is difficult	A system capable to provide precise and individualized healthcare whilst also maintaining data privacy and security, according to wearable activity detection trials and a genuine Parkinson's.
		- Cloud system may fail in case of personalization	
Wu et al. [181]	In house health monitoring system	- Increasing rate of elderly people	A technique based on FL and CNN for monitoring elderly patients with chronic diseases who are unable to walk about regularly.
		- Independent living style of people above 60 years	
Choudhury et al. [182]	Prediction of medication responses	- Healthcare data sensitive in nature	A model to predict the effect of drug reaction in human.
		Lack of existing work on real world scenario.	
Ma et al. [183]	Healthcare Informative, Data Distributive	- Data distributed across multiple edge nodes	Provide necessary design changes towards flexibility of hybrid electronics which can join the quality performing electrical attributes of traditional electronics with the capability of stretching.
Pershad et al. [184]	Patient-physician relationships, Technology, Public health	- Social media platform Twitter for spreading healthcare information include significant amount of misleading information	Examined the practice of using Twitter in delivering quality healthcare and information on medicine and particularly search the potential of Twitter to share data on treatments and research to improve care.
		- Difficult to verify plausibility of source	
Kim et al. [185]	Machine learning, Federated Learning, blockchain	- Complex architecture	Analyzed a latency model of FL dependent on blockchain and represent the optimal block generation rate by taking into account communication and computing delay.
Miotto et al. [186]	Deep learning, healthcare, biomedical informatics, genomics EHR	- Complex, high dimensional, heterogeneous biomedical data	Suggested development of comprehensive and purposeful explicable scheme to reduce the gap between DL models and human understanding ability.
		- Difficult to gain knowledge from complex data.	

Table 5 (continued)

Works	Applications fields	Addressing challenges	Proposed solution
Wiens et al. [187]	Machine Learning, Healthcare	- Privacy issue	Present special considerations for those healthcare epidemiologists who want to use/ apply ML.
		- Data transformation of infectious disease	
Kumar et al. [153]	Data Sharing while preserving security, DL, FL, Blockchain	- Shortage of test kit of COVID-19	Proposed a novel architecture to gather relevant data from several sources and teaches a global DL model using FL based on blockchain.
		- Quick spread of the virus	
		-Issues to differentiate between negative and positive cases of COVID-19	
Nguyen et al. [9]	FL, Blockchain, Edge Computing, IoT.	- Volume of data	To increase the security features and accessibility of implementing FL, Blockchain for realizing decentralized learning through FL without requiring central network.
		- Privacy of data	
Holbl et al. [188]	Blockchain, Consensus, Distributed systems, Healthcare Informative	- Encryption method	To realise the potential of blockchain technology and to focus on the obstacles and possible contributions of blockchain based research in healthcare industry.
		- Complex framework	
Pokhrel et al. [189]	Vehicle Machine Learning, Federated Learning, Blockchain.	- Complex framework	Proposed a FL method based on blockchain algorithm for security-aware and effective communication in vehicles, in which ML model updates are shared and authenticated in a decentralized manner.
		- Privacy of data	
Mcghin et al. [190]	Blockchain, Healthcare Industry, Authentication, IoT, Wireless, Vulnerabilities	- Research gap in the area of blockchain based solutions.	A significant quantity of research methods are detailed in this research.
Lu et al. [191]	Data Sharing, Permissioned Blockchain, Federated Learning, Privacy-preserved Industrial IoT	- Data leakage	Proposed a blockchain based secured data sharing method for several users. Formulated the data sharing problem into a ML issue by introducing FL equipped with security features.
		- Data privacy and security	
Greenberg et al. [66]	Healthcare, Machine Learning	- Unprecendented sutuation	Management of obstacles faced by medical personal mentally during coronavirus pandemic situation.
		- Difficult to take decision and work under extreme pressures	
Kaye et al. [59]	Healthcare, Medical Informative.	- ICU crisis in the time of need	Analysis of impact of coronavirus pandemic on the financial situation of healthcare facilities
Alemdar et al. [70]	Healthcare, HIOT.	- Different format of data in the healthcare sector	Minimizes the complex healthcare system for healthcare officials and assists the disabled and aged to lead an autonomous life.
		- Data security and privacy.	
Xi et al. [192]	Healthcare, Federate Learning	- Problem with data having different feature	An adequate backdoor detection process based on FL by carrying out comprehensive analysis over two ML objectives to display that the methods achieve high precision and well protected from multi-attacker's settings.
Long et al. [193]	Healthcare, Federate Learning, Bio-informative.	- Data with different feature	Analysis on FL to permit the enhancement of an open health ecosystem with the help of AI. Current obstacles and potential remedies for FL are discussed.

