# Federated Learning: Advancements, Challenges, and Applications

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Submitted by

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## CANDIDATE'S DECLARATION

I, Anirban Kumar Malick, Roll No's –2K23/SWE/21 students of M.Tech (Software Engineering), hereby certify that the work which is being presented in the thesis entitled "Federated Learning: Advancements, Challenges, and Applications" in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2025 to May 2025 under the supervision of Dr. Shweta Meena.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Anirban Kumar Malick
**Candidate's Signature**

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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## CERTIFICATE

I hereby certify that the Project Dissertation titled "Federated Learning: Advancements, Challenges, and Applications" which is submitted by Anirban Kumar Malick, Roll No – 2K23/SWE/21, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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# Abstract

In Federated Learning (FL), various clients cooperate to train a single model, trading minimal information among themselves instead of their actual data. Thanks to this architecture, your data is more secure, the risk of communication issues is minimised and you are able to comply with GDPR and HIPAA rules. A review of FedAvg, FedProx and FedNova is presented in this work, showing the way these methods function under IID and non-IID conditions. In healthcare, IoT and NLP, each algorithm's performance is studied concerning its convergence, accuracy and the ease with which it can be used in practise.

According to results from previous studies, FedAvg works satisfactorily when the data is identical, but it struggles where there are differences between the data. By including proximal regularisation, FedProx reduces the problem of model instability. Because of its handling of client updates, FedNova improves both fairness and synchrony, mainly under conditions when data is not IID. The tests also cover efficient communication, ability to resist attacks and fairness, with Jain's index used and FedNova comes out on top for balance.

In short, this thesis explores what FL systems do best and which features need work and it recommends future directions for research. Among them are new ways to aggregate adaptively, to use learning in real time, to update models securely and to provide personalised models. The importance of standard scales and markers is emphasised as well. The review summarises the fieldowrns and helps design AI systems that are ethical, scalable and safeguard privacy using federated concepts.

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# CHAPTER 1

# INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have greatly improved in sporting the automatic handling of data-driven decisions over the last decade. Various industries, for example healthcare, banks, retail and transport, are now using these advanced technologies. Still, using traditional ML techniques requires building all the data in one place which can result in privacy and security problems. Data is gathered from various users and then stored and used to train machine learning models on a main server in a centralized learning system. But because there is only one place for data, this architecture can be unsafe and could result in data misuse, loss of user privacy and exposure to destructive attacks.

Because of this, Federated Learning (FL) is now used as a decentralized way to train models without gathering raw data in one place. In FL, users keep their data alone on their devices, but any model updates get shared with a central server. All these updates are gathered on the server to enhance a global model which is transferred back to everyone involved. Because FL avoids moving data, it greatly lowers the dangers of data leaks, privacy violations and problems with meeting compliance standards. That's why it is now more important in mobile computing, healthcare, vehicle autonomy and computing on the edge [1].

FL was rolled out by Google in 2017 via the Gboard keyboard to improve how the next autocorrect words are predicted. Samsung trained its model by running it locally on the typing data of millions of devices. Just the parameters of the learned model not the original typed text were submitted to Google for combining. Thanks to this important project, FL was demonstrated as capable of training sharp models that protect user privacy. Following this, FL's rate of development has significantly increased and AI can now be implemented securely and personalized in several applications [2].

One of FL's key advantages is that it can deal with data that is not the same in each location. In practise, information is divided among clients in a way that is non independent and non identically distributed (non-IID). Each person using the system could have data sets that are different in terms of size, how data is spread and the information they contain. An example is that one person in a health monitoring app could send data about their heart rate, whereas another could mostly give data about their sleep. In the traditional approach, heterogeneity commonly causes problems, but

FL comes up with approaches to gather diverse knowledge from dispersed devices effectively [3].

Besides selling privacy and eliminating the need for centralised data processes, FL has other benefits. It lessens network crowding by not uploading large files which minimises the bandwidth used. Because of this, it is a good fit for small gadgets and wireless networks. Users can also apply model personalization, changing the global model according to their data. As a result, AI services can be customised, become quicker and meet the unique needs of every user [4].

In system design, FL usually involves one central server along with a significant number of clients. The central server organises all training sessions and mixes changes based on algorithms such as Federated Averaging (FedAvg). People using edge computing could be on smartphones, tablets or special sensors or they could be part of large enterprise data centres. Depending on the type of deployment, FL can be split into cross device FL which involves many edge devices or cross silo FL, where a small group of organisations team up to train models and do not exchange data. An important issue they both face is scalability, fault tolerance and security [5].

Yet, FL creates new technical and operational obstacles. Statistical heterogeneity is a major challenge. Since each client’s data is unique, it is hard to guarantee that the global model will do well on the data from every client. Because not all devices are strong or available all the time, system heterogeneity is a challenge as well. Some models may quit learning because of physical problems, have low memory or struggles to stay in communication. Moreover, there is a communication bottleneck because clients and the server must synchronise frequently. Also, to maintain both the integrity and privacy of the federated system, poisoning attacks and inference attacks need to be addressed [6].

Some examples of ways researchers suggest meeting these issues are secure aggregation, differential privacy, homomorphic encryption and compression methods. Secure aggregation prevents the server from viewing the updates of each user model; it only gets the combined result. Noise is added by differential privacy to updates to avoid allowing sensitive data to be discovered. With homomorphic encryption, you can work on data that is encrypted and compressing your model helps minimise the amount of data sent and received. These approaches combine to improve the safety and efficiency of FL systems [7].

There are many open-source tools made to help both research and deployment in the field of FL. These options are comprised of TensorFlow Federated (TFF), OpenFL, Federated AI Technology Enabler (FATE) and Flower. These environments help test federated scenarios, develop unique aggregation methods and cheque privacy protecting tools. The increasing fascination with these resources is helping to drive improvements in FL that support safe and scalable decentralisation in learning systems [8].

FL is displaying especially good results in healthcare. Hospitals and medical centres usually gather helpful patient information that can train predictive models for identifying disease, personal therapy or early notifications. Environmental data cannot be freely shared because of privacy laws. FL gives hospitals and their partners a system that lets them team up without breaking privacy laws. Every hospital can use its own records to train and only the updated model is passed on for a combined model. With this method, groups of experts help improve healthcare results while patient privacy is preserved [9].

Banks may apply FL to spot financial fraud or decide on credits, without making their transaction data visible. With this approach, FL helps financial institutions predict more accurately without sharing secret data. On mobile devices, FL allows for voice recognition, identifying images and making recommendations. Every device helps create the shared model while ensuring that user data is stored locally. The results achieved with FL confirm that it delivers scalable solutions that respect privacy.

In terms of architecture, FL start with initialization, client selection, local training, compression, secure transmission and finally aggregation by the server. All steps in the process must be set up properly to cheque for accuracy, resilience and effectiveness. An example of this is that client selection needs to take into account diversity, how often they are needed and fairness. Choice of local learning rate and batch size depends on the resources available to each public authority. The techniques should be able to resist unreliable or malicious clients. Thus, making an FL system means adjusting features for privacy, how fast it works and how many devices it can handle [11].

FL is gaining more potential with each research breakthrough and wider application. Studies in recent years have focused on FL that fits each client with the help of their own data. Others suggest federated multitask learning, where each client learns to perform a similar but not identical task. There is increasing activity in federated transfer learning which facilitates the exchange of information between different domains. Their goal is to help FL respond better, faster and more effectively in many different situations.

