Federated Learning in IoMT

Introduction:

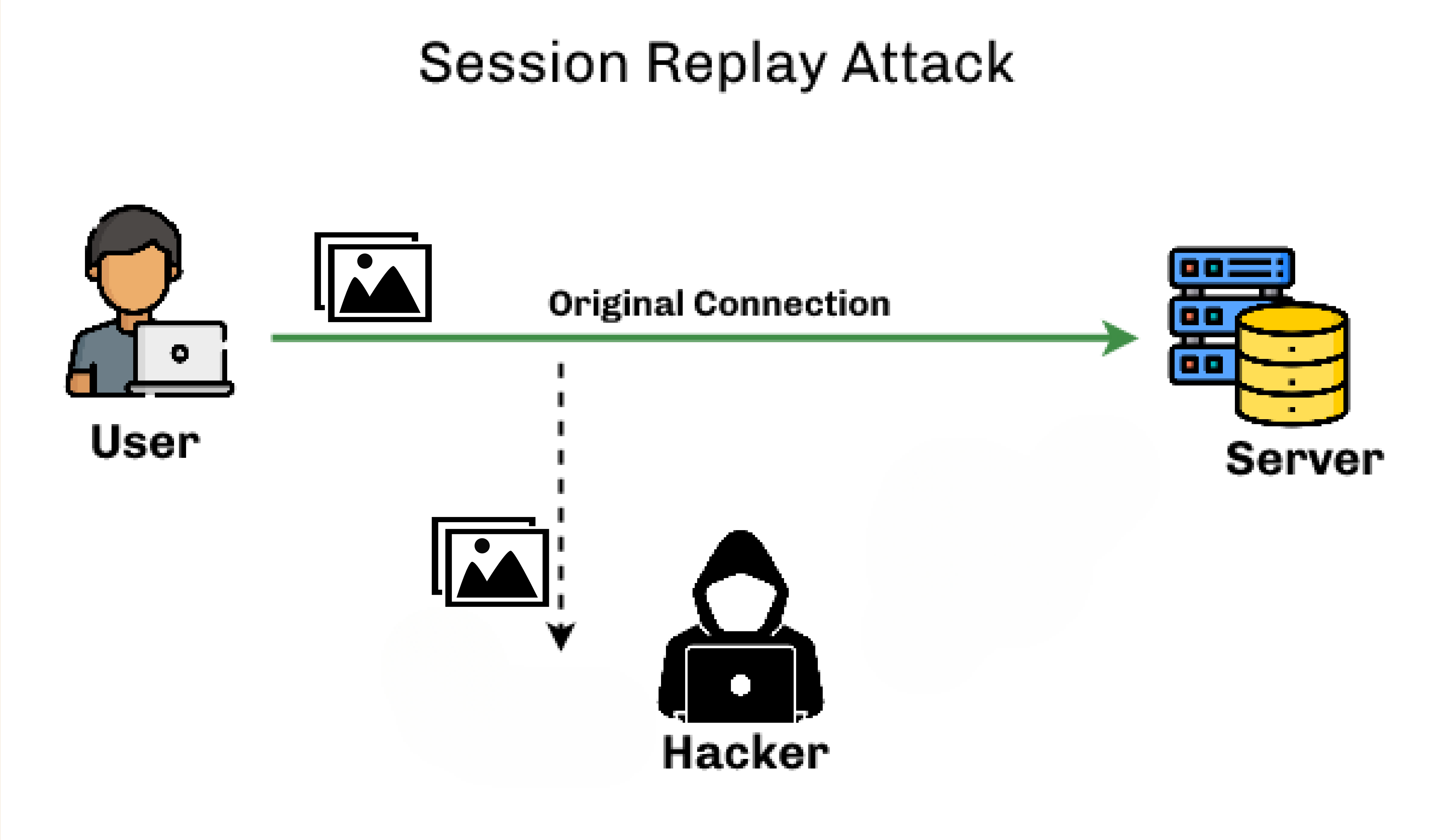
- Internet of Medical Things (IoMT) refers to the interconnected medical devices and applications that collect and share healthcare data.

