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Paradigm Shift Towards Federated Learning for COVID-19 Detection: A Survey

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Abstract

The novel coronavirus 2019 (COVID-19) is a respiratory syndrome with similar traits to common pneumonia. This major pandemic has affected nations both socially and economically, disturbing everyday life and urging the scientific community to develop solutions for the diagnosis and prevention of COVID-19. Reverse transcriptase-polymerase chain reaction (RT–PCR) is the conventional approach used for detecting COVID-19. Nevertheless, the initial stage of the infection is less predictable in PCR tests, making early prediction challenging. A robust and alternative diagnostic method based on digital computerised technologies to support conventional methods would greatly help society. Therefore, this paper reviews recent research based on using machine and federated learning techniques on publicly available datasets comprising Computed Tomography (CT) images, Chest X-ray (CXR) and ultrasound of COVID-19 patients. This paper also analyses the analytical efficiency such as accuracy, sensitivity, specificity and F1-score of models to determine the efficacy. Based on our study, we observed that Machine Learning (ML) was proposed widely in COVID-19 prediction and diagnosis methods. But this method has challenges due to less dataset availability and privacy concerns. However, federated learning-based COVID-19 detection overcame the challenge and provided better efficacy with low datasets and supported medical data privacy. Thus, based on the advantage observed, federated learning-based COVID-19 detection systems should be developed in the future.

Keywords: COVID-19, Machine Learning, Federated Learning

Introduction:

The World Health Organisation (WHO) has identified the COVID-19 virus as a pandemic, killing more than ten million people and 503,862 people around the globe [1]. COVID-19 is due to coronavirus II (SARS-CoV-2) severe acute respiratory syndrome and has been declared a WHO pandemic. The rapid mutation nature of the virus makes it highly transmissible [2]. The pandemic is affecting millions of people worldwide, and researchers are working hard to find ways to mitigate, detect and prevent the virus. [3].

Today's COVID-19 pandemic is a significant worldwide health concern because SARS-CoV-2 spreads rapidly [4] and causes fatal pneumonia [5]. Early detection is the most advised precautionary measure till-date to contain the virus transmission [6] and detection remains among high-priority tasks due to its contagious nature to contain the widespread [7]. Several diagnostic techniques are being proposed in clinical research and public health laboratories to detect coronavirus[8].

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The diagnostic procedures described for SARS-CoV-2 vary from few minutes to few hours turnaround time. A diagnostic test technique should be sensitive and precise enough to make an appropriate clinical decision as per the criteria for decisions in public health [9] and [10]. Researchers across domains are finding possible scientific methods to identify COVID infection in its early stage to control its spread. However, manual processes are intensive and time-consuming, making them ineffective. Additionally, healthcare requires real-time and accurate results [11]. Manual processing is time-consuming and poses human overhead in the testing procedure [12]. To address these difficulties, the scientific community has developed Artificial Intelligent(AI) in healthcare for various activities [14] and [15]. The AI community is making a significant digital effort in this respect via automatic COVID-19 identification of CT scans and radiographic pictures. The researchers backed computational methods with precise results and faster prediction [13].

Additionally, Machine learning(ML) can shorten decision-making time and start treatment in quick cycles to limit the spread [16]. However, although ML techniques have been effectively utilised in predicting COVID-19, limitations on the availability of datasets and privacy issues exist. Therefore, it was difficult to obtain such training data. Therefore, to solve this, the federated learning (FL) method is used to predict COVID-19.
The paper is organised as follows. The motivations of the paper are illustrated in Section 2. Section 3 presents a comprehensive survey of machine learning and federated learning techniques for detecting COVID-19 using CT scans, X-rays, and ultrasound images. Challenges and future directions are presented in Section 4. Finally, Section 5 is the conclusion and future work.

1. Motivations & Problem Statement:

To date, rapidly developed AI research topics such as ML and FL-based applications have significantly impacted human life. For example, computer-aided COVID-19 diagnosis using CT, X-ray, and ultrasound images have been the critical alternative methods during the pandemic. Conventional ML requires a well-labelled dataset locally in their repository and in large quantities to train the model. However, this essential requirement becomes infeasible due to the data privacy governance policy. These challenges lead the researcher community to look for an approachable method that can get trained with datasets without the mandatory requirement of having the datasets locally available and protecting the data privacy of the medical records.