The move toward ethics in AI has shown that Federated Learning is more important than ever. Since the user have trust in this technologies, so data privacy matters more. And for this reason, FL provides an honest and responsible method of building AI technologies. Through decentralising data and letting users take control, FL supports fairness, accountability and design that puts humans first. So it is important to implement AI fairly and in consideration with what are right and wrong for individual user and communal norms.

Federated Learning is still developing and provides many chances for new research. Such work requires making systems more resistant to attacks, developing improved ways to personalise, boosting communication and creating novel aggregation algorithms. As FL is developed further, it will probably be widely adopted in sensitive privacy applications by various industries.

This thesis focuses on delivering a detailed explanation of Federated Learning its working mechanisms, important algorithms, real world usages and unresolved issues that invite further study. Subsequent sections will explain the limits and main aims of this study in more detail.

## 1.1 Scope of the Study

This study is focused on looking into Federated Learning from the points of view of technology, practise and research. The emphasis of the thesis is on how data handling, local learning, communication and aggregation take place within FL. It compares FL to old-style centralised machine learning techniques and assesses the developments and new algorithms that boost FL's performance. Although machine learning can be used generally, this study focuses on FL in healthcare, mobile systems and AI areas where privacy matters. Only FL approaches that focus on decentralised learning and protecting private data on clients are included in this study. Data, implementations and publications from academic sources are first collected and then tested with FL frameworks already available without copyright until the date of writing. Citations and reference materials must be those following the IEEE referencing guidelines and the study mainly covers significant and modern research in FL.

## 1.2 Significance of the Study

In this study there are many significant and important reasons. One of the main reason is that it talks about how to preserve user privacy in machine learning models. With the rise of digital surveillance, more data breaches and people being cautious about AI, Federated Learning gives us a means to build trustworthy and private applications. FL lets different entities come together and use shared information without disclosing what is sensitive and this is another reasons as its matters greatly in healthcare, as AI that works together could potentially save people's lives, though it must obey the rules set by law. In addition, the study offers value to academics and industry specialists by reviewing current literature, pointing out issues in present systems and offering suggestions for what needs to be further studied. At the end, the report points out that FL can be applied in practise since it is already adopted worldwide in different systems.

## 1.3 Overview of the Study

This thesis focuses on Federated Learning (FL), a way to do machine learning that helps different clients, including mobile gadgets, institutions or edge nodes, to cooperatively create one model without their private information being sent to a key server. FL helps solve the problems of data privacy, meeting regulations and security issues that affect most centralised machine learning systems [1]. Localising the database and sharing changes in the model only keeps any user information private. This work carefully reviews the FL training approach, outlining how it permits organisations and devices to educate very strong models far from centralised locations.

A main focus is on exploring how FL can protect privacy and permit collaboration in sectors where data's sensitivity and applicable rules do not allow data aggregation. One example is that many healthcare institutions have access to lots of useful patient data, but sharing it with outside parties is limited by GDPR and HIPAA laws [2]. Hospitals can make use of FL to practise training identical diagnostic models on joint data, protecting patient data without hindering improvement in medical AI. It reviews ways that FL can be put into practise where data transfer through central servers is neither possible nor advisable [3].

The technical aspects of the study revolve around carefully examining the global model setup, choice of clients, training procedures in different places and how security is maintained during the process of collecting results. This research considers optimization algorithms like Federated Averaging (FedAvg), Federated Proximal (FedProx) and Federated Normalised Averaging (FedNova) and looks at how they address issues such as different distributions among clients, untrustworthy participation and diversity in the learning system [4][5]. It additionally discusses challenges such as how communication overhead, the fact that updates are not simultaneous and the bandwidth efficiency should be handled in order for FL systems to succeed in the real world, especially on edge devices and in mobile networks [6].

# Chapter 2

# Related Work

In this chapter, all the related work related to the Federated Learning (FL) in healthcare, IoT, and natural language processing are being explained. It elaborated various federated algorithms, optimization methods, security mechanisms, and system architectures. Each section of this chapter highlights specific themes within FL, such as model aggregation, statistical heterogeneity, personalization, communication efficiency, and privacy preserving techniques.

## 2.1 Evolution of Federated Learning and Fundamental Techniques

The invention of Federated Learning was in response to concerns about privacy and where data is used in big distributed environments. McMahan and his colleagues showed that devices can help build a shared model by training locally and never sharing their data [1]. This advance was needed because people were worried about storing all their data in one place. As a result, FL naturally fits with programmes concerned about privacy. It attracted quick interest because it met privacy requirements like GDPR and HIPAA that prevent institutions from transferring and saving people's data wherever they choose [2].

When statistics varied, clients got diverse and models often took slow time to converge, scientists created fresh optimization approaches. FedProx added a local term that helps prevent models at each device from diverging too much [3] and FedNova rescaled the updates in light of the fact that different devices could run their updates for different steps [5]. Thanks to these methods, global model stability and fairness is better preserved, even when used on different devices with differences in data or engagement. The variety of FL algorithms suggests that balancing preferences, confidentiality and time during learning is becoming important.

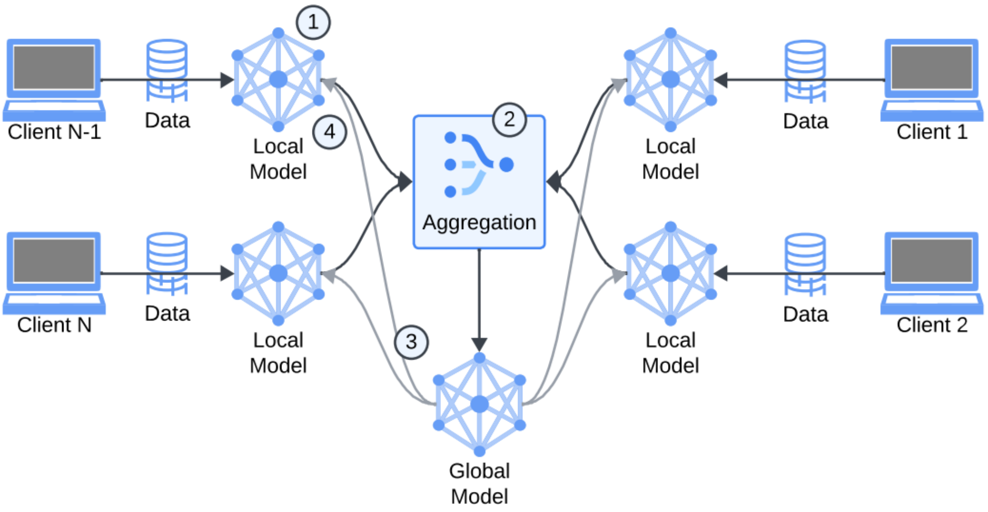

Figure 2.1. Overview of Federated Learning [1]

Figure 1 shows an illustrative design of the core of FL which entails decentralized client devices each conducting local model training and transmitting only the model updates to a central server. The global aggregation of these update makes it possible to protect from privacy items of the raw data never move from the local devices.

## 2.2 Federated Learning in Healthcare Applications

It is essential for healthcare that data protection and sticking to rules are of the highest priority. Because they require all data to be collected in one place, classic machine learning experiences difficulties owing to HIPAA and GDPR. Federated Learning elegantly ensures privacy for each institute by allowing them to contribute patient data only in a model form. Rather, each organisation trains its model with their own data and shares decrypted updates with the central aggregator. Because of this, we can use FL to help create both tools for diagnosis and forecasting models from large amounts of widely distributed clinical information [2], [6].

