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2022_Fall

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Reliability and Performance Assessment of Federated Learning on Clinical Benchmark Data, https://arxiv.org/abs/2005.11756
Federated Learning on Clinical Benchmark Data: Performance Assessment, https://www.jmir.org/2020/10/e20891

삼성병원: 신수용 교수
https://sooyongshin.wordpress.com/2020/11/22/federated-learning/

이제 유명해져서 아는 사람은 다 아는 federated learning..
특히 개인정보 보호가 큰 이슈가 되는 헬스케어 데이터 분석에서 중요한 기술이라고 말이 많은 federated learning..
(*개인적으로 몇년 전부터 이런 기술을 도입해서 사용해야 한다고 강력히 주장하기도 했고.. 특히 가명처리의 대안으로 적극 주장*)
근/데/ 논문이든 뭐든 말만 하지 실제로 하는 사람은 의외로 많지 않은 federated learning.. (*국외 포함. 나도 이 논문 전에는 말만 하던 사람*)
솔직히 말만 많지, 하는 사람이 많이 없어서 그냥 시작했다..

목적은
1. 실제 헬스케어 데이터에서 동작하는지 검증
2. 실제 network 환경에서 동작하는지 검증

의료 데이터에 쓰면 좋다는 논문은 진짜 많은데..
실제로 검증한 논문은 거의 없다.

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[CVPR 2022, NVIDIA] Closing the Generalization Gap of Cross-Silo Federated Medical Image Segmentation, https://openaccess.thecvf.com/content/CVPR2022/html/Xu_Closing_the_Generalization_Gap_of_Cross-Silo_Federated_Medical_Image_Segmentation_CVPR_2022_paper.html
Github: https://github.com/NVIDIA/NVFlare/examples/FedSM
Github: https://github.com/NVIDIA/NVFlare/tree/dev/examples

Cross-silo federated learning (FL) has attracted much attention in medical imaging analysis with deep learning in recent years as it can resolve the critical issues of insufficient data, data privacy, and training efficiency.

However, there can be a generalization gap between the model trained from FL and the one from centralized training. This important issue comes from the non-iid data distribution of the local data in the participating clients and is well-known as client drift.

In this work, we propose a novel training framework FedSM to avoid the client drift issue and successfully close the generalization gap compared with the centralized training for medical image segmentation tasks for the first time. We also propose a novel personalized FL objective formulation and a new method SoftPull to solve it in our proposed framework FedSM.

We conduct rigorous theoretical analysis to guarantee its convergence for optimizing the non-convex smooth objective function. Real-world medical image segmentation experiments using deep FL validate the motivations and effectiveness of our proposed method.

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Reward Systems for Trustworthy Medical Federated Learning, https://arxiv.org/abs/2205.00470
Github: https://github.com/kpandl/Reward-System-for-Trustworthy-Medical-Federated-Learning

Federated learning (FL) has received high interest from researchers and practitioners to train machine learning (ML) models for healthcare. Ensuring the trustworthiness of these models is essential. Especially bias, defined as a disparity in the model's predictive performance across different subgroups, may cause unfairness against specific subgroups, which is an undesired phenomenon for trustworthy ML models.

In this research, we address the question to which extent bias occurs in medical FL and how to prevent excessive bias through reward systems.

- We first evaluate how to measure the contributions of institutions toward predictive performance and bias in cross-silo medical FL with a Shapley value approximation method.
- In a second step, we design different reward systems incentivizing contributions toward high predictive performance or low bias.
- We then propose a combined reward system that incentivizes contributions toward both. We evaluate our work using multiple medical chest X-ray datasets focusing on patient subgroups defined by patient sex and age.

Our results show that we can successfully measure contributions toward bias, and an integrated reward system successfully incentivizes contributions toward a well-performing model with low bias. While the partitioning of scans only slightly influences the overall bias, institutions with data predominantly from one subgroup introduce a favorable bias for this subgroup. Our results indicate that reward systems, which focus on predictive performance only, can transfer model bias against patients to an institutional level. Our work helps researchers and practitioners design reward systems for FL with well-aligned incentives for trustworthy ML.

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서울과기대 박종혁 교수, https://scholar.google.com/citations?hl=en&user=IshTErgAAAAJ&view_op=list_works&sortby=pubdate
- FusionFedBlock: Fusion of Blockchain and Federated Learning to Preserve Privacy in Industry 5.0, https://www.sciencedirect.com/science/article/abs/pii/S1566253522001658
- Federated Learning-based secure Electronic Health Record sharing scheme in Medical Informatics, https://ieeexplore.ieee.org/abstract/document/9774951