- While Using machine learning, Healthcare institutes face privacy concerns as they need to send personal healthcare data to a model at some other place.

- So, to solve the problem of the centralized model, privacy concerns, and no security of data Federated Learning comes into action.

AI/ML in IoMT data:

Problems using AI/ML:



To solve such a problem, **Federated Learning** comes into action

Federated Learning

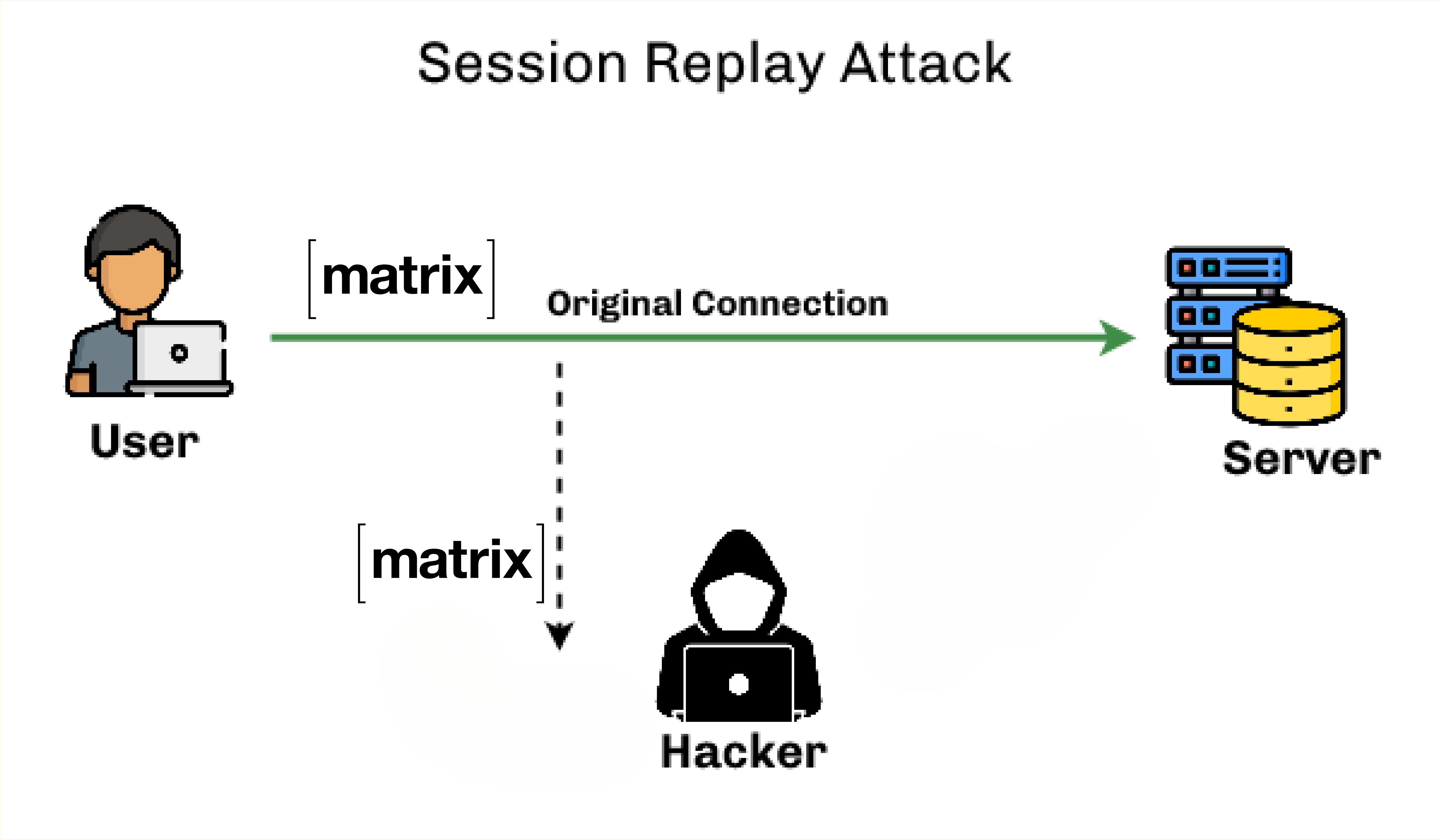
- Federated Learning is a decentralized machine learning approach where the model is trained across multiple edge devices without exchanging raw data.