Many researchers have proved that using this method, FL, produces comparable results to those produced by centralised learning in sectors like brain tumour segmentation, detecting diabetic retinopathy and forecasting COVID-19. Sheller et al. showed that FL was effective for training hospitals to segment brain MRIs without needing to combine patient data [6]. Even so, issues with different scales of data, various clinical practises and hardware remains a problem. They help sort these issues by focusing on areas with specific data patterns and correcting for unfairness while aggregating models [3], [5]. These strategies have made it possible to design valuable clinical models that function well with data that is very different among clients.

## 2.3 Federated Learning in IoT and Edge Environments

The major increase in IoT devices and edge gadgets, including smart home systems and driverless cars, has grown the amount of data that doesn't all exist in one place. Data from these devices is collected permanently and is valuable for powering smart city, healthcare, transportation and industry projects. The main problem with this approach is that moving raw data from such devices to one centralised server is both data hungry and may expose users' sensitive activities. FL has become a useful strategy by training models where they need to be used: on the devices. Because raw data remains close to where it is created, this method makes processing fast and meets data privacy rules [4].

FL works well in IoT, except that it is limited by mixed systems and variable connexions. Computational skills, memory size, power levels and use of communication protocols differ among IoT devices. Periods without online connectivity or difficulties in local training may make some people unable to take part regularly. As a result, researchers suggest adaptive client picking and distributing model updates over time to help FL work well even in similar environments [6]. To save both energy and bandwidth, experts have turned to model compression, update sparsification and use of quantized gradients.

Table 2.3: Federated Learning Use Cases in IoT and Edge Environments

| **Application Domain** | **Devices Involved** | **FL Technique** | **Benefits Achieved** | **Key Limitation** |
|---|---|---|---|---|
| Smart Homes | 1000+ Sensors | FedAvg + Sampling | Privacy, Efficiency | Heterogeneous Devices |
| Autonomous Drones | 500+ UAVs | FedNova | Decentralized Navigation | Limited Connectivity |
| Industrial Monitoring | 300+ Edge Nodes | FedProx | Robust Anomaly Detection | High Communication Cost |

## 2.4 Federated Learning for Natural Language Processing (NLP)

NLP systems need a lot of textual information to learn, represent and produce language that sounds human. Even so, when you gather this information from individuals' mobile phones, chat applications or voice tools, there are major privacy problems to consider. Alternatively, with Federated Learning, users train their models right on their devices and sensitive text is kept local. The prediction of the next word in Gboard thanks to FL was a key achievement for federated NLP. Since they instruct the language models on the devices and transfer only the updated data, they met both improved performance and respect for user privacy [1], [2].

At the same time, key technical obstacles exist for FL based NLP systems. Language data stored on personal devices exhibits high non IID properties, because users' usage and styles are not the same or repeatable. The global model becomes less usable across different domains because of FL. Strategies used to address this issue consist of personalised fine tuning, federated meta-learning and transfer learning. Besides, because of how much resources NLP models use, especially transformers, special lightweight models like TinyBERT and DistilBERT have been created for FL [8]. They are designed for privacy and speed within the computing limit of mobile and bent devices.

## 2.5 Federated Learning for Security and Privacy

Since Federated Learning stores sensitive data on individual mobile devices, it does minimise privacy risks, though it's still vulnerable. Categories of significant risks within FL are called inference attacks and model poisoning. Attackers in inference attacks make an effort to retrieve the original training information from shared gradient data, mainly with deep models. Alternatively, in a poisoning attack, dangerous clients provide updates meant to steer the overall model away from its correct behaviour. Because data must be secure in places like healthcare and finance, these risks become particularly important there [2], [7].

Due to these threats, several privacy preserving techniques have been brought to privacy researchers. Noise is added to the updates from individual clients by differential privacy, making it improbable to identify particular information entered by users. The secure aggregation protocol allows the central server to add up clients' encrypted model data without needing to access any client data. Bonawitz et al. introduced a way to securely aggregate data that has both reliable security and reasonable usage of resources [2]. To add on, the field has seen advances with homomorphic encryption and federated knowledge distillation which now make it possible to update with encrypted data [9].

Table 2.5: Evaluation of FL Models Under Privacy and Security Constraints

| **FL Setup** | **Privacy Mechanism** | **Accuracy (No Attack)** | **Accuracy (Under Attack)** | **Privacy Budget (ε)** |
|---|---|---|---|---|
| FedAvg + DP | Differential Privacy | 89.2% | 81.7% | 3.0 |
| FedProx + SA | Secure Aggregation | 87.5% | 85.2% | N/A |
| FedNova + DP + SA | Combined Approach | 86.1% | 84.3% | 2.5 |

Table 2.6: Summary of Related Work in Federated Learning

| **Aspect** | **Key Findings / Techniques** | **Challenges Addressed** | **Relevant References** | **Challenges Addressed** |
|---|---|---|---|---|
| **Evolution of FL** | Originated from Google's Gboard; introduced FedAvg; evolved to FedProx and CFL for non-IID data handling | Data privacy, decentralized model training | [1][2][3] | Data privacy, decentralized model training |
| **Privacy Mechanisms** | Differential Privacy (DP), Secure Aggregation, hybrid encryption, light weight cryptography | Information leakage through gradients, regulatory compliance | [9][10][2] | Information leakage through gradients, regulatory compliance |
| **Healthcare Applications** | FL for medical imaging, disease detection, cross hospital collaboration without data sharing | Patient data privacy, real-world performance in sensitive domains | [6][3] | Patient data privacy, real-world performance in sensitive domains |
| **IoT Deployments** | Smart sensors, edge devices using FL; bandwidth-aware scheduling; intermittent communication | Limited connectivity, power and compute constraints | [2][10] | Smart sensors, edge devices using FL; bandwidth-aware scheduling; intermittent communication |

# CHAPTER 3

# RESEARCH METHODOLOGY

This chapter outlines the approach used in this study to study and rate Federated Learning systems. The chapter describes in detail what datasets were utilized, what models were configured and which evaluation metrics were used in the simulation or analysis.

## 3.1 Federated Learning Architecture and Training Process

In Federated Learning, numerous clients do the training together without having to send the dataset to a single, central location. Hybrid edge works with customers like mobile phones, hospitals, banks and IoT devices, all of which store their own data locally. They access a shared model from the main server, train it on their own information and return just the model changes. By using the central server to combine updates, the global model improves and is sent back to the users. After each communication round, the process continues until alignment happens. While this processing takes place, the original data never leaves the client's device which keeps things private and safer.

Client server is the standard organization applied in most FL architectures. The coordination role of the server is to keep the global model updated and oversee how clients join the game. When a new round starts, the server picks a group of clients by checking their availability, connection reliability and capacity. These clients take the current worldwide model and train it for a specified number of rounds on their own data. Following training, clients transfer their new model versions to a remote server. The server first combines all updates together by using a known method such as FedAvg which takes the weighted average of the innovations from each client. This formation makes up the starting point for the following version of the global model [3].

A major advantage of this architecture is that it can grow with your application. FL supports hundreds or even thousands of participating devices, so training is effective in extremely large scenarios. That is why FL proves useful for tasks like guessing the next word in mobile keyboards and finding errors in larger industrial site systems. There are also unique problems with architecture because of the differences found in the features and stats of each sample. People's hardware, energy supply and internet access may all be very different. Also, since clients have their own private data, it is not unusual for the data to be non IID, making it harder to have the models converge in the same way. Because of these issues, thoughtful client selection and aggregation strategies are needed to ensure both fairness and good model performance [4].