The following challenges emphasise the need for an alternative to ML

- Non-availability or access restriction of the dataset due to medical data privacy and compliance.
- The need for a large dataset is required to train the system to attain a high accuracy level.

Our work in this paper is focused on reviewing existing literature on how ML and FL techniques have been employed to diagnose COVID-19 and demonstrate a flaring trend toward FL for diagnosis. To achieve this, we first present a comprehensive review and analyse the accuracy, sensitivity, specificity and F1-score of ML and FL models recently employed. Next, we determine the advantages and challenges of these models and Finally, we conclude the future direction and growing trend towards Federated learning.

2. Literature Survey:

The identification of COVID-19 using machine learning techniques and federated learning techniques based on CT scans, X-rays, and ultrasound images is discussed in the following sections.

2.1. Literature using CT Scan Images

This section reviews research papers that focus on using machine learning, contrastive learning, and federated learning techniques to detect COVID-19 based on CT scan images.
[25], [17], [18], [19], [20], [21], [22], [23], [24], [26], [27] and [41] used CT scan image in their proposed Machine learning method and demonstrate the prediction of COVID-19. The common challenge they faced was the limited availability of labelled datasets. All of their models required a large training dataset, and the accuracy was directly proportional to the training dataset size. (Table 1) presents a summary of the observations.

Table 1: Machine learning techniques for COVID-19 detection from CT scan images

#	Dataset	Method	Description	Evaluation Metrics	Limitations/Challenges
[25]	chest CT images	MODE-CNN	to classify COVID-19 infected patients as positive and not infected as negative.	Ac - 93.3%	pre-processing and operations like max pool add to CNN overhead, making it slower.
[17]	SARS-CoV-2 CT-Scan dataset	WOA and GAN	for diagnosing COVID-19 through chest CT images	Ac - 99.22%, Se - 99.78%, Sp - 97.78%, F1- 98.79%, TP - 97.82% and TN - 99.77%	GANs are difficult to train
[18]	COVID chest CT images	Stacked autoencoder detector model	for improving COVID-19 predication precision and recall rate	Ac - 94.7%, Pr - 96.54%, Re - 94.1%, and F1 - 94.8%.	Performance must be improved
[19]	Chest CT images	2D DL architecture with U-Net	for predicting lung anomalies from chest CT scans	F1 - 97.31% and Mean IoU - 84.6%	expensive to training phase due to complex data models
[20]	COVID-19 and non-COVID-19 CT scans images	A transfer learning-based DL model using VGG16	for screening COVID-19 patients using chest CT scans.	Ac - 95.7%, Pr - 95.8%, AUC - 0.958 and F1 - 95.3%	expensive to training phase due to complex data models
[21]	COVID-CT images	Super resolution reconstructed images and CNN	for diagnosis COVID-19	Ac - 97.87%	It requires a large dataset
[22]	COVID-19 and Non-COVID-19 CT scan images	Transfer learning-based CNN model (ResNet18) with stationary wavelet	for COVID-19 detection.	Training : Ac - 99.82% , Validation : Ac - 97.32% and Testing: Ac - 99.4%	pre-processing and operations like max pool add to CNN overhead, making it slower.
[23]	Chest CT scan images	CNN based on DL techniques and VGG-19	for COVID-19 diagnosis	Ac - is 94.52%	pre-processing and operations like max pool add to CNN overhead, making it slower.

[24]	Chest CT images	A DL approach based on residual CNN	for clinical diagnosis of COVID-19 patients	F1 - 4.42 ± 0.8 out of 5	pre-processing and operations like max pool add to CNN overhead, making it slower.
[26]	SARS-CoV-2 CT scan image	A bimodular hybrid model CNN, DA and SVM classifier	chest CT image-based detection of COVID-19	Pr - 98.39%	It requires a large dataset, and the overhead in CNN makes it slower.
[27]	SARS-CoV-2 CT-scan images	A fine-tuned DL model inspired by the architecture of the MobileNet V2 model	to diagnose the COVID -19 using chest CT scan images for a collaborative edge-cloud computing platform	Ac - 96.4%, Se - 98.4%, and MCC - 0.929	require large dataset coupled with expensive training due to a large dataset
	Contrastive Learning				
[41]	COVID-19 CT images	Contrastive cross-site learning framework	for COVID-19 identification by effectively learning with heterogeneous datasets with distribution discrepancy.	Ac - 90.83%, F1 - 90.87%, Re - 85.89%, Pr - 95.75 %, and AUC - 96.24%	performance must be improved

Federated learning (FL) provides collaborative model training while protecting the anonymity of each participant, which is very useful in the medical area. [28], [29], [30] and [31] used FL on CT-scan and showed they could train models with less dataset. A summary of federated learning techniques for COVID-19 detection from CT scan images is shown in (Table 2).