Table 5 (continued)

Works	Applications fields	Addressing challenges	Proposed solution
		- Data security and privacy	
Yu et al. [16]	AI, Healthcare, Federate Learning.	- Complex model	Outlining of current developments in AI technologies and applications in healthcare sector, identification of potential challenges for future developments for AI in healthcare. Summarized the impact of AI in healthcare from economic, legal and social perspective.
		- Data leakage	
		- Ethical issue.	
Esteva et al. [194]	AI, Healthcare, Federate Learning, Computer Vision, NLP.	- Difficult to train the NLP model	A thorough analysis of computer vision on biomedical image analytics, and description of the use of NLP in areas such as EHR data.
		- Require massive data to build efficient model	
		- Data collection	
Xu et al. [195]	Federate Learning, AI, Medical Data.	- Data security	Provided a descriptive solution regarding the privacy preservation of patients with depression, implementation of FL to analyze and diagnose depression.
		- Data Leakage	
		- Ethical issue regarding data sharing	
Lu et al. [196]	Healthcare, Federate Learning, Distributive learning.	- Communication cost and delay	A detailed analysis to improve the communication efficiency using distributed FL over a graph, wherein the algorithm enacts local updates for multiple iterations to permit communications among several nodes.
		- Networking issues	
		- Interruption in the communication setup	

raise a question of trustworthiness. For instance, when intruders are capable of encrypting compassionate information from a system, the question of whether the system is reliable or safe to transfer data through remains open [202].

4.1.3 Confidentiality issues

Existing healthcare solutions necessitate the relocation and merging of data from multiple nodes to provide a long-term solution. However, because the data being moved is very sensitive, this data migration creates a confidentiality concern [203]. Another issue in IoT-based systems is heterogeneity. Because the sensors are from diverse vendors, the system's anonymity isn't always guaranteed. Furthermore, securing data security while transferring susceptible data from one node to another remains a difficult task [204]. However, in order to produce information, the data must travel from one end to the other. The transit of data or sensitive information causes security breaches, which, in turn, causes a confidentiality problem in an IoMT-based system [205].

4.1.4 Scalability problem

In today's healthcare systems, a huge number of inbound and outbound networks must be managed. As a result, there is a problem with supporting a large number of high-speed wireless systems without causing system speed degradation [206]. However, with the current growing number of networked devices, ensuring speed, quality, and cheap cost at the same time is becoming increasingly difficult. With the growth in data traffic, the network's bandwidth is once again challenged [207]. Furthermore, the network's architecture has scalability challenges due to its hybrid nature, including several providers' devices. Another challenging task is to manage several devices remotely and without any loss in time or management. Because in this type of framework, there is a need to integrate devices along with their data and information coming from different aspects [208].

4.2 Solving the existing challenges using FL with AI in the healthcare system

4.2.1 Role of FL

To execute learning tasks in something like a decentralized environment, where one central server controls the global learning procedure and numerous devices train local models with their own data [21] is the process known as the Federated Learning process. FL can be used in a variety of settings, including healthcare and education. Models based on machine learning logic necessitate a huge quantity of information to train the model from various parts of the system, such as hospital data in the healthcare sector. The healthcare industry handles a lot of sensitive data that, if tampered with, could bring the entire system down. In this case, FL devised a privacy-preserving approach that does not require the transfer of sensitive data from the source, instead of training local models with their own data and then sharing results with the global network [209]. As a result, this strategy can protect the privacy of patient information by using an iterative process in which model parameters are constantly exchanged and modified, but raw data is not disclosed. As a result, to preserve the security and privacy of the hospital system, FL provides a privacy-preserving method while also providing the benefits of machine learning models to solve numerous difficulties related to healthcare systems [193, 210].

4.2.2 Role of FL with AI

The new breed of AI is called Federated Learning, and it is based on a decentralized training and learning mechanism. A new AI model architecture that can be spread over a large number of devices without knowing personal user data. This technique assures user privacy and data security because it does not access raw data [21]. The demand for user privacy has evolved in tandem with the advent of artificial intelligence. The FL, which sits at the intersection of AI-cloud and AI-user equipment, plays a key role in bringing the UE and cloud together to create a significantly more secure and robust system than earlier architectures. Again, due to FL's properties, imbalanced and non-IID information can be handled appropriately, ensuring that the AI system's performance is not limited and that a large device in multiple contexts may be trained with their local data and local model without difficulty [211].

4.2.3 Role of FL with XAI in healthcare

Although AI in a federated context can address the concerns described previously, deep learning has an explainability difficulty. Because deep learning algorithms are typically black-box models, there is no acceptable explanation for a given prediction. Deep learning in healthcare is limited due to this ambiguity. Explainability is vital in healthcare since we need to explain why a given prediction for sample input is made to persuade a clinical healthcare practitioner and a patient. Humans can understand and describe how an AI system reached a decision using Explainable Artificial Intelligence (XAI) [212]. Artificial intelligence approaches such as deep learning with the integration of FL have recently played a revolutionary role in healthcare, particularly in terms of diagnosis and surgery. In these fields, these strategies have been proven to be beneficial. Some deep-learning-based diagnosis jobs are even more accurate than human medical specialists. The deep learning model's black-box character, on the other hand, hinders its explainability and practical application in medicine.