- Models are trained locally on individual devices, and only model updates (not raw data) are sent to a central server.

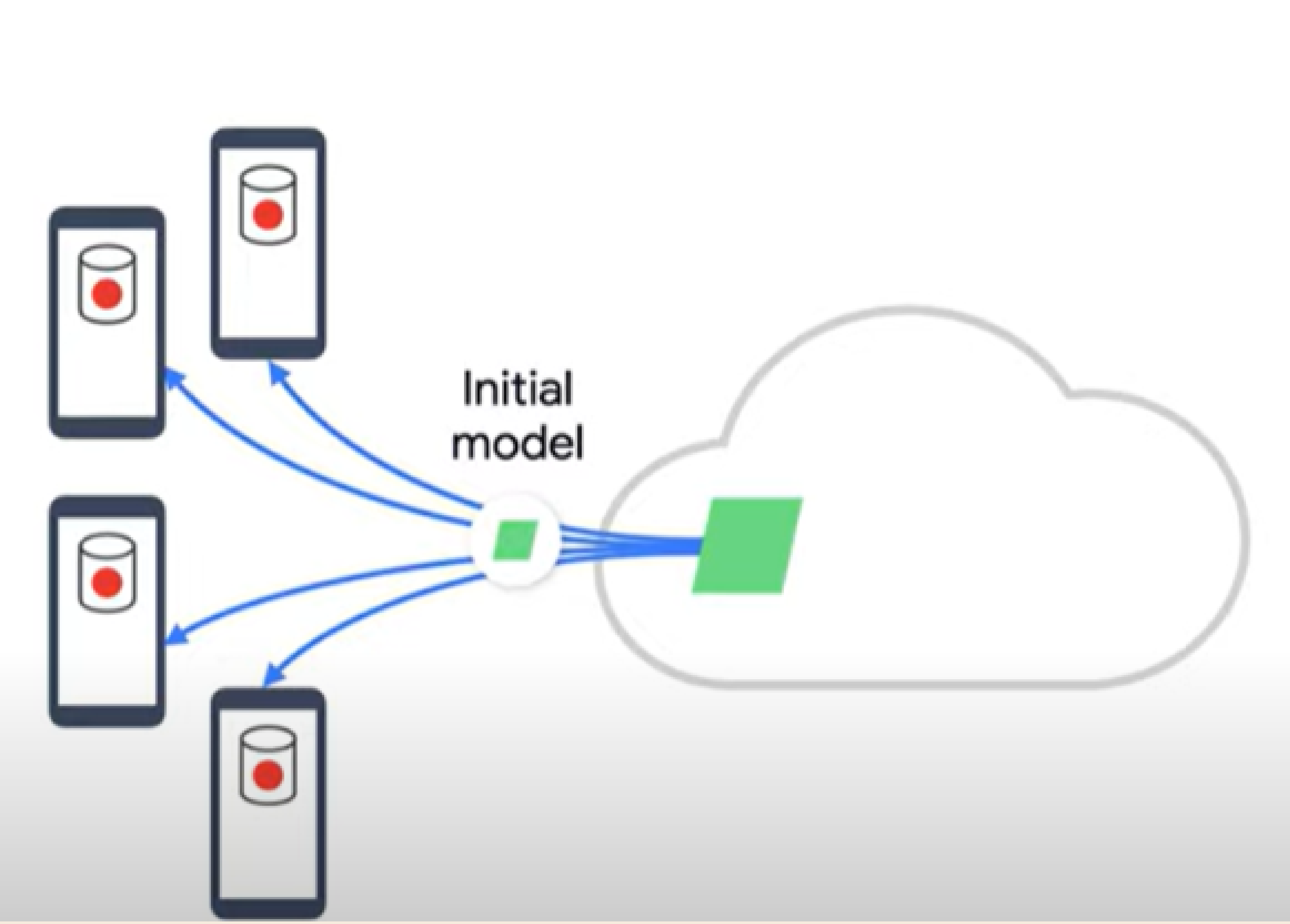
- Raw patient data remains on local devices, reducing the risk of centralized data breaches.