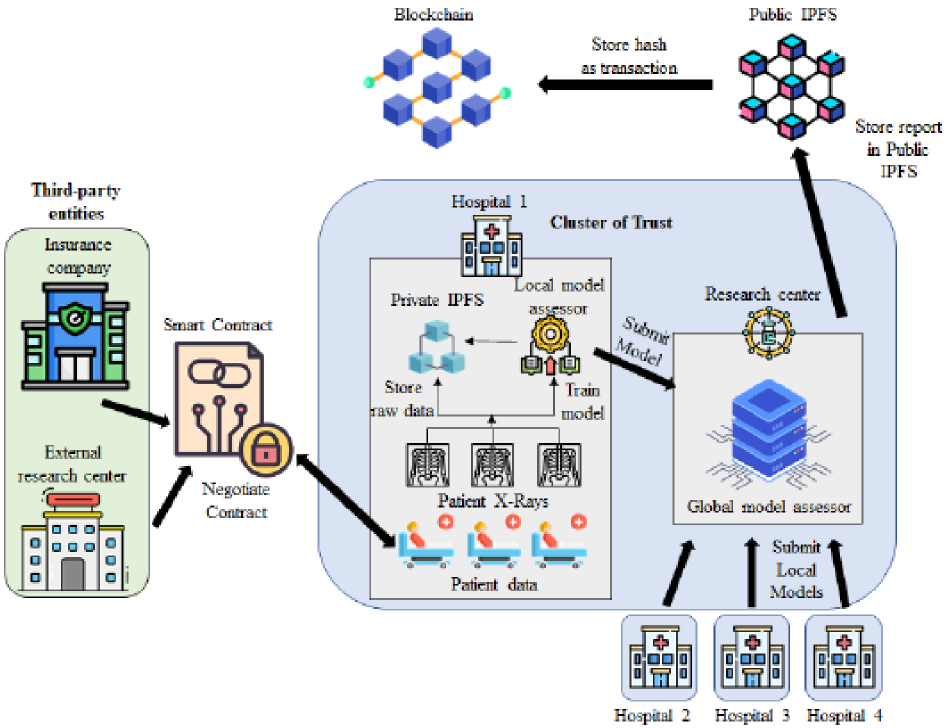

Fig. 1. Secure EHR Sharing Scheme Overview

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Federated Learning-based secure Electronic Health Record sharing scheme in Medical Informatics, https://ieeexplore.ieee.org/abstract/document/9774951