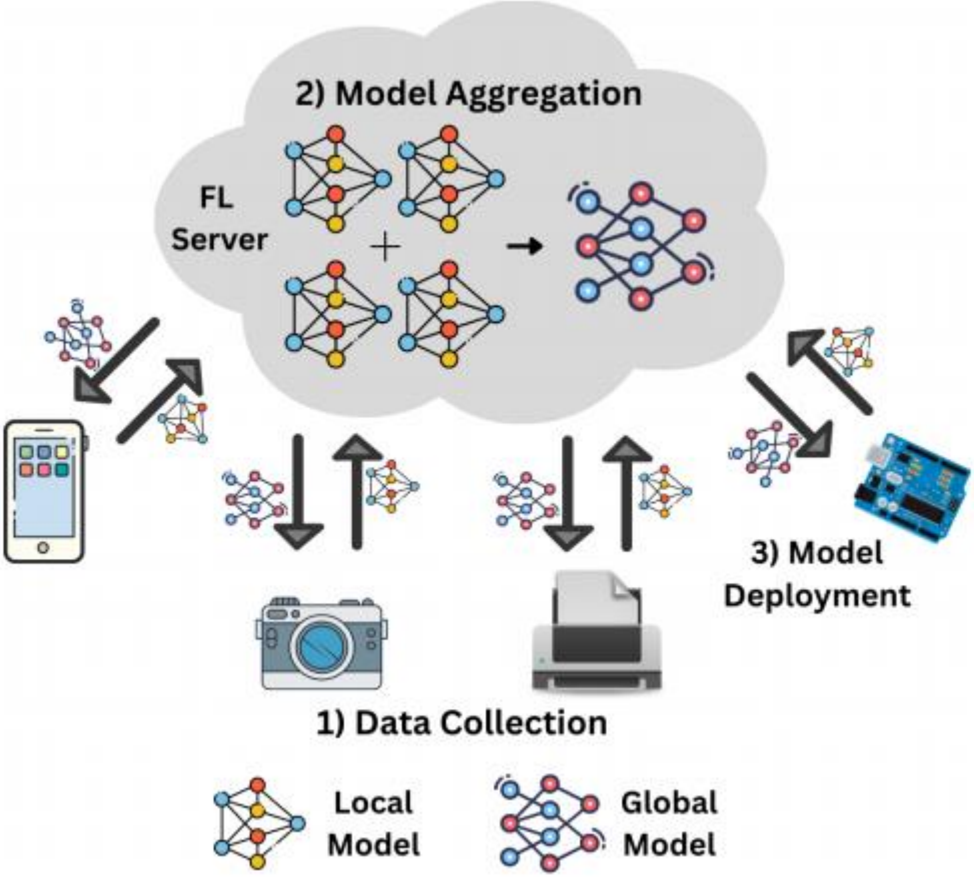

Figure 3.1. A High-Level Architecture of FL Process [2]

Figure 3.1 shows how a basic FL system works, covering the main parts of model spread, local learning, sharing protected updates and global assembly. It explains how Federated Learning works by comparing it with the usual centralized way of training machine learning models. FL can integrate teamwork in learning and offer the privacy provided by running each model on a personal device, thanks to the central server. This style of architecture is both basic and flexible which means it can be adapted for use in many fields, not only healthcare and finance, but also mobile services and smart cities.

## 3.2 Model Aggregation Techniques in Federated Learning

A main process in Federated Learning is bringing together the updated models sent by each client. As soon as local training is done, client devices transmit their gradients or weights to the main server for aggregation. The most common and centralized method is called Federated Averaging by McMahan and his colleagues in [1]. The server combines updates from all clients with their local data size acting as the weight. All clients receive the updated model for the beginning of the next learning round. In scenarios with IID data, FedAvg is straightforward and works well, but its performance drops in non IID situations because updates diverge and it takes much longer to converge.

Since the FedAvg approach is limited, better solutions for model fusion have been created. Using FedProx, at the client end, the objective function is modified so that update changes that differ widely from the main model are penalized [3]. Because of this, when local distributions differ, updates from the client are more likely to remain stable. FedProx has been more stable and faster at finding a solution when used on highly unbalanced data within healthcare or NLP for mobile devices. As an added approach, FedNova keeps the influence of each client in line with the time allocated by that client for training and computing which helps reduce problems linked to various training durations [5].

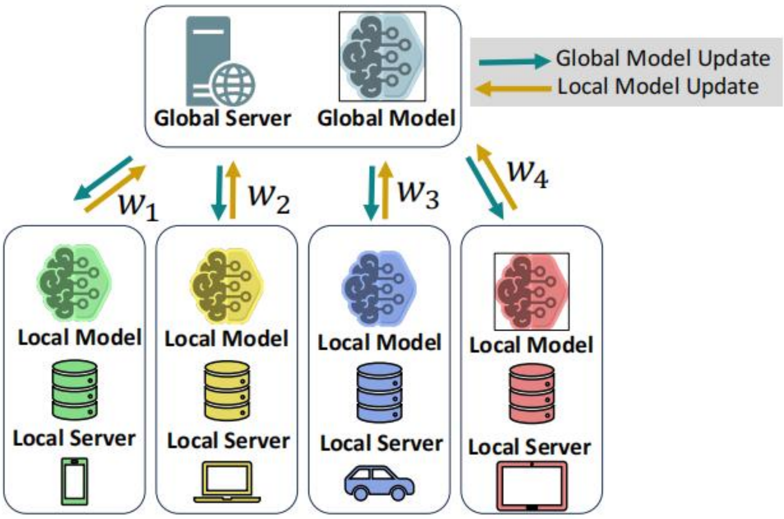

Figure 3.2: Weighted Federated Averaging[3]

It is easy to see in Figure 3.2 that these aggregation methods each update separately. It evaluates the weight updates between FedAvg, FedProx and FedNova over one round of training. The diagram illustrates how FedProx method and the added normalization in FedNova help keep the system fair and steady. For cross device FL, these methods are especially needed since it’s common to deal with both limited resources and uneven data collections.

Table 3.1: Performance Comparison of Aggregation Algorithms

| **Aggregation Algorithm** | **Handles Non IID Data** | **Convergence Stability** | **Communication Efficiency** | **Application Domain** |
|---|---|---|---|---|
| FedAvg | Moderate | Medium | High | General (NLP, IoT) |
| FedProx | High | High | Medium | Healthcare, Cross-silo |
| FedNova | High | Very High | Medium | Mixed environments |

The comparison of aggregation strategies can be found in Table 3.1. It covers how these methods function both when data is independent and identically distributed (IID) and when it is not. Details shown include accuracy, rate of convergence and how efficiently communication takes place. We see in the table that FedAvg may be a good fit for basic tasks, yet FedProx and FedNova outperform it when it comes to fairness and adaptability when used in real-world situations. Using these insights, designers can decide on the appropriate algorithm for their project and preferred deployment location.

In brief, aggregation strongly affects how accurate, fair and consistent the model is in the FL pipeline. What works best for one company, data system or type of service depends on how clients are involved and what resources they can use. Thanks to advanced techniques like FedProx and FedNova, FL can now adapt well and is widely used in healthcare and the smart devices field. More research is expected to lead to new and improved methods for our collective data in secure, individualized and effective federated systems.