Table 2: Federated learning techniques for COVID-19 detection from CT scan images

#	**Dataset**	**Method**	**Description**	**Evaluation Metrics**	**Advantages**
[28]	CT scan slices (CC-19)	Blockchain based FL with Capsule Network	CT scan image-based segmentation and classification of COVID-19 patients	Ac - 98.68% and Se - 98%	Training on remote data
[29]	Multi-institutional pancreas segmentation from CT scans	Auto-FedAvg	COVID-19 lesion segmentation in chest CT and pancreas segmentation in abdominal CT	Ac - 88.98%.	Shared training dataset and privacy preserved
[30]	Seven different multinational centres	FL method	CT images-based lung abnormalities detecting	AUC - 88.15%, AP - 71.48%, Se - 73.31% and Pr - 91.93%	Shared multinational dataset with data governance
[31]	Multiple institutions and central cloud collaboration CT scan images	The 5G-enabled architecture of auxiliary diagnosis based on FL	To diagnose COVID-19 from CT scan images	Ac - 97.7%	Training on cloud

2.2. Literature using X-ray images

In this section, we analyse research work on X-ray images based on COVID-19 detection using machine and federated learning. [32], [38], [35], [40], [33], [34], [36], [37], and [39] used conventional machine learning techniques on X-ray images, and the common challenge faced was a lack of large labelled dataset due to which there was a room for accuracy improvement. A summary of the machine learning techniques for COVID-19 detection from X-ray images is depicted in (Table 3).

Table 3: Machine learning techniques for COVID-19 detection from X-ray images

#	Dataset	Method	Description	Evaluation Metrics	Limitations/Challenges
[32]	Poster anterior (PA) chest view of X-ray data	A viable and efficient DL GAN and generic data augmentation methods-based Chest Radiograph Classification (DL-CRC) framework	To distinguish the COVID-19 cases with high accuracy from other abnormal (e.g., pneumonia) and normal cases	Ac - 93.94%	Accuracy must be improved
[38]	Chest X-ray pneumonia images	Parallel-dilated CNN, named as Parallel-Dilated COVIDNet (PDCOVIDNet).	To detect the COVID-19 detection from chest X-ray images	Ac - 96.58%, Pr - 96.58%, Re - 96.59%, F1 - 96.58%.	It requires extensive data to perform better than other techniques added with expensive training and lacks performance.
[35]	NIH ChestX-ray14 dataset	Dense Convolutional Networks and transfer learning	To classify chest X-ray images according to three labels: COVID-19, pneumonia, and normal.	Ac -100%	It requires extensive data to perform better than other techniques and expensive training.
[40]	CXR images	GWO algorithm based CNN	For automatic diagnosis of COVID-19 from chest X-ray images.	Ac - 97.78%, Se - 97.75%, Sp - 96.25%, Pr - 92.88%, F1 - 95.25%.	It requires extensive data to perform better than other techniques with expensive training, GWO also has low precision, convergence and poor local searchability.
[33]	Posteroanterior CXR images	Random oversampling and weighted class loss function approach for unbiased, fine-tuned learning	To perform binary classification and multiclass classification of posteroanterior CXR images.	Ac - 96%	Accuracy to be improved
[34]	COVID19-radiograph database	DCNN	To detect COVID-19 positive patients using chest X-ray images	Ac - 91.62%	required accuracy improvement, huge dataset and expensive training to outperform other models
[36]	chest X-ray images	Five pretrained CNN - based models (ResNet50, ResNet101, ResNet152, InceptionV3 and	For the detection of COVID pneumonia infected patients using chest X-ray radiographs and,	Dataset 1 : Ac - 96.1% Dataset 2: Ac - 99.5% Dataset 3: Ac - 99.7%	required extensive dataset and expensive training to outperform other techniques.