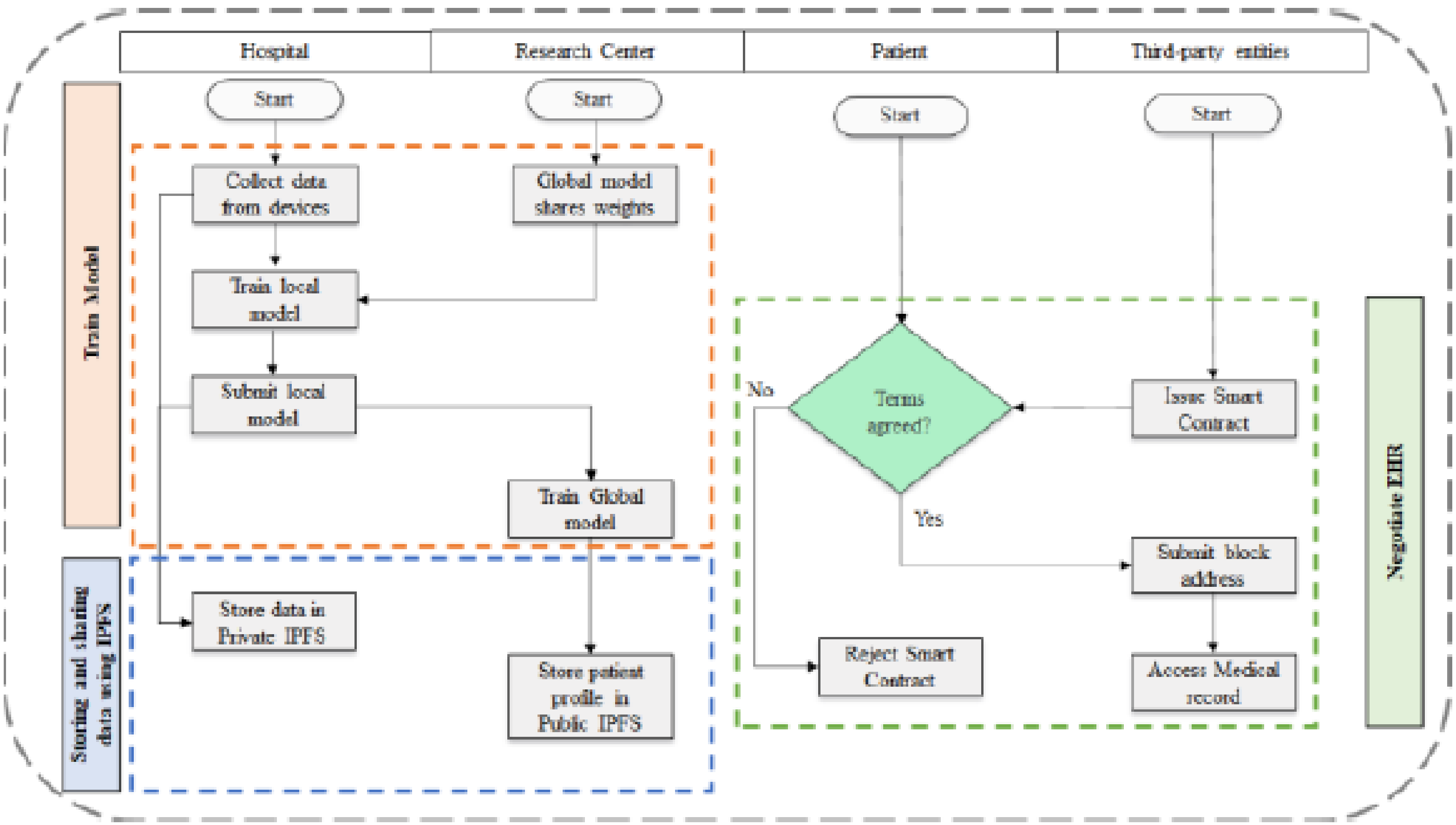

Fig. 2. Secure EHR Scheme process-flow

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

It provides fair and explainable FL participant contribution evaluation in an efficient and privacy-preserving manner, and optimizes the FL model aggregation approach based on the evaluation results.

- Since its deployment in Yidu Cloud Technology Inc. in March 2021, CAreFL has served 8 well-established medical institutions in China to build healthcare decision support models.
- It can perform contribution evaluations 2.84 times faster than the best existing approach, and has improved the average accuracy of the resulting models by 2.62% compared to the previous system (which is significant in industrial settings). To our knowledge, it is the first contribution-aware federated learning successfully deployed in the healthcare industry.

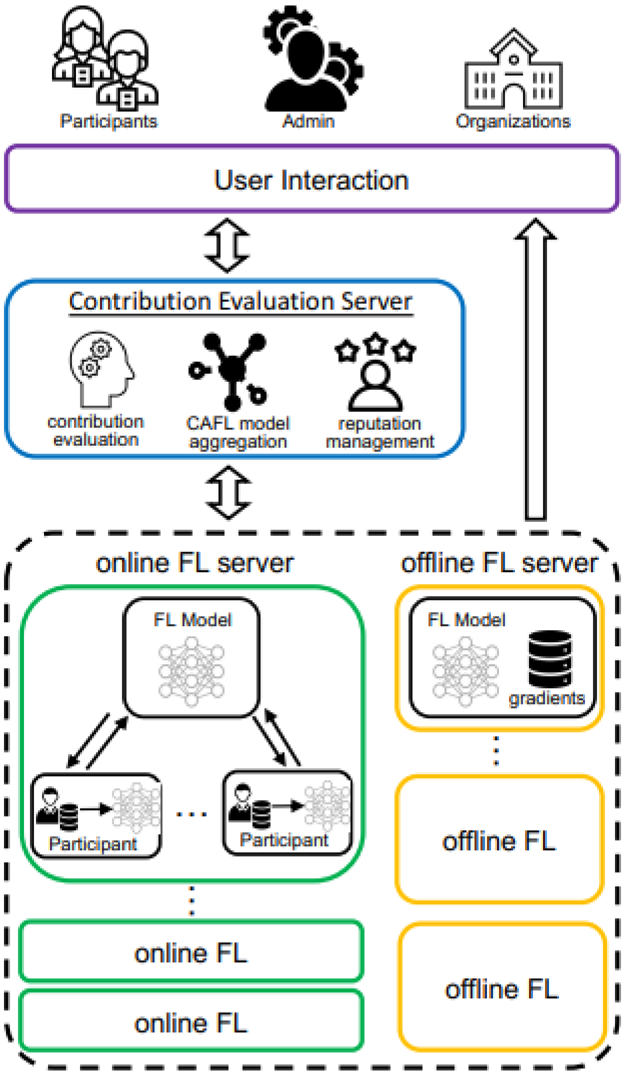

Figure 1: The CAreFL system architecture.

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

FL participant **contribution evaluation** is an active subfield of FL (Ghorbani and Zou 2019; Jia et al. 2019; Song, Tong, and Wei 2019; Wang et al. 2020; Wei et al. 2020). The aim is to estimate the value of each FL participant by evaluating its impact on the performance of the resulting FL model, without exposing their sensitive local data. To bridge the aforementioned gaps in FL frameworks for smart healthcare, we propose the Contribution-Aware Federated Learning (CAreFL) framework.

The advantages are:

1. **Fast and Accurate Contribution Evaluation**: it is incorporated with our proposed GTG-Shapley (Liu et al. 2022) approach, which can evaluate fair and accurate FL participant contribution in a highly efficient manner.
2. **Contribution-Aware FL Model Aggregation**: during the contribution evaluation process, GTG-Shapley builds a large number of aggregated FL sub-models involving local model updates from different combinations of FL participants. With this knowledge, CAreFL provides a novel FL aggregation approach which selects the best performing sub-model to be distributed to the FL participants for the next round of local training. This differs from FedAvg-based approaches (which always aggregate all received local models), and can better deal with data heterogeneity issues.
3. **Contribution-based FL Participant Reputation Management**: historical contribution evaluation records are converted into reputation values for the FL participants. This information can serve as a basis stakeholder management decision support.

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

- Hence, the canonical SV cannot be directly used for contribution evaluation in the context of FL.
- The key idea of GTG-Shapley is to opportunistically reduce the need for sub-model retraining with model reconstruction and strategic sampling of combinations of participants. It truncates unnecessary sub-model evaluations to reduce computational costs, while maintaining high accuracy of estimated SVs.

