# The potential of Federated Learning in Healthcare settings

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# Introduction

The increased adoption of internet connected devices, known as the Internet of Things (IoT) has driven both advances in artificial intelligence (AI), thanks to vast amounts of data and processing power now available to researchers, and public concerns over data privacy, with a Pew Research Centre survey finding that 79% of American adults are concerned with how their personal data is being used by companies [1]. As AI researchers look to balance the need for technological advancement with the desire for privacy, federated learning (FL) [2] has emerged as a possible solution.

FL is a type of machine learning (ML) architecture made up of many local clients, and a central server. In FL, the central server transmits an initial model to the clients. The clients will gather data and train models locally – each client will train its own model on its own data, thereby keeping the data private. Clients can be something as small as a smart watch, or as large as a hospital. Once a client has trained the local model on the local data, the model updates are transmitted to a central server. When all selected clients have transmitted their model updates, these are aggregated into a new global model which is transmitted back to the clients. This process is repeated until a desired level of performance has been reached.

# Potential of FL in healtcare

Given the ability for FL to keep client data private, there is now the potential to use this data to improve outcomes for patients. An example of this is in the area of FL models to be used for disease prediction, for example in detecting cancers through an analysis of medical images, as well as drug discovery by identifying patterns in numerous patient’s genetic makeup, their medication plans and responses to treatments. Another area of interest is personalised federated learning (PFL), where a global model is refined for the purpose customising it to the unique traits and needs of an individual client [3]. An example of PFL is the development of a system to aid in the diagnosis of Parkinson’s disease by using data gathered by an application on a patient’s smartphone which gathered data on the motor symptoms usually associated with Parkinson’s disease [4].

# challenges in fL

While FL shows promise in a number of areas, there are a number of open challenges [5]. One challenge is on data and system heterogeneity, which is introduced by differences in data distributions across clients or servers or by differences in architecture of any devices involved in the learning process (i.e., differences in CPUs, RAM, etc.). Heterogeneity can have a negative impact on model convergence and accuracy. Another challenge is in the area of communications. Constant communication between the clients and the server can be expensive, and depending on the network topology the communication bandwidth can be limited, which can lead to bottlenecks. Working with multimodal data poses another challenge – what impact will data from various sources (audio, video, numerical data) have on the ability of a FL system to learn and produce accurate models? A fuller list of challenges can be found in Figure 1.

A diagram of a learning structure

Description automatically generated with medium confidence

***Figure 1*** *Challenges in Federated Learning*

# CONCLUSION

My PhD research aims to address some of the challenges to advance FL in real-world applications.

# References

[1] Engström (*et al.),* Computers in Human Behavior Reports, Vol 9, 2023

[2] McMahan (*et al.),* Artificial Intelligence and Statistics, pp. 1273-1282, 2017

[3] Fahad Sabah *(et al.)*, Expert Systems with Applications, Vol. 243, 2024

[4] Yiqiang Chen *(et al.)*, IEEE Intelligent Systems, Vol. 35, Issue 4, 2020

[5] Badra Souhila Guendouzi *(et al.)*, Journal of Network and Computer Applications, Vol. 220, 2023