Amoroso et al. provided an XAI framework for breast cancer therapeutics in their paper [213]. The experiment findings showed that the framework could outline an essential clinical feature for the patient and design oncological medicines using the clustering and dimension reduction method. Dindorf et al. proposed an explainable disease in a spinal posture-dependent classifier [214]. EI-Sappagh et al. suggested an RF model for detecting Alzheimer's disease (AD) progression and diagnosis in [215]. The fuzzy rule-based system could also generate natural language forms to assist patients and physicians in comprehending the AI model. Peng et al. established an XAI framework to help doctors predict the prognosis of hepatitis patients in [216]. In this work, the authors compare intrinsic XAI approaches like logistic regression (LR), decision tree (DT), and kNN to complicated models like SVM, XGBoost, and RF. The authors also used the SHAP, LIME, and partial dependence plots (PDPs) post-hoc approaches. Sarp et al. proposed a CNN-based model for chronic wound categorization in [170], after which they used the XAI approach LIME to explain the CNN-based model. Rucco et al. introduced an XAI program to diagnose glioblastoma in [217], which combined topological and textural characteristics. Table 6 presents overviews of different datasets used in FL, AI, XAI, and Healthcare.

4.2.4 Analysis of performance metrics

To give a manual describing different binary classification assessment metrics, we use examples of metrics and evaluations collected from a number of published papers, including top AI algorithms used in FL. Note that, we do not comment on the quality of these studies; rather, we use them to demonstrate how different measures provide diverse interpretations of an AI model's quality. A mixture

Table 6 Overviews of Different Datasets used in FL, AI, XAI, and Healthcare

Works & Year	Data Sets Used					Application area
	Data Sets Discussion	FL	AI	XAI	Healthcare	
Raza et al. [218] (2022)	Arrhythmia database from Massachusetts Institute of Technology - Boston's Beth Israel Hospital (MIT-BIH)	✓	✓	✓	✓	ECG-based prediction to identify arrhythmia using clean and noisy data.
Anand et al. [219] (2022)	ECG signals from the PTB-XL dataset, which is freely accessible & arrhythmia dataset	X	✓	✓	✓	To assist clinicials for the easy diagnosis of cardiac arrest symptoms.
Shukla et al. [220] (2022)	3DIRCAD datasets	X	✓	X	✓	Predicting Liver Cancer.
Kobylinska et al. [221] (2022)	Domestic Lung Cancer Database	X	✓	✓	✓	Accessing risk of lung cancer.
Thomsen et al. [222] (2022)	Danish Colorectal Cancer Screening database and Statistics Denmark (Private Data)	X	✓	✓	✓	Colorectal cancer screening.
Kerkouche et. al. [223] (2021)	Premier healthcare database	✓	✓	X	✓	To predict mortality rate of patients.
Flores et. al. [224] (2021)	Chest xray image from Mass General Brigham	✓	✓	X	✓	To predict COVID-19 cases from chest xray analysis.
Jimenez et. al. [225] (2021)	Hologic, Siemens Dataet	✓	✓	X	✓	To detect breast cancer or tumor.
Barbiero et al. [226] (2021)	CUB data set	X	✓	✓	X	Method of logical explanation (Entropy-based).
Rao et al. [227] (2021)	3MR & Benzene (Single-rationale), Mutagenicity & Liver (Multiple-rationales) , hERG & CYP450 (Property cliff)	X	✓	✓	X	To predict properties of molecule.
Vaid et al. [228] (2020)	Mount Sinai Brooklyn, Mount Sinai Hospital, Mount Sinai Morningside, Mount Sinai Queens, and Mount Sinai West Hospital COVID-19 patients data	✓	X	X	✓	Mortality prediction for patients with COVID-19.
Dang et.al. [229] (2020)	eICU synergetic Database	✓	X	X	✓	To Predict the likelihood of a patient's death, particularly in ICU circumstances.
Vaid et.al. [228] (2020)	New York City Hospital dataset (COVID-19)	✓	X	X	✓	COVID-19 patient mortality prediction.
McKinney et al. [230] (2020)	Northwestern Medicine OPTIMAM database (Licensed)	X	✓	X	✓	To detect breast cancer.
Halling-Brown et al. [231] (2020)	NIDDK (Diabetes dataset), Dataset from heart study of Framingham, Wisconsin dataset (breast cancer)	X	✓	X	✓	To predict clinical diseases (Diabetic, breast cancer).

model can be used to explain binary classification problems, with the overall data distribution modeled as:

$$p(X, \alpha) = \alpha p_P(X) + (1 - \alpha) p_N(X) \tag{6}$$

where X represents data samples, $p_{P/N}$ denotes the positive/negative class distributions, and α the parameter of the positive class, calculated as $\alpha = \frac{N_P}{N_P + N_N}$, with $N_{P/N}$ the total number of positive/negative class data samples. The four entries in the confusion matrix are the key parameters for determining the metrics for a binary classifier which are discussed below.

$$\mathbf{M} = \begin{pmatrix} \mathrm{TP} & \mathrm{FN} \\ \mathrm{FP} & \mathrm{TN} \end{pmatrix} \tag{7}$$

- *True Positive (TP):* The number of accurately categorized positive samples is referred to as the true positive.
- *True Negative (TN):* The number of correctly categorized negative samples is known as the true negative.
- *False Positive (FP):* The number of samples incorrectly categorized as positive is known as the false positive rate.