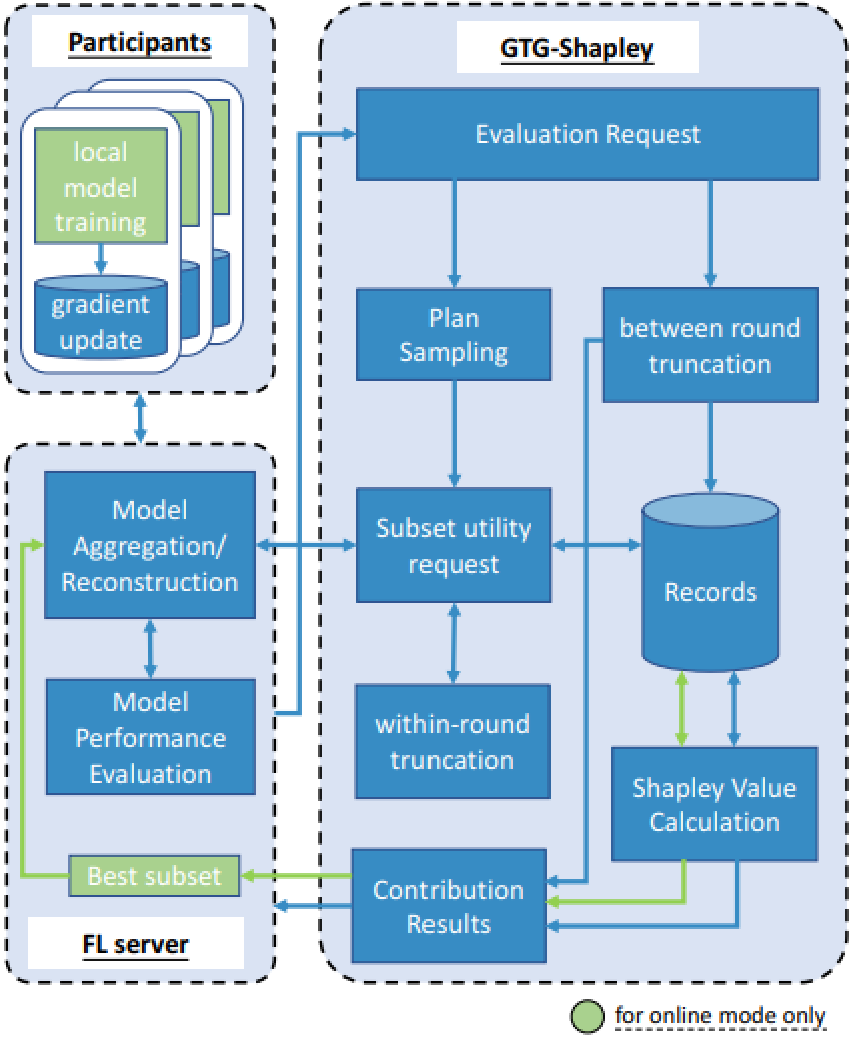

Figure 3: The CAreFL AI Engine

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smar
Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

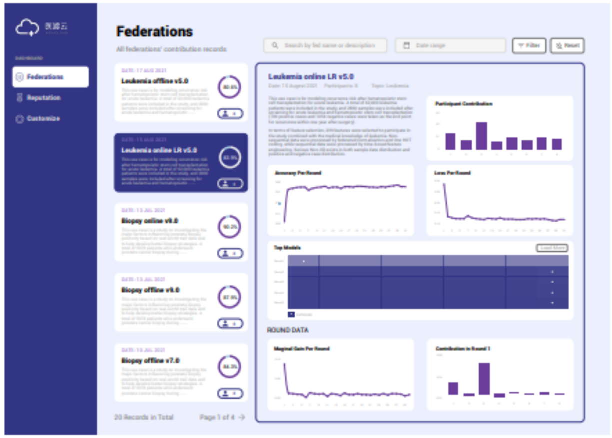


Figure 5: The main user interface of CAreFL.

Application Use and Payoff
The CAreFL framework has been deployed in Yidu Cloud Technology I
lines of their business:
1. clinical research services : Clinical research focuses on training FL m
from multiple hospitals.
2. real-world trial research services. : Real world trial research is often initiated by a pharmaceutical company which aims to leverage data from multiple hospitals to build models.