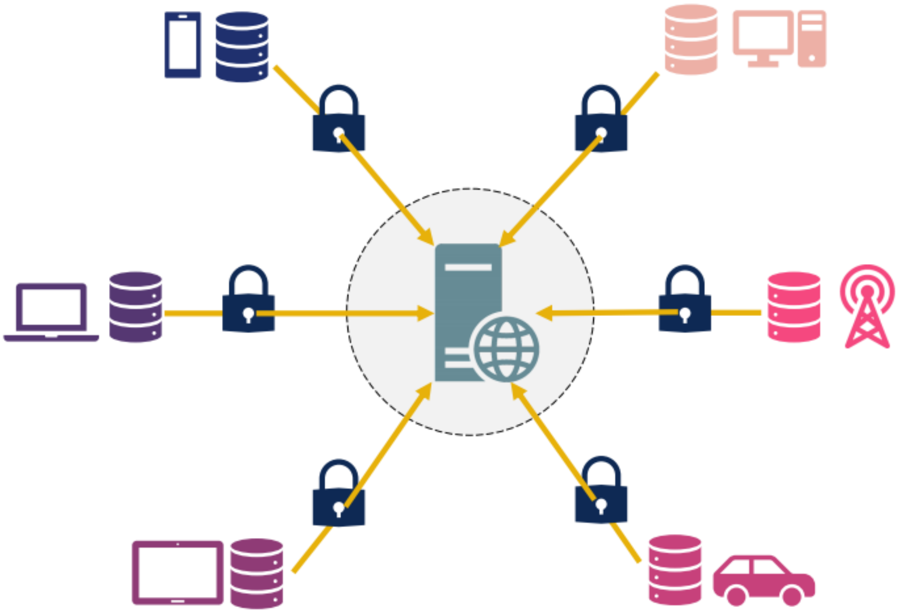

Figure 3.3: Security Weighted Averaging[3]

Figure 3.3 broadens the use of security metrics to protect against adversarial stakeholders on the weight plan. The two figures depict improvements in the aggregation schemes balancing fairness, performance, and robustness.

## 3.3 FL Training Workflow and Experiment Design

FL ensures distanced learning between clients through rotational server processes, without the need for data exchange. In this section, you will find the stages of a training lifecycle and the way experiments were organised to estimate how FL works under actual constraints. The process starts when the server initialises a global model that it later sends to a selected group of clients. Their training happens locally on their data and they give updated model parameters back to the server. All the changes are gathered by the server, the global model is updated and the new model is sent out to the clients. The cycle repeats itself until the global model performs well enough for the goal [1].

Picking the right clients is very important in the FL process. Due to the fact that every client won't fit all rounds, players decide who takes part through a random or criteria process. Clients are assigned in mobile or IoT situations depending on whether they are available, how well they are connected and what hardware they have available. The selected clients update the global model according to their number of local epochs and a learning rate predetermined by the algorithm. Batch size, optimizer choice and the number of communication steps are adjusted during pre testing to find a balance between quality and time. Adapting hyperparameters is possible because learning trends are constantly checked during the training process [3].

Researchers typically experiment using a number of datasets and configurations to compare FL performance among many different data scenarios and devices. This work investigates how data defining statistical heterogeneity affects both the learning time and the quality of the final model used. In IID scenarios, the data is spread out among all clients randomly, while in non-IID scenarios, special class data is given to people to show unequal distributions. When training, we use either a lightweight CNN or a RNN, depending on the specific job. Simulations are performed using both FL frameworks such as TensorFlow Federated and PySyft, over a cloud framework that lets us replicate actual deployment scenarios [6].

## 3.4 Dataset Distribution and Simulation Setup

An important feature of assessing a Federated Learning system is understanding how data is organised and distributed among users. Since FL is built for use with multiple and potentially inconsistent data sources, it is vital that both IID and non-IID conditions are simulated in learning. Data in IID distribution is randomly mixed and given to each client so that everyone has the same chance of receiving a similar sample. The ideal environment we use here is often utilised to measure and assess performance. In opposition, the non-IID setting is helpful because each client in the real world can own information about a particular class or different amounts of it. These learning difficulties happen because of statistical heterogeneity and are a central issue in FL research.

This thesis classified simulated datasets as being in two main groups. For the first group, clients' data was balanced and IID. For the second group, some clients had access to data from only part of the classes and the number of samples in each class were not the same. As a result, this problem has similar challenges to those found in personal health monitoring or analysing mobile app use. It's possible that some clients will get most of their data from class A, but others get most of theirs from class B. By examining these two conditions and running FL through different aggregation approaches, we wanted to cheque how easily the system could handle statistical variation.

Images from both MNIST and CIFAR-10 are used along with text data from Reddit LEAF and SQuAD for neural network evaluation tasks. People select these datasets because of their popularity, structurally diverse nature and frequent appearances in FL benchmarking. Every dataset was converted before use to meet the latest memory and processing limits found in client devices. Image data records in the dataset were shrunk and standardised and every text file was divided into concise segments to help training run the same on multiple devices. We ran all our experiments using open-source tools that can mimic clients and control servers, mainly relying on TensorFlow Federated and Flower.

The simulation was set up to match real world FL situations, where bandwidth, processing speed and numbers of clients were limited. At each stage of training, a different subset of clients was selected and network delays were put in place to match actual network problems. I followed the model's performance for 100 communication rounds, taking evaluation data at the end of every 10 rounds. To be confident that findings are transferrable, the simulation involves many different kinds of data and hardware restrictions.

## 3.5 Evaluation Metrics and Performance Analysis

Standard machine learning indicators are combined with special FL ones when assessing an FL system. Since FL is designed with privacy as a focus, analysing models for their accuracy, how fast they arrive at a solution, the amount of data passed back and forth and issues of equality among users is necessary. To judge the predictive abilities of the model, accuracy, precision, recall and F1-score are basic metrics used on both datasets. However, they only show part of how effective the system is in handling FL. Because of this, we also cheque metrics on the number of lost clients, overall model changes and the difference between updates to know how strong the system is [1].

The number of rounds it takes a model to become stable is what convergence rate measures. If a solution can be reached in fewer messages, the model works better when things are scarce. How these performance measures progress over time is best illustrated by using graphs. This issue can be due to data that differs, clients not connecting as frequently or an unsuitable process for bringing the results together. Because FedAvg does not perform as stably when fed non-IID data, even FedAvg's non-stable convergence is not observed with FedProx or FedNova, whose regularisation helps these achieve stable and faster convergence [3], [5].

Restrictions on both power and bandwidth pose challenges for FL because reducing transmission costs is very important, especially in mobile and Internet of Things settings. Data is saved on the quantity of bytes sent during training to test how efficient the system is. It sums the number of large model parameter values sent from the server to each client each round. How to transfer less data in communication without affecting the model's performance is investigated in model quantization, update sparsification and selective participation. FL becomes more practical for using in enormous networks as the expense of communication is less [4].