- *False Negative (FN):* The number of samples incorrectly categorized as negative is referred to as false negatives.

The following measures are used to assess the performance of leading AI algorithms or models used in FL:

- *Accuracy (ACC):* The ratio of correctly identified samples to the total number of samples in the evaluation dataset is the accuracy. This metric is one of the most often utilized in medical applications of machine learning. The accuracy ranges from [0, 1], with 1 representing properly predicting all positive and negative samples and 0 representing successfully predicting none of the positive or negative samples.

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{8}$$

- *Area Under the ROC Curve (AUC):* AUC is a metric that combines effectiveness throughout all categorization criteria. The AUC indicates the percentage of correctly categorized positive samples. Rather of measuring absolute values, it assesses how well predictions are ordered. It assesses the accuracy of the model's predictions regardless of the categorization level used.
- *Specificity (SPEC):* The specificity indicates the percentage of correctly categorized negative samples. It's measured as the proportion of correctly categorized negative samples to all negative samples. The specificity is limited to [0, 1], where 1 denotes flawless negative class prediction and 0 denotes inaccurate negative class sample prediction.

$$\mathrm{SPEC} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{9}$$

- *Sensitivity/Recall (REC):* The recall, also known as the sensitivity or True Positive Rate (TPR), is the ratio between correctly classified positive samples and all samples assigned to the positive class, and it is calculated as the ratio between correctly classified positive samples and all samples assigned to the positive class. The recall is limited to [0, 1], with 1 representing perfect positive class prediction and 0 representing inaccurate positive class sample prediction. This statistic is also considered one of the most significant in healthcare, as it is desirable to overlook as few good cases as possible, resulting in a high recall.

$$\mathrm{REC} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{10}$$

- *Precision (PREC):* Precision is calculated as the ratio between correctly identified samples and all samples assigned to that class, and it indicates the proportion of recovered samples that are relevant. The precision is limited to [0, 1], with 1 representing all accurately predicted samples in the class and 0 representing no valid predictions in the class.

$$\mathrm{PREC} = \frac{\mathrm{TC}}{\mathrm{TC} + \mathrm{FC}} \tag{11}$$

where C stands for "class" and can be either positive (P) or negative (N) in binary classification (N).

However in Table 7 the results of several research which have been discussed throughout this article in terms of accuracy and AUC have been shown and also depicted graphically in Fig. 7 and Fig. 8, respectively. In the graph the X axis represents the studies that achieved the scores and the Y axis represents the performance score in percentage. Inside every bar the data that have been considered in the work is indicated and on the top of every data bar the method used have been shown.

5 Open issues and future direction

We cover this section on the additional issues as open discussion and guide some matters for further discussion in 5.1 and 5.2, respectively. We also present the existing work analysis of FL-AI with Healthcare based on central idea, applications, approaches, open issues and further opportunities in the Table 8.

5.1 Open issues

Federated Learning is a continuous process where a model keeps updating over time. That's why different challenges and problems were brought out with further developments. The issues are open to the researchers so that they could be solved efficiently within a short time. Since the whole procedure runs over the internet, privacy and security are always a major concern in this field, especially when it comes to competent health care systems. The health-related data is susceptible compared to the others. In this regard, people are utilizing various technologies into the health care systems such as SDN, Blockchain, etc [234, 235]. However, it is an advanced machine learning method that needs large datasets [233, 236]. A suitable dataset is essential for such problems. It is not so easy to manage such datasets for medical cases, which is a demerit for this field. Also, the datasets are not present at the user end, where the distributed training would be performed as a minor update of the global model. Apart from this, the performance obtained from the health data is not satisfactory because the domain of the information is not the same and also contains outliers into the data points. Processing the health data and training machine learning models is

Table 7 The Results of Several Research Discussed in this Article in terms of Accuracy and AUC