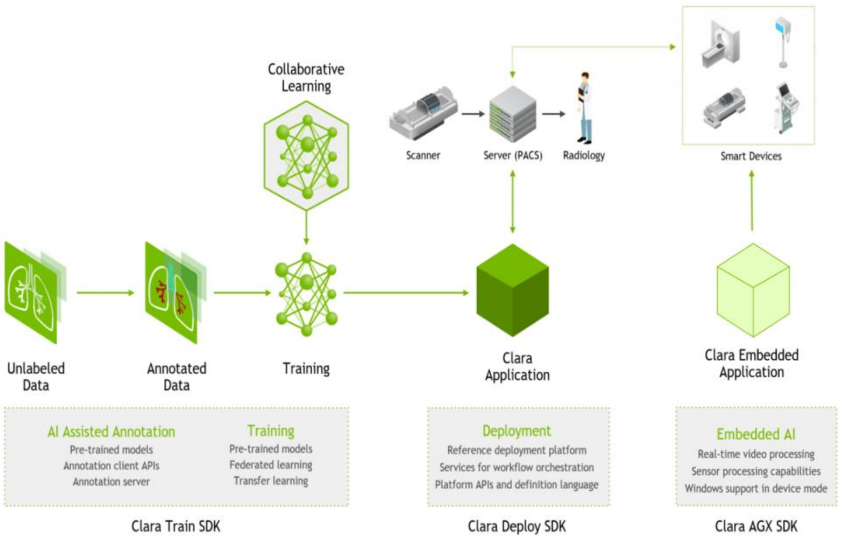
Both services require data which need to be collected by the hospitals over months or years under their respective Institutional Review Board (IRB) supervision. So far, CAreFL has been used to help eight well-known medical institutions in China to train AI models for risk prediction, disease diagnosis and influence factor analysis.

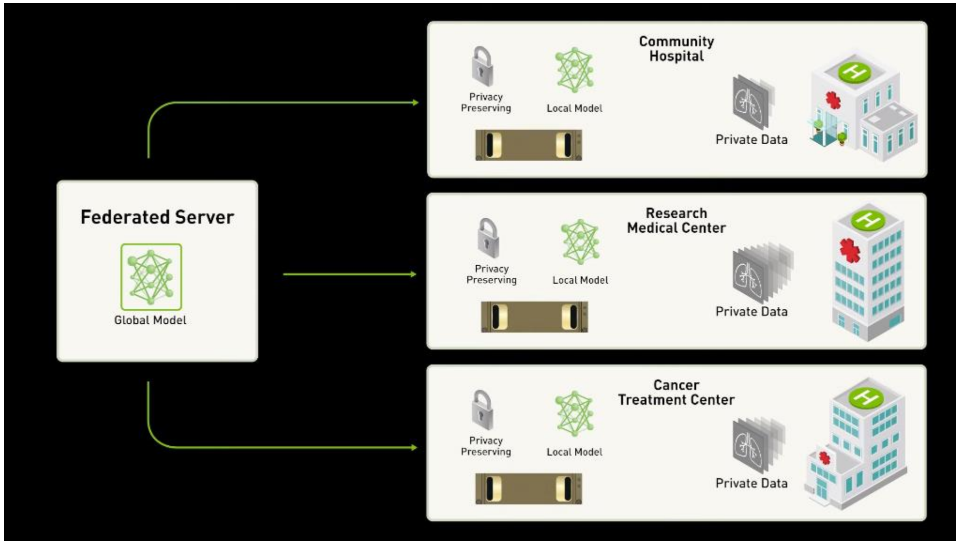
Conclusions and Future Work
In future, we will continue the explore the applicability of CAreFL in other smart healthcare application scenarios. We will also extend the CAreFL framework with contribution-based data pricing mechanisms (Pei 2020) to support the emergence of an **FL-based healthcare data exchange marketplace**. Eventually, we aim to incorporate these functionalities into the opensource FATE framework and make them available to more developers, researchers and practitioners.

Federated Learning powered by NVIDIA Clara

- An Application Framework Optimized for Healthcare and Life Sciences Developers, https://developer.nvidia.com/clara
- Federated Learning powered by NVIDIA Clara, https://developer.nvidia.com/blog/federated-learning-clara/

- Transforming AI Healthcare with Federated Learning, https://news.developer.nvidia.com/transforming-ai-healthcare-with-federated-learning/
- https://www.nature.com/articles/s41746-020-00323-1





Google Health Studies

Advancing health research with Google Health Studies,
https://blog.google/technology/health/google-health-studies-app/
https://play.google.com/store/apps/details?id=com.google.android.apps.health.research.studies

COVID-19 has highlighted the importance of research in providing information about disease and treatments. However, it's challenging for researchers to recruit enough volunteers so that studies are representative of the general population. To make it easier for leading research institutions to connect with potential study participants, we're introducing the Google Health Studies app with the first study focused on respiratory illness.

Keeping participant data private, safe and secure
Studying respiratory illnesses
We've partnered with researchers from Harvard Medical School and Boston Children's Hospital for the first study, which will help scientists and public health communities better understand respiratory illnesses, including influenza and COVID-19.

- This Respiratory Health Study will be open to adults in the U.S., and will focus on identifying how these types of illnesses evolve in communities and differ across risk factors such as age, and activities such as travel.
- Study participants will use the Google Health Studies app to regularly self-report how they feel, what symptoms they may be experiencing, any preventative measures they've taken, and additional information such as COVID-19 or influenza test results. By taking part in this study, volunteers can represent their community in medical research, and contribute to global efforts to combat the COVID-19 pandemic.