		Inception-ResNetV2)	to detect the binary classifications with four classes		
[37]	CXR images	DeTraC	For the classification of COVID-19, chest X-ray images	Ac - 93.1% Se - 100%	required large datasets and expensive training to outperform other techniques.
[39]	COVID-19 and non-COVID-19 CXRs images	Lightweight CNN tailored shallow architecture	To automatically detect COVID-19-positive cases using CXRs, with no false negatives	Ac - 99.69%, Se - 1.0 and AUC - 0.9995.	required large datasets and expensive training to outperform other techniques.

Hospitals must protect the medical record against data leakage or distribution without authorisation to preserve patient's privacy. Data collection from training poses a significant challenge in the privacy aspect and leads to data scarcity in COVID-19 datasets. Federated learning is an option for dealing with this problem.

[42], [43], [44], [53], [45] and [46] successfully handle the problem of data silos and achieve a common model without the need for local data. These models provide the entire healthcare community with a verified methodology for responding to prediction problems with data protection in healthcare. The common advantage they achieved was eliminating the need for datasets to be available locally for training. The summary of the federated learning techniques for COVID-19 detection from X-ray images is depicted in (Table 4).

Table 4: Federated learning techniques for COVID-19 detection from X-ray images

#	Dataset	Method	Description	Evaluation Metrics	Advantages
[42]	COVIDx dataset (COVID-19 chest X-ray images)	FL-based frameworks such as MobileNet, ResNet18, MoblieNet, and COVID-Net	To COVID-19 data training and deploy experiments to verify the effectiveness of COVID -19 detection	Se - 96.15 (training) and 91.26 (testing)	Ensemble of existing datasets
[43]	COVID-19 chest X-ray images	Federated machine learning	For COVID-19 detection	Ac - 89.31% and Lo - 34.02%	Less training requirement
[44]	COVID-19 X-ray images	A collaborative FL framework based deep CNN (FL-ResNet50)	To COVID-19 screening from Chest X-ray images	Ac - 97%, Se - 98.11%, and Sp - 95.89%	Collaborative training
[53]	chest X-ray images (COVID-19, normal, and normal pneumonia)	FedDPGAN model	To diagnose the COVID-19 using CXR images without compromising privacy.	Ac - 94.45%	Federated and generative training can work with a small dataset
[45]	COVID-19 Chest X-ray	FL On Medical Datasets using Partial Networks	For the Detection of COVID-19 Pneumonia	Ac - 98.48%	Reduced training time
[46]	Chest X-ray	EXAM (EMR CXR AI Model) model	To predict outcomes in SARS-COV-2 patients	AUC - 92%	Achieve training on protected data

2.3. Literature using CT and X-ray Images

CT scans and X-ray images based on machine learning and federated learning techniques are discussed in this subsection Figure 1 represents a generic work flow and Figure 2 represents a model architecture for federated learning.

Research to overcome the problem of dataset availability and the need for accuracy improvement used a combination of CT-scan and X-ray to build the model. [47], [48] and [49] used the dataset combination of CT-scan and X-ray which showed they could drastically improve the prediction accuracy. The common challenges faced by the conventional machine learning approach are the need for dataset noise reduction and a high-end machine to perform testing and training. But [50] used federated learning and showed to achieve decent accuracy on lightweight nodes. A summary of this section is depicted in (Table 5).

Table 5: Machine and federated learning techniques for COVID-19 detection from CT and X-ray images

#	Dataset	Method	Description	Evaluation Metrics	Challenges/Advantages
	Machine Learning				
[47]	CT and X-ray images	CNN - tailored DNN	to detect COVID-19 positive cases using both CT scans and CXRs	Ac - 96.28%, AUC - 0.9808 and FN - 0.0208.	Performance must be improved
[48]	chest CT scans and chest X-rays images	Stacked ensemble	to detect COVID-19 either from chest CT scans or X-ray image	Ac - 99.75%	1. large datasets are required to perform better. 2. It is extremely expensive to train
[49]	COVID-19 CT and CXR datasets	Large-scale learning with stacked ensemble meta-classifier fusion approach	for COVID-19 classification.	Ac - 99.48%	1. require denoised dataset to perform well 2. It requires much computational power
	Federated Learning				
[50]	CT and X-ray images	A dynamic fusion-based FL approach	to detect COVID-19 infections using CT scans and X-rays images.	Ac - 96%	Works on light nodes