Works	Datasets	Methods	Accuracy	AUC
Chang et al. [232]	Pima Indians diabetes Database	BlockFL	0.84	NA
Islam et al. [233]	Abalone dataset	Random forest	0.97	NA
		KNN	0.94	NA
		Naïve Bayes	0.98	NA
	Wine dataset	Random Forest	0.99	NA
		KNN	0.91	NA
		Naïve Bayes	0.98	NA
Vaid et al. [228]	MSB Hospital Dataset (NYC)	FL(Lasso)	NA	0.802
	MSH Hospital Dataset (NYC)	FL(Lasso)	NA	0.773
	MSM Hospital Dataset (NYC)	FL(Lasso)	NA	0.776
	MSQ Hospital Dataset (NYC)	FL(Lasso)	NA	0.693
	MSW Hospital Dataset (NYC)	FL(Lasso)	NA	0.805
	MSB Hospital Dataset (NYC)	FL with out Noise(MLP)	NA	0.827
	MSH Hospital Dataset (NYC)	FL with out Noise(MLP)	NA	0.801
	MSM Hospital Dataset (NYC)	FL with out Noise(MLP)	NA	0.796
	MSQ Hospital Dataset (NYC)	FL with out Noise(MLP)	NA	0.822
	MSW Hospital Dataset (NYC)	FL with out Noise(MLP)	NA	0.834
	MSB Hospital Dataset (NYC)	FL with Noise(MLP)	NA	0.812
	MSH Hospital Dataset (NYC)	FL with Noise(MLP)	NA	0.767
	MSM Hospital Dataset (NYC)	FL with Noise(MLP)	NA	0.785
	MSQ Hospital Dataset (NYC)	FL with Noise(MLP)	NA	0.822
	MSW Hospital Dataset (NYC)	FL with Noise(MLP)	NA	0.83
Flores et al. [224]	Hologic	FL	NA	0.78
	GE	FL	NA	0.65
	Siemens	FL	NA	0.83
	Hologic	Fed-CL	NA	0.8
	GE	Fed-CL	NA	0.63
	Siemens	Fed-CL	NA	0.61
	Hologic	Fed-Align	NA	0.79
	GE	Fed-Align	NA	0.69
	Siemens	Fed-Align	NA	0.85
	Hologic	Fed-Align-CL	NA	0.84
	GE	Fed-Align-CL	NA	0.7
	Siemens	Fed-Align-CL	NA	0.83
Shukla et al. [220]	CT scan images from 398 individuals	Unet	0.94	NA
Anand et al. [219]	PTB-XL of ECG signals	ST-CNN-GAP-5	NA	0.934
	ECG dataset of arrhythmia patients	ST-CNN-GAP-6	0.95	0.99
Rucco et al. [217]	The Cancer Imaging Archive (TCIA)	VGG16	0.97	0.97
Peng et al. [216]	Hepatitis classification dataset from UCI	Random Forest	0.919	
El-Sappagh et al. [215]	Alzheimer's Disease Real dataset	Random Forest	87.76	0.953

expensive and time-consuming. Efficient methodologies are still critical to find out.

However, to upgrade the performances of such systems in the field of medication, researchers are trying to apply novel methods and technologies. Increasing the security of the healthcare systems remains the vital concern of the personnel. The patient's personal and sensitive data needs to be processed to develop smart healthcare systems. To make them more reasonable and available everywhere, the Internet of Medical Things is being used. So, the security could be given utilizing SDN, Blockchain, NFV, etc [237, 238]. In this era of artificial intelligence, we can use data augmentation to imitate the existing datasets to prepare more data since Federated Learning requires a vast

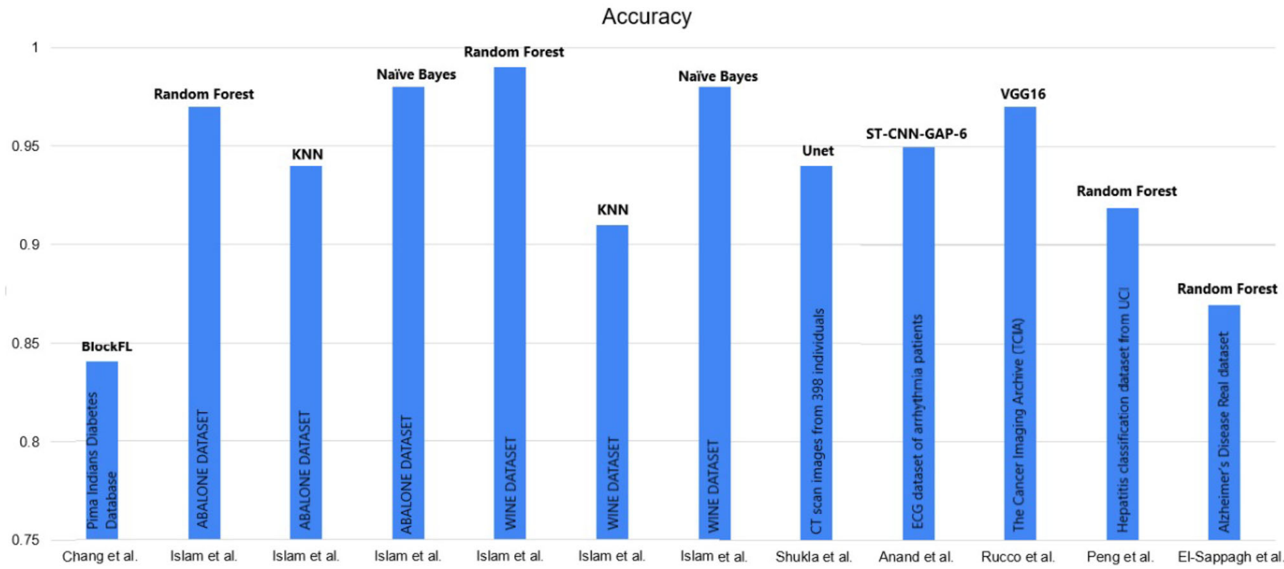

Fig. 7 Results analysis of different research in terms of Accuracy (%)