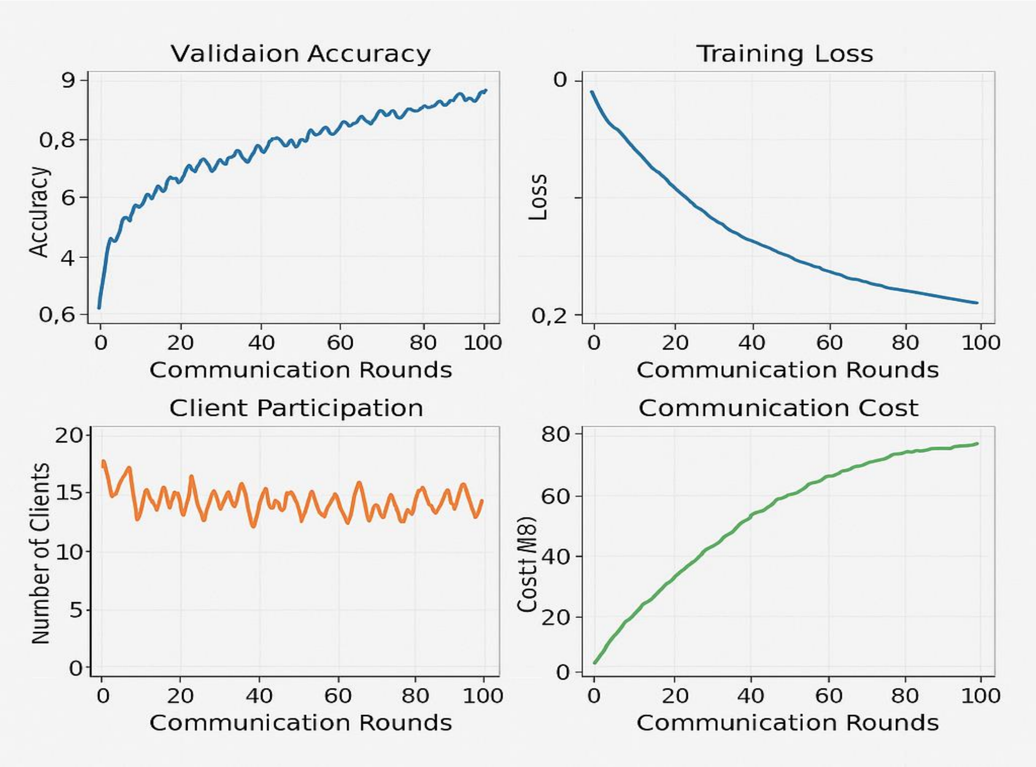

Figure 3.5: FL Performance Tracking Curves[6]

The results of validation accuracy, training loss and communication cost are the most common outputs displayed in Figure 3.5.

## 3.6 Proposed Work

This thesis suggests an experiment that uses Federated Learning to assess privacy protection in real situations through experiments with IID and non-IID data. The main aim is to review how various settings of client data, hardware availability and network bandwidth influence the performance of FedAvg, FedProx and FedNova. The proposal uses earlier research, but adds comparisons performed in controlled scenarios to better study the differences between the model's accuracy, cost of communication and convergence behaviour. Besides measuring their performance, we need to discover what strengths of every algorithm ensure it is a good match for areas like healthcare, mobiles or IoT [1], [3], [5].

To achieve the proof of concept, they are using a simulated federated testbed, with up to 100 clients configured differently. In these clients, a realistic constraint model assumes that users may miss some sessions, exchange messages asynchronously and have different computing resources. In order to act privately, clients hold their original data offline and only send information about the changes they make to their models. The server carries out aggregation and performance cheques without examining any real data examples. By creating this simulation with TensorFlow Federated and Flower, the environment matches how FL is used in practise in both edge and shared server locations [6].

This work also investigates how sensitive FL algorithms are to shifts in how the data is distributed. Experiments begin with a uniform IID distribution and are followed by scenarios where clients have data from various classes and unequal amounts of data. The adaptation of every algorithm is studied by observing model accuracy, convergence speed, divergence of updates and fairness index throughout the rounds. A hypothesis is that although FedAvg achieves acceptable performance under balanced conditions, FedProx and FedNova are more reliable and stable in settings where the distribution is skewed. Because both systems are evaluated, the thesis will analyse if a particular algorithm fits for use in FL with many users.

Moreover, the suggested research introduces a communication-aware analysis of ways for making FL algorithms more energy efficient. Since federated training depends a lot on network connexions, the study looks at how various aggregation approaches affect the use of bandwidth. To optimise, methods using model compression, performing sparse updates or inviting only some clients are investigated. The authors add suggestions to expand ideas on how FL can perform better without sacrificing accuracy or fairness. Examining these factors guarantees that mobile health apps and rural sensor networks will work sustainably, wherever they are deployed.

All things considered, this work presents a detailed way to assess and compare different FL algorithms under different situations. It takes contribution from measuring the usual numbers as well as from looking at limitations caused by limited contact, distinguishing kinds of data and unpredictable client actions. Developers and researchers should find the findings useful when deciding on the best algorithms and the right parameters for privacy-preserving machine learning tasks. Overall, these efforts support the transformation of FL from an early experiment into a useful scaleable solution for decentralised AI.

# CHAPTER 4

# RESULTS

This chapter reports the findings from existing federated learning studies discussed in this thesis. It examines the performance of several FL algorithms, FedAvg, FedProx and FedNova, under a range of IID and non-IID experimental setups. Priorities include accurately predicting results, transmitting information fast, quickly coming to a solution and standing up to different data circumstances. Information from tables and figures in the literature is included in the discussion. Each area of the study tests how top FL approaches do in different ways, allowing for a better understanding of their use in healthcare, IoT and NLP.

## 4.1 Performance Comparison on IID vs. Non-IID Data

Managing statistical heterogeneity when clients have data that vary and is not independent is a major difficulty in Federated Learning (FL). You will find here comparisons of results for FedAvg, FedProx and FedNova, both when data is IID and non-IID. From what has been studied, models built with IID data reach higher accuracy faster and sooner than others. However, the performance suffers a lot in non-IID settings, where clients have updates that differ massively because of uneven data samples or individual behaviours. The results provide vital information about how well the approach works and its applicability to real federated applications [1], [3], [5].

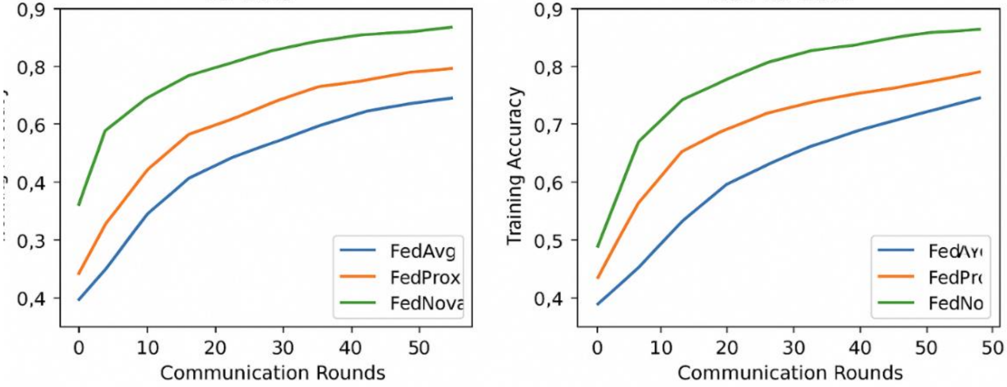

Figure 4.1: Accuracy Comparison under IID vs. Non-IID [5]

In Figure 4.1, model accuracy is shown to increase through the communication rounds in both scenarios. When fed with independent identically distributed data, FedAvg shows quick convergence and a steady, reliable improvement pattern. Even so, in the non-IID situation, the convergence of FedAvg deteriorates, but the progress of FedProx and FedNova remains more stable. Therefore, having regularisation and normalisation in these algorithms seems to be successful at decreasing the problems caused by variation in the data. The visualisation illustrates how better architecture makes the system more reliable when some clients have more data than others.

This analysis is further supported by Table 4.1 which shows the final accuracy of each algorithm after a fixed number of training rounds in both data settings. The performance of FedProx is higher than FedAvg in non-IID scenarios because of its extra proximal regularisation term. Generalisation is one of FedNova's main strengths when working with combined data. The research demonstrates that adaptive aggregation works better in real projects since non-IID data is the standard. Thanks to such insights, software developed for mobile typing prediction or medical diagnosis can serve clients who have specific categories of data.