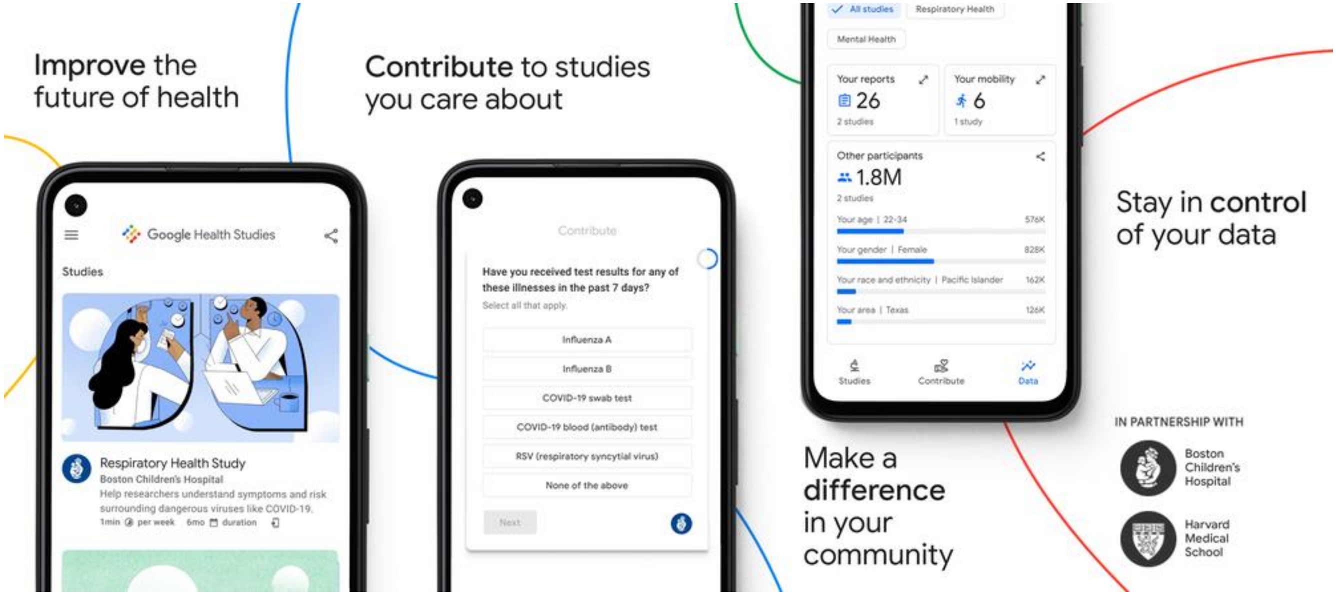
In collaboration with Google Research, this first study utilizes federated learning and analytics—a privacy technology that keeps a person's data stored on the device, while allowing researchers to discover aggregate insights based on encrypted, combined updates from many devices.

Google Health Studies : 연합학습 적용

Blog: https://blog.google/technology/health/google-health-studies-app/
App: https://play.google.com/store/apps/details?id=com.google.android.apps.health.research.studies

The Google Health Studies app is now available in the Google Play Store, and we're inviting people to download the app to join this initial study. We look forward to partnering with health researchers and to making it possible for more people to participate in these important studies.

… this first study utilizes federated learning and analytics—a privacy technology that keeps a person's data stored on the device, while allowing researchers to discover aggregate insights based on encrypted, combined updates from many devices. This means researchers in this study can examine trends to understand the link between mobility (such as the number of daily trips a person makes outside the home) and the spread of COVID-19, This same approach powers typing predictions on Gboard, without Google seeing what individuals type.

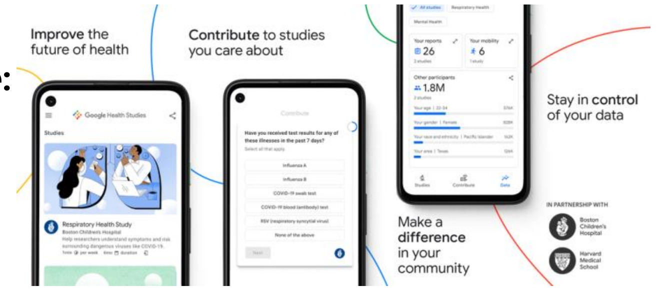


Google Health Studies : 연합학습 적용

Blog: https://blog.google/technology/health/google-health-studies-app/
App: https://play.google.com/store/apps/details?id=com.google.android.apps.health.research.studies

Google Health Studies lets you securely contribute to health research studies with leading institutions, right from your phone. Volunteer for studies that matter to you and represent your community.

Simply download the app and enroll in a study.



Help researchers make advancements in medicine and healthcare:
- Self-report symptoms and other data
- Volunteer for multiple studies in one app
- Track your information with digital health reports
- Learn research findings from the studies you participate in

Help scientists better understand respiratory diseases.
The first study available is a respiratory health study conducted by Boston Children's Hospital and Harvard Medical School. If you participate in this study, you'll provide data to help researchers understand how demographics, health history, behavior, and mobility patterns contribute to the spread of respiratory illnesses. Upcoming studies will research mental health and diabetes.

You're in control of your data: In the respiratory health study, your personal information is kept on your device. Researchers only see aggregated study data combined from all participants. This allows researchers to collect the information needed to advance the study without seeing individual details.

Your input matters: Google Health Studies aims to create opportunities for more people to participate in health research. By contributing, you'll represent your community and start improving the future of health for everyone.