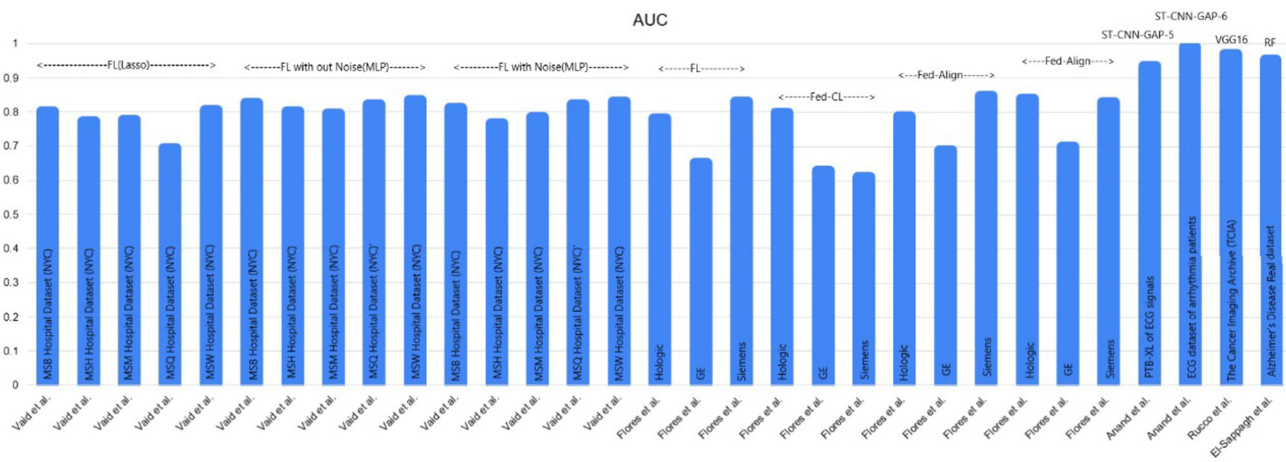

Fig. 8 Results analysis of different research in terms of AUC (%)

amount of data. More data analysis needs to be performed to find out an optimal training time and maximum performance. The generalization power of the current machine learning models is not satisfactory when it comes to the medical sector. Some melioration of CNN could be designed and tested in this context. The cost analysis for the models should be performed using some statistical methods before applying them to the field.

5.2 Future directions

5.2.1 Role of FL in data science

Data generation in all industries is extensive with the increasing usage of IoT-based methods in the current system. This is the data scientist's current challenge. One of the most important is to ensure data security, and the sensors that are associated with the IoT-based mechanism have less memory. They do, however, generate a massive amount of data for every nanosecond. As a result, storing or transferring these data in a short period of time is both difficult and critical [239]. The benefit of utilizing FL in this scenario is that the data storing mechanism is avoided and distributed among multiple clients, and because the data is trained locally on each client, the security of individual data is ensured [240].

5.2.2 AI with blockchain in security

Artificial Intelligence is the most potent agent for any applications areas. Sometimes AI acts as a communicator bridge of real-life applications. On the other Blockchain is a

Table 8 Existing work analysis of FL-AI with Healthcare based on Central Idea, Applications & Approaches, and Open Issues and Further Opportunities

Authors	Approaches	Central idea	Applications	Open issues and further opportunities
Ma et al. [183]	Revolutionizing the transformation of traditional healthcare to digital healthcare.	Electronics solution to many issues in healthcare sector	Healthcare Informative, Data Distributive.	Provide flexible hybrid electronics with structural design routes that can integrate high-performance electrical qualities.
Pershad et al. [184]	Threats regarding the use of Twitter for healthcare data include significant amount of misleading information.	The importance of use of social media as a source of information for research, study and gathering knowledge.	Understanding between the patient and healthcare official, Technology coupled with public health	They explored the potential of Twitter in the sphere of healthcare and medicine and particularly aim towards improve care for the patients.
Kim et al. [185]	Proposes a blockchained Federated Learning (BlockFL).	Enables on-device machine learning without any centralized training data or coordination by utilizing a consensus mechanism in blockchain.	On-device machine learning, Federated Learning, blockchain, latency	Analyze a model of blockchain based FL and characterize the block generation rate by taking into account delays in communication and consensus.
Miotto et al. [186]	Access of information and technical insights from complex biomedical information acts as a critical issue to revolutionize health care.	Suggestions towards DL approaches to be the driving force for translating large biomedical information for uplifting healthcare	Deep learning, health care, biomedical informatics, translational bioinformatics, genomics electronic health records	Suggestion towards development of meaningful schemes to close the gap between DL models and human understand ability.
Wiens et al. [187]	Application of ML to change patient risk stratification in the area of medicine, and particularly for contagious diseases	ML towards the study of methods for identification of patterns in data	Machine Learning, Healthcare.	Presented distinctive evidence for healthcare workers towards the use of ML.
Kumar et al. [153]	Propose a data normalization technique that deals with data heterogeneity because the data is acquired from several hospitals with various types of Computed Tomography (CT) scanners.	Issue of diagnosis of coronavirus due to the scarcity and reliability issue of testing kits	COVID-19, Privacy-Preserved Data Sharing, Deep Learning, Federated-Learning, Blockchain	Proposed an architecture to gather data from several sources and drills a global deep learning model using FL based on FL.
Nguyen et al. [9]	Addressed the requirements for a more patient-centric reach for healthcare facilities and to improve the precision of EHR.	Potential application of blockchain in healthcare industry	Blockchain, Consensus, Distributed systems, Healthcare Informative.	The research focuses towards the applications of blockchain in healthcare industry.
Holbl et al. [188]	A mathematical algorithm to display the features of controllable network and blockchain based FL parameters to record its effect on system performance	Application of FL in the realm of vehicle communication medium that is effective.	Vehicle Machine Learning, Federated Learning, Blockchain.	Proposed an independent blockchain based FL architecture for preserving privacy and implement effective vehicular communication networking.
Pokhrel et al. [189]	As outlined in this survey paper, many cryptocurrencies studies are currently being investigated.	Scientists in academic and industrial have begun to investigate applications aimed toward healthcare use, based on the existing blockchain technology.	Blockchain, Healthcare Industry, Authentication, IoT, Wireless, Vulnerabilities, Survey.	As this study paper points out, many healthcare applications have particular requirements that are not addressed by many of the blockchain trials now being investigated. This report also discusses a number of potential research opportunities.