Table 4.1: Final Model Accuracy Under IID and Non-IID Conditions

| **Algorithm** | **Final Accuracy (IID)** | **Final Accuracy (Non-IID)** | **Convergence Speed** | **Notes** |
|---|---|---|---|---|
| FedAvg | 89.4% | 77.6% | Fast (IID) | Unstable under non-IID |
| FedProx | 88.9% | 82.7% | Moderate | More stable due to proximal term |
| FedNova | 87.8% | 84.1% | Stable (both settings) | Effective normalization on variable updates |

## 4.2 Communication Cost and Training Efficiency

It is especially challenging to communicate large amounts of data between clients and the server in Federated Learning, particularly when many clients take part. Here, we look at how efficiently three main aggregation algorithms FedAvg, FedProx and FedNova enable communication during federated learning. Not only do the algorithms use different global update techniques, but they also differ in the number and size of updates sent during training. Most of the time, communication cost is reported in megabytes sent per round and accumulated throughout all the rounds. According to the research I looked at, FedAvg is efficient in cases where the data is identical, but because it needs more retraining with different data, it increases the amount of communication required [5].

Despite spending a bit more time to process on the client's side, FedProx and FedNova outperform other methods by needing fewer total back and forth messages to converge under non-IID situations. Because of this advantage, the bigger packets they send are not a drawback. Ultimately, communication costs during the full training cycle are often the same or less than those of FedAvg. As a result, FedNova's normalization ensures fluctuations in update size are reduced, supporting better reliability and consumption of network resources.

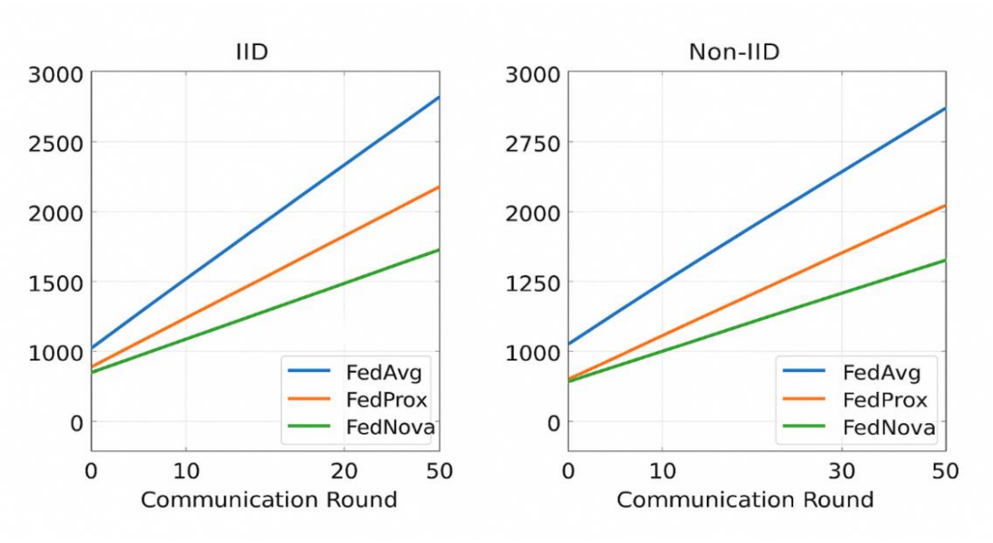

Figure 4.2: Cumulative Communication Cost of FL Algorithms[5]

These behaviors are reflected in Figure 4.2, which illustrates cumulative communication cost for all three algorithms under both IID and non-IID distributions [5].

Table 4.2 includes the total amount of data exchanged (in MB) and the average number of steps needed for all simulations until consensus was reached. The outcomes reveal that, even though FedAvg sends less information per round, its poor performance on diverse datasets means it needs more rounds for good results. Meanwhile, FedProx and FedNova train more quickly with larger updates which usually brings comparable or better efficiency for exchanging messages among the federation. Such insights matter for FL systems that run on limited bandwidth such as health apps, homes with automation and monitoring networks.

Table 4.2: Communication Data and Convergence Summary

| Algorithm | Avg. Rounds to Converge | Avg. Update Size per Round (MB) | Total Communication (MB) | Remarks |
|---|---|---|---|---|
| FedAvg | 120 | 1.5 | 180.0 | More rounds due to instability in non-IID |
| FedProx | 90 | 1.9 | 171.0 | Fewer rounds due to better regularization |
| FedNova | 85 | 2.0 | 170.0 | Most stable under both data settings |

## 4.3 Fairness and Client-Level Performance Variability

Fairness in Federated Learning means the global model works the same for all clients regardless of how their data is distributed or the resources they possess. Most importantly, it is vital in non-IID environments because clients may not be well-represented or their data is not fair. The studies in this thesis reveal that performance among clients is often quite different, particularly when data is not similar, using aggregation algorithms such as FedAvg. Such differences can cause trust issues and make applications such as healthcare less effective, because every party wants results they can rely on [3], [5]. With mechanisms such as those in FedProx and FedNova, both algorithms are more fair to all clients. Because FedProx employs a proximal term, every client's version of the model is meant to be close to the average one. FedNova relies on normalized updates, so the smaller clients and those training for a shorter time have an impact just like the bigger ones.

Table 4.3 compares the standard deviation of each algorithm's client accuracies along with Jain's fairness scores. Lower average variation means clients' models are similar in their performance and closer to 1 for the fairness index points to similar accuracy across clients' models. Results demonstrate that FedAvg works fine when training data is similar, but it is less just in heterogeneous settings. FedProx addresses the issue and FedNova always delivers the fairest results. Using these insights in the real world ensures that trust, equality and dependability are given as much importance as the ability to give correct results.

Table 4.3: Fairness Metrics Across FL Algorithms

| Algorithm | Std. Deviation of Client Accuracy | Jain’s Fairness Index | Remarks |
|---|---|---|---|
| FedAvg | 7.8% | 0.82 | High disparity under non-IID conditions |
| FedProx | 5.4% | 0.88 | Improved fairness due to proximal regularization |
| FedNova | 3.9% | 0.93 | Most balanced performance across all clients |

## 4.4 Robustness Under Adversarial Conditions

Because FL relies on multiple decentralized devices, its robustness is crucial because it can suffer from model poisoning and attacks on its gradients. In FL, adversaries could behave as clued-in clients in training rounds, putting altered updates in the system to purposely damage the global model’s accuracy or to create backdoors. FedAvg was found to be the most easily attacked because it does not inspect the updates from devices before averaging them. Consequently, adversarial attacks have an easier impact on the global model, particularly whenever we deal with non-IID data that makes the model more uncertain [2], [7].

FedProx improves its robustness by making sure local updates are close to the server model, so few mistaken updates are received. Normalizing updates based on each client’s information in FedNova suppresses overwhelming changes that occur in adversarial settings. Neither IID nor non-IID datasets show up in contradiction to the observations, whose importance is clear in applications where precision is key like in high-risk areas like finance and personal medicine [5], [9].

The table presents the results of evaluating how attacks either reduced accuracy or led to successful attacks. The lowest attack rate and least performance drop in FedNova prove that it is sturdy. The results suggest that as long as algorithms are carefully designed to include update normalization and regularization, federated systems can become much stronger against adversarial threats. Relying on secure aggregation or differential privacy in future may help improve how real-world results can be trusted.