Google Health Studies

- https://health.google/for-everyone/health-studies/
- App: https://play.google.com/store/apps/details?id=com.google.android.apps.health.research.studies
- Blog: https://blog.google/technology/health/google-health-studies-app/

Benefit the public, in private

Protecting your information in the respiratory health study.

Your study data stays on your device

After joining a health study, you'll begin completing weekly surveys. At all times, your individual survey responses, location history and other personally identifiable data stays on your device.

Your device computes statistics based on your study data

During the study, your device receives different queries, computes and summarizes the results based on your individual study data, and encrypts these results for subsequent aggregation with federated analytics.

Participant data gets aggregated

Encrypted summaries from many devices are combined together, using the federated analytics technology. Google and study partners do not receive any individual study data about you.

Research that values your privacy

Combined insights are sent securely to the researchers conducting the study. You can safely contribute to health research knowing your personally identifiable study data will never be available to Google or third parties.

Google Health Studies

Paper: Privacy-first Health Research with Federated Learning, https://www.nature.com/articles/s41746-021-00489-2,
Patent: Privacy-First On-Device Federated Health Modeling and Intervention, https://patents.google.com/patent/US20210090750A1/en

We show—on a diverse set of single and multi-site health studies—that federated models can achieve similar accuracy, precision, and generalizability, and lead to the same interpretation as standard centralized statistical models while achieving considerably stronger privacy protections and without significantly raising computational costs.

At this point, however, only specific large homogenous units of federation, such as at the level of a healthcare system, have been studied in detail in prior work, and the focus has been on traditional classification tasks.

Specifically, health study data is typically non-IID—not independent and identically distributed—which is compounded by the fact that in the federated regime, individual data points are distributed across many devices that participate asynchronously.

This work's primary focus is on cross-device (cross-patient) settings, where the unit of federation is a single individual.

By contrast, in this work, we focus on those scenarios commonly found in epidemiological health studies, specifically studies with many participants, each of whom has relatively small amounts of non-IID, labeled data. The approach described here can be appropriate for health studies involving smartphone/wearable data and virtual clinical studies (also called decentralized clinical studies) that directly recruit individual research participants without relying on clinical sites for recruitment.

Google Health Studies

Paper: Privacy-first Health Research with Federated Learning, https://www.nature.com/articles/s41746-021-00489-2,

Study Topic	Sample Results	Comparison Metric	Traditional Centralized Model[a]	Federated Replications	
				Per-Patient	Per-Silo[b]
Heart Failure	1. Survival Prediction (full model) 2. Survival Prediction (with variable selection)	AUC	0.82 0.82	0.85 0.83	N/A
Diabetes	1. Diabetes prediction at 5-years	AUC	0.84	0.875	N/A
MIMIC-III	1. Inpatient mortality prediction	AUC	0.780± 0.012	0.777 ± 0.011	0.777 ± 0.014
SARS-CoV-2	1. CV2+ve in Female vs. Male 2. CV2+ve in Recent vs. Never Cancer	OR	0.35 (0.32–0.38) 1.88 (1.36–2.60)	0.35 (0.32–0.38) 1.99 (1.45–2.68)	0.35 (0.32–0.38) 2.07 (1.50–2.86)
Avian Influenza	1. Fatality with each day before hospitalization 2. Fatality in Indonesia vs. group of countries	OR	1.33 (1.11–1.60) 0.23 (0.04–1.27)	1.34 (1.12–1.61) 0.25 (0.05–1.37)	1.33 (1.11–1.60) 0.24 (0.04–1.33)
Bacteraemia	1. Relapse with line-associated infection source 2. Relapse with presence of immunosuppression	Coefficient	1.57 (SE: 0.45) 1.07 (SE: 0.41)	1.59 (SE: 0.23) 1.12 (SE: 0.30)	N/A
Azithromycin	1. Adverse events in azithromycin treated	Coefficient	−0.11 (SE: 0.09)	−0.29 (SE: 0.19)	N/A
Tuberculosis	1. Extrapulmonary TB in individuals with HIV	Coefficient	1.16 (SE: 0.09)	1.35 (SE: 0.08)	0.15 (SE: 0.07)[c]

Google Health Studies

Patent: Privacy-First On-Device Federated Health Modeling and Intervention, https://patents.google.com/patent/US20210090750A1/en