Table 8 (continued)

Authors	Approaches	Central idea	Applications	Open issues and further opportunities
Mcghin et al. [190]	Incorporate Federated Learning within the blockchain network consensus process so that the consensus computing activity may also be used for federated training.	Data providers face significant challenges in sharing their data through wireless networks due to security and privacy concerns (e.g., data leakage).	Data Sharing, Permissioned Blockchain, Federated Learning, Privacy-preserved, Industrial IoT	They start by creating a secure data sharing architecture for distributed multiple parties using blockchain technology. The data sharing challenge is thus transformed into a machine learning problem.
Lu et al. [191]	Suffer from moral harm or mental health issues.	The covid-19 outbreak is going to place healthcare professionals all across the world in an unprecedented scenario, forcing them to make hard judgments while working under great pressure.	Healthcare, Machine Learning.	Handling the symptoms of depression that healthcare professionals face during the covid-19 disease outbreak.
Greenberg et al. [66]	Factors for Delivering Safe Post surgical and Critical Care in the Event of a Medical Emergency	The difficulties that healthcare facilities across the world have encountered are mostly the result of a lack of preparedness. COVID-19 highlighted these weaknesses, leading healthcare organizations all across the world to take action.	Healthcare, Medical Informative.	International Perspectives on the Economic Impact of the COVID-19 Pandemic on Health Care Facilities and Systems.
Alemdar et al. [70]	Provide numerous cutting-edge examples, as well as design factors such as adaptability, conventionality, efficiency, reliability, and productivity, as well as a full analysis of the benefits and limitations of these systems.	With continuous monitoring, pervasive healthcare systems give extensive relevant information and alerting mechanisms against unusual circumstances.	Healthcare, HIoT.	Reduces the complexity of the healthcare system for providers and enables severely ill and elderly people to live independently.
Yu et al. [16]	Optometric physician and computer engineers are collaborating to test and deploy an automated image categorization system that will scan millions of diabetic patients' retinal pictures.	AI is influencing medical practice in a positive way. Thanks to recent advancements in digitized data collection, machine learning, and computing infrastructure, AI applications are moving into domains that were previously thought to be only the domain of human expertise.	AI, Healthcare, Federate Learning.	They explore recent breakthroughs in AI technology and their biomedical applications, as well as the future challenges that medical AI systems will confront, and also the financial, ethical, and sociological implications of AI in healthcare.
Esteva et al. [194]	Standardized deep learning models for genomics are reviewed, as well as reinforcement learning in the context of robotic-assisted surgery.	Deep learning techniques for healthcare presented, with a focus on computer vision, NLP, reinforcement learning, and generalized methodologies.	AI, Healthcare, Federate Learning, Computer Vision, NLP.	They explain the applicability of NLP to fields such as EHR data, and they explore computer vision mostly in terms of medical imaging.

provider of distributed ledger for any vulnerable components [241]. BC also offers a temporary ledger for performing security and confidentiality parameters efficiently. AI applications need a secured platform to continue its activities in the applications environments. BC easily collaborates with AI and shows their better performance for the desired system. In the BC environment, AI agents are solely attached during communications. Combined, they produce a highly protected environment that can continue their services to the current and future users incredibly [242, 243].

5.2.3 Controlling robots using FL-AI

In today's modern technological environment, robots are used in numerous sectors to relieve humans of many dangerous tasks. Again, AI-based agents have a very efficient processing capability and can handle heterogeneous data transactions. Furthermore, with the modern cloud storage system, effective data and information storage with very high memory storage in the cloud system is conceivable. Continuous learning and training are now possible because of the ability to retrieve data from numerous sources in a short period of time. In today's Industry 4.0 era, the implications of autonomous agents have grown. Robots are used in a variety of industries, including hospitals, educational institutions, the military, and even several hotels. However, because training an agent necessitates the collection of large amounts of data from many sources, it is vital to provide secure data collection for training. In this regard, FL is a well-suited solution since the key demanding task, data transfer, is forbidden in this scenario, ensuring data privacy while maintaining the autonomy system's efficiency [244].