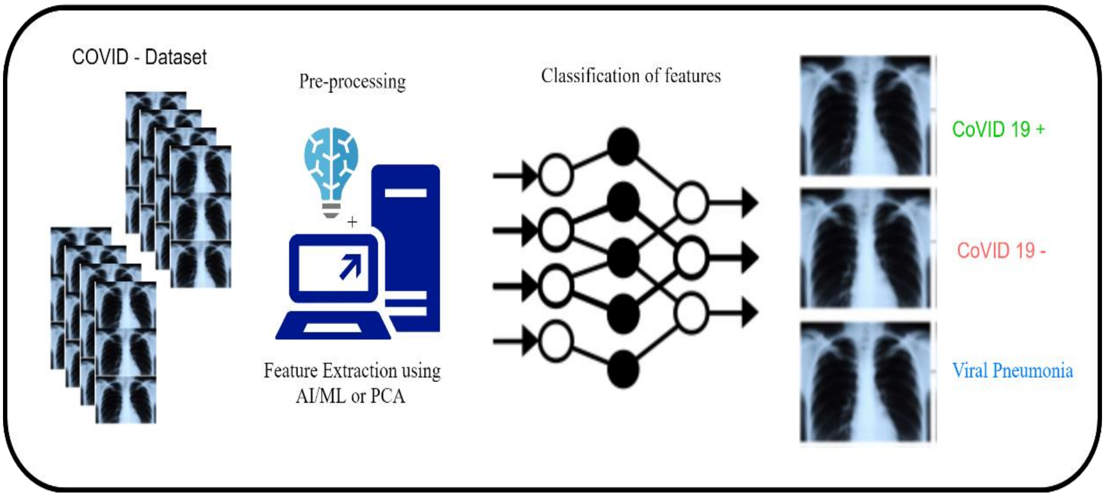

Figure 1: A generic workflow of AI/ML-based COVID-19 diagnosis.

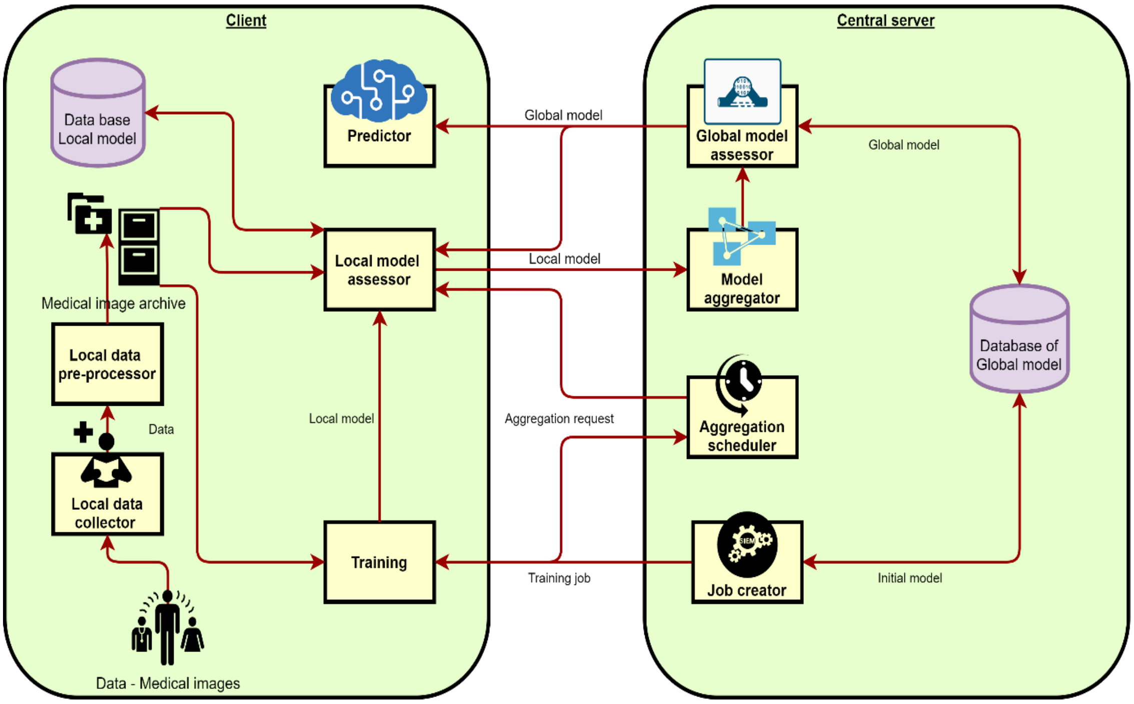

Figure 2: A model Architecture of federated learning systems for medical diagnostic image analysis [50].