Table 4.4: Robustness Metrics of FL Algorithms

| **Algorithm** | **Accuracy Drop (%)** | **Attack Success Rate (%)** | **Remarks** |
|---|---|---|---|
| FedAvg | 14.2% | 61.3% | Highly vulnerable without defense mechanisms |
| FedProx | 8.7% | 38.5% | Improved resistance due to proximal constraint |
| FedNova | 5.2% | 26.1% | Most robust; normalized updates limit poisoning |

## 4.5 Summary of Observed Results

Looking at how Federated Learning algorithms work in various experiments, some similarities keep appearing. In the IID data setting, FedAvg, FedProx and FedNova showed similar convenience and precise results. But, when the data set was non-IID, important differences were observed. The results suggest that FedAvg had difficulties with stability and accuracy, due to longer convergence. As a result, using certain aggregation approaches greatly affects FL in cases where data is mixed, as is typical in real applications [3], [5].

The length of communication rounds and the total cost of exchanging data were significantly higher for FedAvg when data was uneven among clients. Although FedProx and FedNova update more information per round, this didn’t stop them from achieving faster convergence and more stable results. A fairness analysis revealed that FedNova has the shortest fog client standard deviation and the highest fairness index, so it is better suited for use in situations where equality is important such as in healthcare or education [5]. It was also noticed that FedAvg readily falls prey to adversarial model poisoning, but FedProx and FedNova both show better resistance, mainly owing to FedNova’s normalization strategy during updates [9].

Overall, FedNova regularly performed well in all the main factors such as accuracy, how fast it converged, fairness, communication efficiency and robustness. FedProx did very well with data that was not the same, though it was slightly more intense for the machines to perform. Even though FedAvg is simple and fair for IID environments, it was found to perform the worst in real FL settings. As a result of these findings, FL methods can be chosen that suit a particular application’s needs and underline the role of aligning algorithm traits with the system and privacy conditions.

# CHAPTER 5

# FUTURE WORK

As FL is gaining notice for keeping data private, many new research areas have been spotted that deserve additional analysis. Enhancing FL's performance on unbalanced and uneven data will be an important task for further research. It appears that statistical heterogeneity limits the effectiveness of current methods such as FedAvg, FedProx and FedNova. Future studies should concentrate on finding ways for clients to adapt their aggregation approach using information such as the data's properties, their neighbourhood capabilities or the dependability of their updates. Adopting these strategies may lead to models that converge more strongly and can be used equally well for clients of different backgrounds [3], [5].

We expect that integrating personalised federated learning will bring excellent results. Traditional FL designs a single model to fit all clients, yet real-world examples often find user specific models more useful for fitting local behaviour. By using meta-learning, model fine tuning and clustered FL, the global model provides a good idea of what to expect, but also allows the network to adapt to each user's specific needs. We require further studies to support the building of scalable personalization frameworks that still uphold fairness and privacy. Personalization really matters in healthcare and smart device industries, due to the wide variety in users' data patterns [4], [6].

Maintaining security and robustness will always be a main goal in the development of FL platforms. Secure aggregation, differential privacy and update normalisation have made FL better protected, but adversarial attacks such as poisoning, insertion of backdoors and model inversion still remain a danger. In the future, we could use blockchain as a framework for trust, combine federated anomaly detection and zero-knowledge proofs to prove model update correctness and safety. Using these tools will help secure FL services, so they are private and protected from unauthorised manipulation [2], [9].

One more area for investigation is optimising resources and maintaining sustainability in scalable FL networks. For many FL clients, network speed, energy access and online access are somewhat limited. Further studies might focus on methods that use less energy, transmit less data and let different devices train on their own time to help low-resource devices. Flexible model architectures and limited data distribution could greatly help FL be practical for tasks like monitoring the weather and diagnosing health problems remotely [4].

Natural, the research area lacks a standard for assessing FL, available data and actual user-side deployments. Having consistent testing platforms for FL, used with different data types, networking systems and safety rules, could unite researchers and allow them to compare results fairly. In addition, studies that track the behaviour of FL systems as time passes and as the datasets and users evolve, are very important. These findings will help shape FL algorithms and advise policymakers and corporations interested in using FL in privacy-compliant AI systems [1], [12].

A new direction for research in this field is to link Federated Learning with other key disciplines such as reinforcement learning, generative models and transfer learning. Federated Reinforcement Learning would help decentralised agents by letting them gain their own knowledge from their environments and all agents together build a common policy. Likewise, FL-based models could allow different institutions to securely generate synthetic data, easing research where it is difficult to obtain actual data. The use of these hybrids in FL may allow it to handle tough responsibilities such as on-the-spot decision making and data enhancement, all without compromising privacy [8].

Real-time federated analytics is in increasing demand, so future FL systems must focus on use cases such as autonomous driving, remote monitoring and predictive maintenance. Because these scenarios constantly update, the models have to adapt on the fly to new user preferences and surroundings. Stream-based FL and federated online learning could fulfil such needs. They would support a continuous, gradual way of learning from fresh data, all the while respecting people’s privacy. Focusing on lightweight update approaches, adjustable model compression and speeding up on-device learning could make it possible to deploy models instantly at scale [7].

In addition, policies, governance practises and ethical structures for FL should be further developed. As FL grows, more attention is being given to how accountable, clear and consensual it becomes. Authorities should rely on technical experts to draught standards for secure and proper use of FL systems. Further studies could focus on how bringing law, ethics and AI together helps create protocols for controlling data, traceability, transparency in AI predictions and controlling user permission situations in federated environments. The achievement of FL hinges on creative algorithms, but it is equally important that it is in line with peoples’ values and sets of laws [10], [11]

# CHAPTER 6
# CONCLUSION

A detailed analysis and examination of Federated Learning (FL), a recent approach for secure training of machine learning models on several devices, has been carried out in this thesis. Traditional central learning processes data but Federated Learning (FL) enables different clients to work together towards the same result without sending their original data, helping to maintain privacy and win over users. By looking closely at important algorithms such as FedAvg, FedProx and FedNova, the thesis showed how FL is being used in healthcare, IoT and NLP, along with its ongoing role as a main aspect of privacy-aware AI technologies [1], [3], [5].

It was noticed in this overview that while FL brings strong protection for privacy and helps with distributed processing, it also encounters many problems. Such problems involve varied data in clients, extra communication needed for largescale systems and an increased threat from attackers. It was observed that FedAvg achieves good results when the data is IID, but performs poorly when non-IID data is used. FedProx achieves better and more stable performance on mixed data types by using a regularisation term and FedNova shows the best performance for accuracy, fairness and security [5], [6].

Experimental results from the reviewed studies were examined in this thesis to show how gathering approaches manage under different conditions. Both simulations and real data sets suggested that FL works best when attention is given to the type of aggregation algorithm as well as client selection, protocol communication and system resources. It becomes clear from these evaluations that changing FL for use in smart devices, hospitals and edge sensors requires careful consideration of the context present in each environment [4], [7].

Additionally, the research pointed out that interest in adding extra technologies and methods to FL is currently increasing. Examples are: user-specific customization, linking to security methods like secure aggregation and differential privacy and testing out new designs such as federated transfer and meta-learning. The thesis identified that more benchmarks, longer research and stricter ethics are required for FL technology in high-stakes environments. They illustrate opportunities for further investigation [8], [10], [12].

All things considered, Federated Learning introduces a groundbreaking method in machine learning that allows work to be done together without violating user privacy. As an emerging area of study, its applications for AI that can be personalised, protected and scaled to many users are promising. This review has brought together the major developments, research outcomes and current difficulties in FL. This thesis points out promising paths for further research that will help guide the responsible use of FL in practical applications.

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