5.2.4 FL with big data analytic

The primary idea behind Big Data is that must-have data volume, velocity, and variety. The basic job in extensive data analysis is to collect data from various sources and generate a dataset with a diversity of data from various sources. With the development of wireless networking resources such as 5G or even 6G, as well as IoT and Industry 4.0, this has become easier. All of these developments aid in data collection and in a real-time environment. The industrial sector collects and generates big data from a variety of sources, including heterogeneous sources. This technique is difficult because when data flows from source to destination, it can be manipulated by an intruder or hacked in the middle, resulting in a violation of critical user data privacy. FL is a new breed of AI technology in which the ML models are locally trained using the data of the local system. Continuous training is ensured by using the source data, as are the significant data criteria. As a result, data privacy is also ensured, and there is no need to transmit sensitive user data from one location to another [245].

5.2.5 FL with blockchain in industry 5.0 applications

The future IR 5.0 is designed with the primary goal of connecting smart machines and the general public. The usage of IoT devices allows for the collection of data even in remote regions, and with the gathered information, communication may be established without any additional effort on the approach is the data collected from the IoT devices and transferred to the owner. However, the acquired data is raw and may not be in the suitable format for the computer to understand the nature of the data. This is when the ML algorithm's AI is put to use. The essential computations are carried out using AI algorithms, and the resultant analysis is promptly processed using edge computing. But, there is a challenge of protecting sensitive data from the attack of the intruder. As the transmission of data from device to device, there is a possibility of attack at the nodes of the data hub be attacked by intruders. In this case, FL and blockchain can be a possible solution where the data of each side is collected, trained, and processed on each local place, and the result is passed to the server. The initial parameters then passed through the blocks of the blockchain technology for secure transmission [246, 247].

5.2.6 Applying FL-blockchain for accessing medical data

An essential issue is examining medical disease or medical sector data from the healthcare system. However, medical data is extremely sensitive, and any changes could result in a massive loss for the entire system. In this case, Federate learning combined with the blockchain mechanism can produce a secure yet efficient model for the smart healthcare system that benefits from sophisticated learning and training algorithms while without transferring sensitive data to the network. For the secure aggregation, the initial parameters, number of rounds, and the keys, which is the public one of all clients, are collected in the secured blockchain. While an alternate block is generated after the verification procedure is completed, the parameters are obtained by the clients or the local models. Thus the medical data through the blockchain and Federated Learning security is ensured, and an efficient model can be assured [232].

5.2.7 FL with healthcare in smartindustrial IoT

With the increasing use of IoT devices, it is being employed by various industries, including education, healthcare, data science, data analysis, and so on. In the era of smart IIoT, the necessary data for analysis, such as MRI images, test samples of a specific disease, information of a patient staying in the hospital, or even data of hospital staff or hospital management, is easily gathered and sent to a central server for further processing in the healthcare system with the help of IoT [248]. However, as these technologies have advanced, collecting data has become the main draw for attackers. As a result, while these data are being sent from source to destination, an attacker can simply gain access to them and take over the system. In this regard, FL may be a viable solution because it keeps data safe on the local machine while processing tasks are performed at each client. The output is then sent back to the central server for additional examination using a secure scenario.

5.2.8 AI-FL in smart healthcare using big data

There is a high demand for standardization throughout the data collection, processing, and result generation processes. Again, a platform that can gather information from numerous sources and perform a task, solve critical problems, or make a decision without the need for human participation would be tremendously beneficial to the healthcare industry. In healthcare, AI performs a vital and crucial role in understanding the human thinking process through the computer using various effective AI-based algorithms to make complex examinations easier for healthcare professionals [83]. Data aggregation using FL and smart wearables with AI benefits to create an intelligent and secured system, predicting mortality and length of hospital stay period using electronic health records where the FL model assists the secure data collection and building a brilliant AI model and predicting mortality and length of hospital stay period using electronic health records where the FL model helps the secure data collection and building an intelligent AI model.

6 Conclusion

The recent progress in healthcare has designed a keen interest in the research community as well as FL to integrate AI in the desired networks. This survey comprehensively mines the immense information regarding emerging topics–FL, AI, XAI, and e-Healthcare. Moreover, we discuss in details the cutting edge developments of FL and AI in intelligent healthcare applications. The FL-AI, FL-Healthcare, and AI-Healthcare have been incorporated with each other significantly. Also, we address different issues–security, privacy, reliability, scalability, and confidentiality using our mentioned terms. Although we have studied both FL and AI-XAI techniques for the healthcare system and categorized them into different types of solutions, however, healthcare is not limited to only AI and FL techniques. Still, various problems and challenges that need to be addressed. The following study analyses the progress of security, state-of-the-art discussion, benefits of integration, taxonomies, and open issues have been presented. Additionally, we have offered several future research guidance in this regard.

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Declarations

Conflict of interest The authors declare no competing financial and non-financial interests.

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