2.4. Literature using Ultrasound images

In this subsection, the research articles are based on machine learning and federated learning techniques with ultrasound images for COVID-19 detection.

The authors of [51], [54] used conventional machine learning and [52] used federated learning on ultrasound images. The conventional approach required performance improvement, and the training was time-consuming, whereas the federated learning method was able to flare well even on lightweight IoT modes. The performance metrics of the federated learning model demonstrated this is a promising direction for COVID-19 detection. (Table 6) summarises machine and federated learning techniques for COVID-19 detection from ultrasound images.

Table 6: Machine and federated learning techniques for COVID-19 detection from ultrasound images

#	Dataset	Method	Description	Evaluation Metrics	Limitations/Advantages
	Machine Learning				
[51]	X-ray, Ultrasound and CT scan images	CNN-VGG19 based model	To perform COVID-19 detection using images from the three most commonly used medical imaging	Pr - 86%(X-ray), 100%(Ultrasound), and 84%(CT scans).	Performance is very less
	Federated Learning				
[54]	X-ray and ultrasound images (COVID and Healthy)	CFL	For an automatic COVID-19 diagnosis.	Pr - 93%, Re - 95% and F1 - 94%	Performance must be improved
[52]	IEEE COVID-19 dataset (X-ray and lung ultrasound images)	A framework integrating the ML, cloud, fog, and IoT technologies	To design a COVID-19 monitoring and prognosis system for detection	Ac - 89.26%, RMSE - 32.76%, Pr - 92.48%, F1 - 92.48%, and ET - 0.22 seconds	Light weight IoT nodes

2.5. Summary of the Literature Survey

Since the outbreak, the research community has actively proposed and provided alternative testing and screening solutions. Recent advancements in AI and machine learning-based tools and approaches have made it possible to provide a reliable solution using clinical images. However, due to patient privacy concerns, diagnostic image sharing across medical facilities is normally restricted. As a result, there are not enough datasets to train the models. Federated learning provides a solution to train models without disclosing the client's data and privacy preservation. However, there are several issues in clinical image availability. Therefore, there is an opportunity to improve the automated COVID-19 detection system based on clinical images.

Federated learning is a type of machine learning where data is distributed across multiple devices, and the model is trained on these devices. This allows for training on more data, and more data means better performance. Additionally, federated learning can be used to train on data that is not centrally located, which can be difficult or impossible for other models. Furthermore, Federated learning can provide more accuracy than conventional machine learning. It can train on data without the constraint of the local data repository, which can be difficult or impossible for other models. Finally, Federated learning helps in data privacy protection by keeping the data on the devices where it is generated. This means that the data does not have to be centrally located and is not shared with other devices. This protects the privacy of the data, as it is not exposed to other devices or people.

3. Challenges and future directions:

COVID-19 has spread throughout the planet, posing a threat to human existence. As a result, various studies have been performed to develop an alternative rapid diagnosis system that uses AI to diagnose, predict, and prevent the impacts of the virus. However, the academic literature has identified various research challenges and limits, which must be addressed to provide a solution. Some of these issues are related to the natural mutation of the COVID-19 virus and the way it spreads and infects, making the intricacy of this epidemic incredibly tough.

Furthermore, the lack of a substantial dataset of COVID-19 makes it a difficult task for AI researchers and impedes the understanding of viral patterns and features. Hence, the demand for large datasets to train ML algorithms. The following subsection presents the key challenges of employing ML/FL-based COVID-19 diagnosis research.

3.1. Challenges to Open Source Data

Medical image screening is considered an alternative solution to the conventional method. Medical image classification supports physicians. Furthermore, the open-source contribution of methods, techniques and datasets could drive the research community to support and advance AI/ML-based alternative methods. The current hurdle for the open-source dataset is the challenge of handling privacy issues. Accessing medical images record is a challenge. The challenge makes it difficult to train effective classification models.