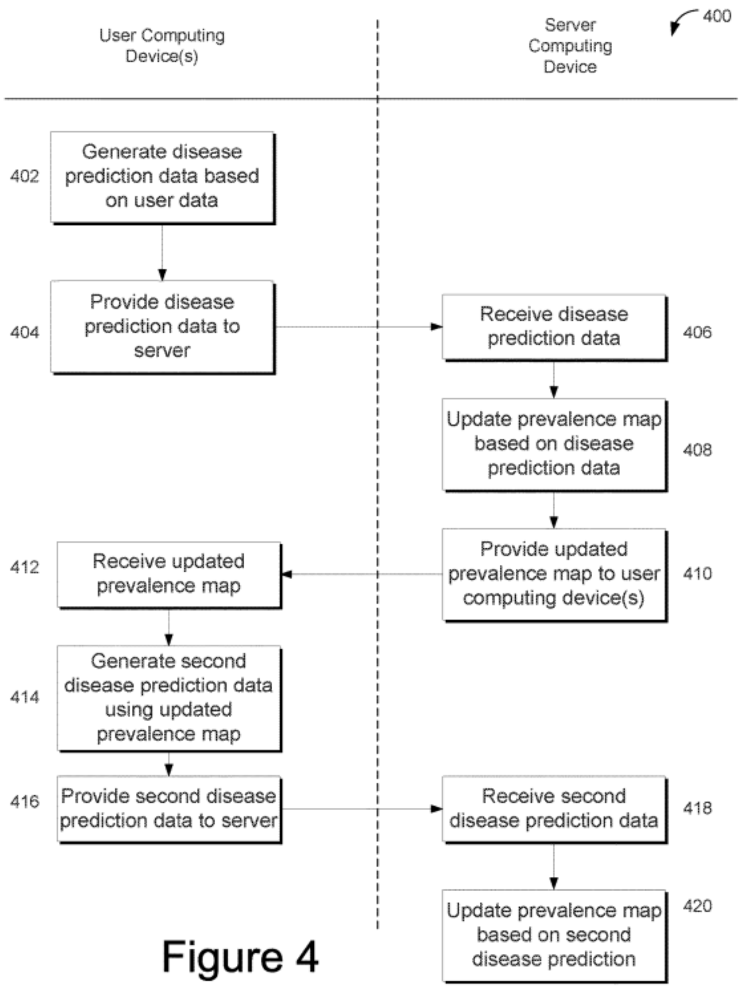


Figure 4

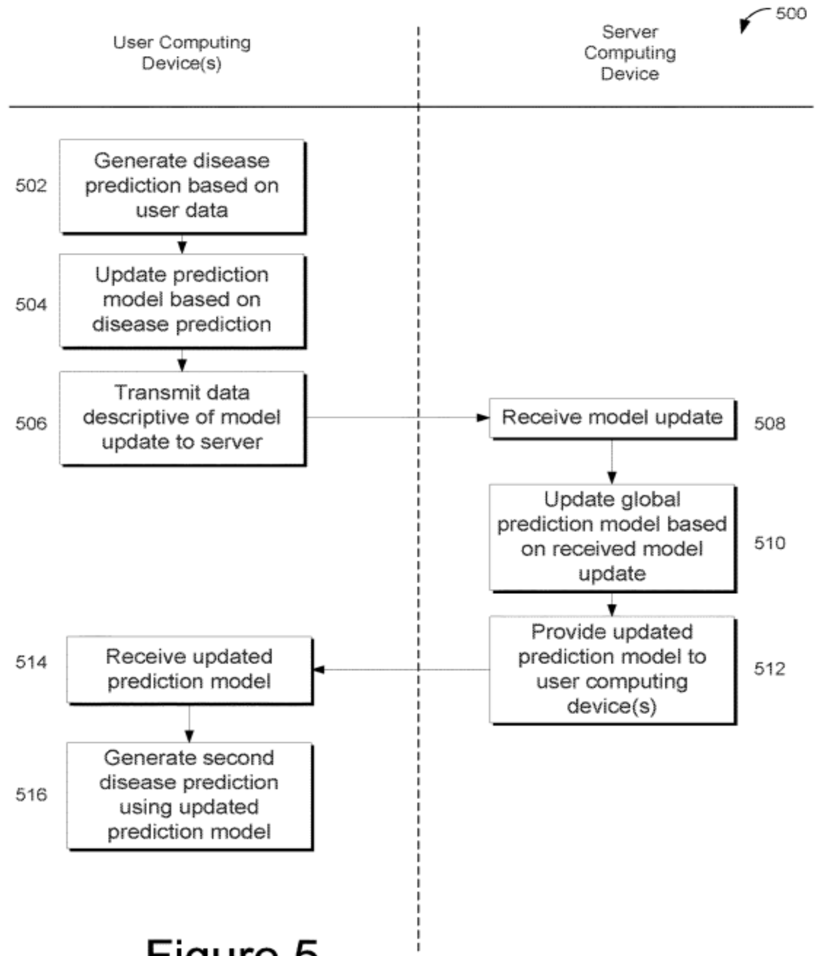


Figure 5

Google Health Studies

Wide Scale Monitoring for Acute Respiratory Infection Using a Mobile-Based Study Platform, https://clinicaltrials.gov/ct2/show/results/NCT04663776

- Sponsor: Boston Children's Hospital
- Collaborator: Google LLC.
- Information provided by (Responsible Party): John Brownstein, Boston Children's Hospital

Brief Summary:
This is a prospective observational study using a mobile study platform (app) that is designed for use on Android phones.

- Study participants will provide baseline demographic and medical information and report symptoms of respiratory infection on a weekly basis using the app.
- Participants will also report use of prevention techniques on the weekly survey.
- Mobility data will be collected passively using the sensors on the participant's smartphone, if the participant has granted the proper device permissions.
- The overall goals of the study are to track spread of coronavirus-like illness (CLI), influenza-like illness (ILI) and non-specific respiratory illness (NSRI) on a near-real time basis and identify specific behaviors associated with an increased or decreased risk of developing these conditions.

Study Population
The study population will be adult Android mobile device users who live within the United States.