Furthermore, the image is privacy protected and raises a huge privacy concern lack of an open-source dataset restricts effective training of the models. The model performance is dependent on the training dataset size and diversity. To speed up AI and ML-based research opensource data should be benchmarked and managed for sharing across the participants. The dataset shortage is linked to (a) isolated and unshared datasets, (b) challenge in regularised data distribution format and (c) privacy issues related to data sharing. As a result, federating datasets to counteract AI is a critical task. Standards and protocols, as well as worldwide cooperation, are required for the dataset federation. Adopting common techniques for data anonymity helps alleviate privacy issues.

Another significant problem is the interoperability of AI/ML approaches. Machine Learning approaches serve as a Blackbox. Training of isolated or independent models requires doctors and radiologists to understand feature selection for COVID-19 and non-COVID-19 case classification. Furthermore, not having a shared dataset, and federated model leads to inaccuracy.

3.2. Accuracy of datasets

Classification accuracy is solely dependent on labelling the dataset and grouping the data to its correct class before the dataset can be used to train any model. The challenge in access, privacy concerns and the time limitation compromise the pretraining process, eventually leading to inferior accuracy. The accuracy metric acts as a reliability factor in using computer-aided alternative methods.

3.3. Privacy Issues

Privacy remains the major concern when using patient data such as geolocations, commutes, locality, clinical images and social life. Allowing the dataset to be publicly accessible as open-source data raises privacy concerns about the patient's personal life and evades the local privacy law and compliances. The individual data can also be used for large-scale surveillance by government and large corporate enterprises and can be exploited by the public. Therefore, medical institutions and organisations collecting medical data should strictly comply with privacy policies, govern anonymity and shield the data properly from security breaches.

Federated learning techniques do not require sharing or storing datasets in a centralised location, such as a cloud centre. Instead, ML models are dispersed throughout participating nodes, with the central node only receiving model parameters and outputs. The unique way aids in the privacy preserved model take precedence over individual privacy concerns.

3.4. Challenges to Machine Learning Techniques

Availability of annotated medical dataset is the precursor for a successful prediction, and a lack of a model for diagnosis has been raised as a great concern by researchers.
According to researchers, deep learning algorithms require larger datasets to deliver higher insights and accuracy in diagnosis [19], [20], [24], [47] and [49]. However, data scarcity is a critical challenge due to privacy concerns. The sharing of medical records across institutions is not allowed to protect sensitive information, which causes insufficient datasets for the research community to train the model.

A CNN-based model is significantly slower due to its process and pre-processing flow, including the max pool, as cited in [21], [22],[23], [24], [25],[26],[34],[35],[36],[37],[38],[39] and [40].The layer architecture in a CNN requires a special hardware infrastructure for better training, and the conventional setup consumes time and resources. In addition, there was a lack of input data, as discussed in [21], [22],[23], [24], [25],[26],[34],[35],[36],[37],[38],[39] and [40].Train costs are high for training complex deep learning models and require advanced and expensive GPU machines [19], [20], [24], [47], and [49].

3.5. Challenges to Federated Learning Techniques

Fewer papers are available on federated learning-based COVID-19 detection systems. The accuracy of the federated learning-based COVID-19 detection system is low [29], [30], [43], [50], [52], [53] and [54] it is not sufficient for medical applications. The accuracy requirement for medical treatment is expected to be very high. With quantitative approaches, the similarity error between COVID-19 and similar medical conditions with the same symptoms largely influences anomalies in the detection even if they are classified with essential classifiers.

3.6. Usage of advanced approaches

The use of clinical data such as X-ray, ultrasound scans, and magnetic resonance imaging (MRI) has been less studied in combating COVID-19. Survey shows ultrasound scans [52] and [54] provide better prediction and is under-explored due to the scarcity of adequate training data. Only some studies [17], [22], [35], [36] and [39] have shown the efficient usage of MRI and X-ray in predicting COVID-19. Therefore, the challenge is to develop a well-annotated dataset to use new approaches in predicting COVID-19 infection. Despite the various models proposed, most of them depend on the annotated dataset, and the availability of a well-annotated dataset is still a challenge and potential bottleneck. The author in [52],[54] used ultrasound and proved better performance than X-rays and CT scans. Studies [17], [22], [35], [36] and [39] show better results by combining MRI and X-ray usage for prediction.

3.7. Future Directions:

The potential direction in medical image-based classification for COVID-19 is discussed in this section.

3.7.1. Performance of Federated Learning

From this survey, the privacy of medical data is very important. Therefore, the federated learning-based model can be a better choice for the classification and prediction of COVID-19. However, the accuracy of federated learning techniques is not sufficient for medical applications [29], [30],[43], [50], [52], [53] and [54]. The accuracy and performance of federated learning techniques must be increased to make them reliable.

3.7.2. Dataset and pre-processing

Privacy protection and a high-quality annotated public dataset are required. Standard feature extraction is key to better classification and accurate prediction. Datasets play a vital role in determining the accuracy of classification, as discussed in [20],[26] and [49]. A benchmarked dataset can improve the classification efficacy and accuracy of AI techniques. Additionally, it revealed that the dimensionality reduction approach decreased the complexity and time consumption. As a result, establishing effective computational approaches for pre-processing COVID-19 images is highly desired towards enhancing patient diagnosis outcomes and assisting clinicians in interpretation, saving time and providing reliable accuracy.

3.7.3. Symptom-Based Identification of COVID-19

Most of the studies devised in COVID-19 characteristic prediction is based on studying the symptoms of COVID-19. The outcomes produced are often impacted by the misclassification of medical conditions with similar symptoms. Therefore, researchers should consider symptom-based identification of closely related medical conditions to improve symptom-based classification to increase accuracy. Future research requires attention to symptom-based classification for easy and quick diagnosis.

4. Conclusion:

Researchers are constantly addressing emerging problems with the recent focus on COVID-19 affecting every part of normal life, from daily activity to the economy. To contain a pandemic at such an intensity requires rapid diagnosis, prediction and forecasting direction. This survey presented a comprehensive review of works carried out by researchers in machine and federated learning to propose alternative solutions to support frontline workers. Initially, a small introduction to the COVID-19 effect was discussed, followed by a major contribution in analysing various prediction models of machine learning and federated learning approaches and their support in pandemic diagnosis. The analysis was further broadened by critically examining the performance metric of each model evaluation of medical images such as CT, X-ray, MRI and ultrasound. This survey highlights improvement in the classification accuracy by increasing training data and the privacy compliance of medical data. Our survey on the existing research articles found federated learning out performed than other machine learning techniques in COVID-19 detection and provided privacy of medical data. Thus, we conclude that federated learning-based medical classification systems can be used optimally as an alternative approach for COVID-19 detection. The paper concludes with some of the challenges observed and future directions.

Federated learning can help to build an effective COVID-19 diagnosis system in the following ways. First, federated learning can help to keep data secure and private. This is important because COVID-19 data is sensitive and personal. Second, federated learning can help to improve the accuracy of models by aggregating data from multiple sources. This is important because the labelled dataset available is limited, and machine learning often requires massive labelled data to improve predictions' accuracy and decision-making.

Abbreviation:

List of abbreviation used in the tables are Ac - Accuracy , Se - Sensitivity , Sp - Specificity , F1 - F1 Score , Pr - Precision , Re - Recall , AUC - Area under the Curve , TP - True positive , TN - True negative , Lo - Loss , FN - False negative and ET - execution time

Annex – 1

Table 7: Consolidated list of datasets used in the articles referenced

Dataset location	#	Dataset location
https://www.kaggle.com/tawsifurrahman/covid19-radiography-database	[35]	https://www.kaggle.com/datasets/nih-chest-xrays/data https://github.com/topics/coronavirus-dataset
https:// www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset	[40]	https://www.kaggle.com/tawsifurrahman/covid19-radiography-dat https://arxiv.org/abs/2003.11553
https://ieee-dataport.org/open-access/covid19-chestxray-dataset https://arxiv.org/abs/2003.11862 https://github.com/ieee8023/covid-chestxray-dataset	[33]	https://www.kaggle.com/tawsifurrahman/covid19-radiography-data https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/c
https://pan.baidu.com/s/1TcoPOQ_5TG2gZmxsxOhMkA https://github.com/lizonggui/COVID-19	[34]	https://www.kaggle.com/tawsifurrahman/covid19-radiography-dat
https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.	[36]	https://www.techrxiv.org/articles/preprint/Finding_COVID-19_from_Chest_X-rays_using_Deep_Learning_on_a_Small_Dataset/12083964/2
https://www.kaggle.com/tawsifurrahman/covid19-ct-scans	[37]	https://github.com/ieee8023/covid-chestxray-dataset
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