- Models improve over time by leveraging insights from diverse datasets without centralizing the data.

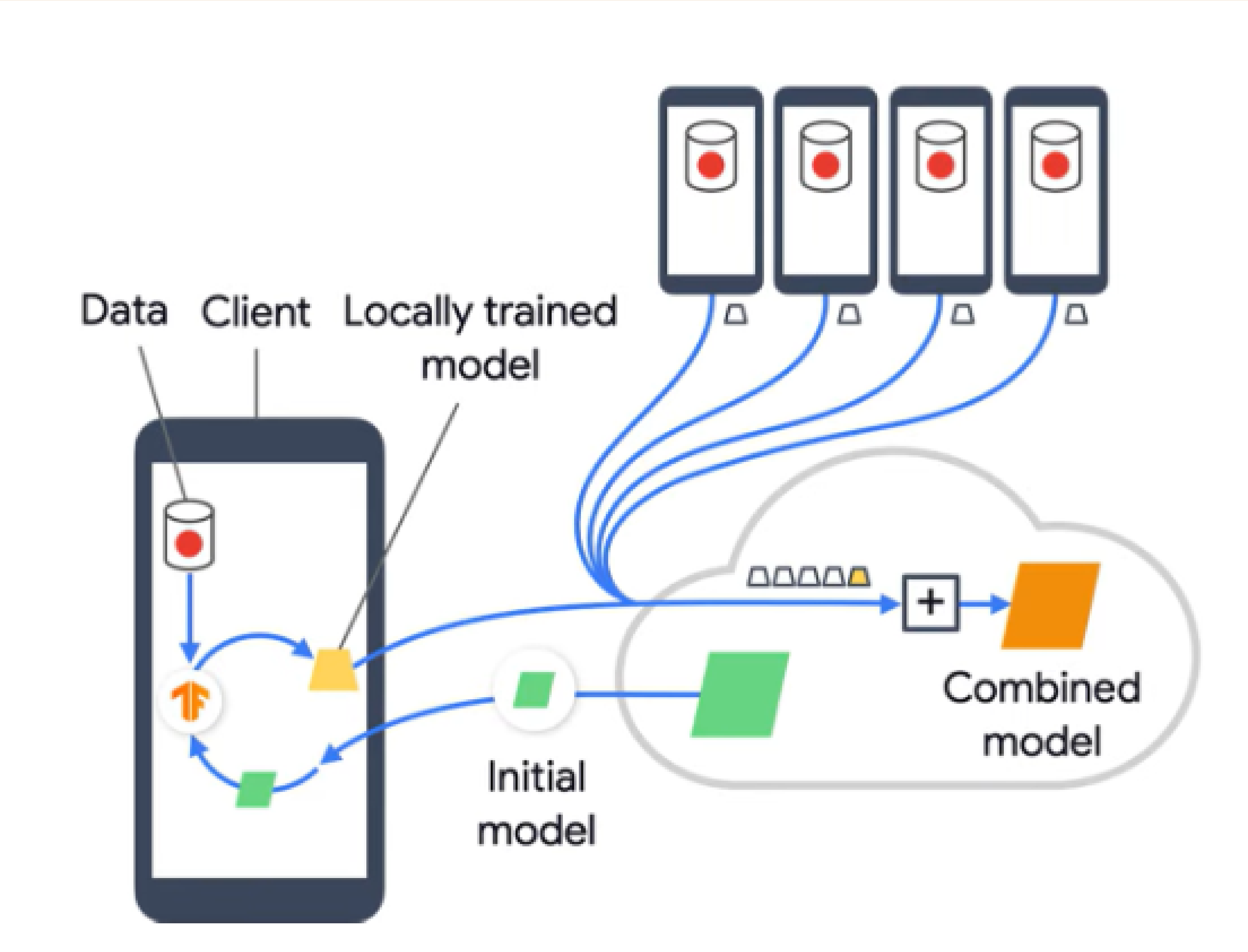
With Federated Learning:



How it works?

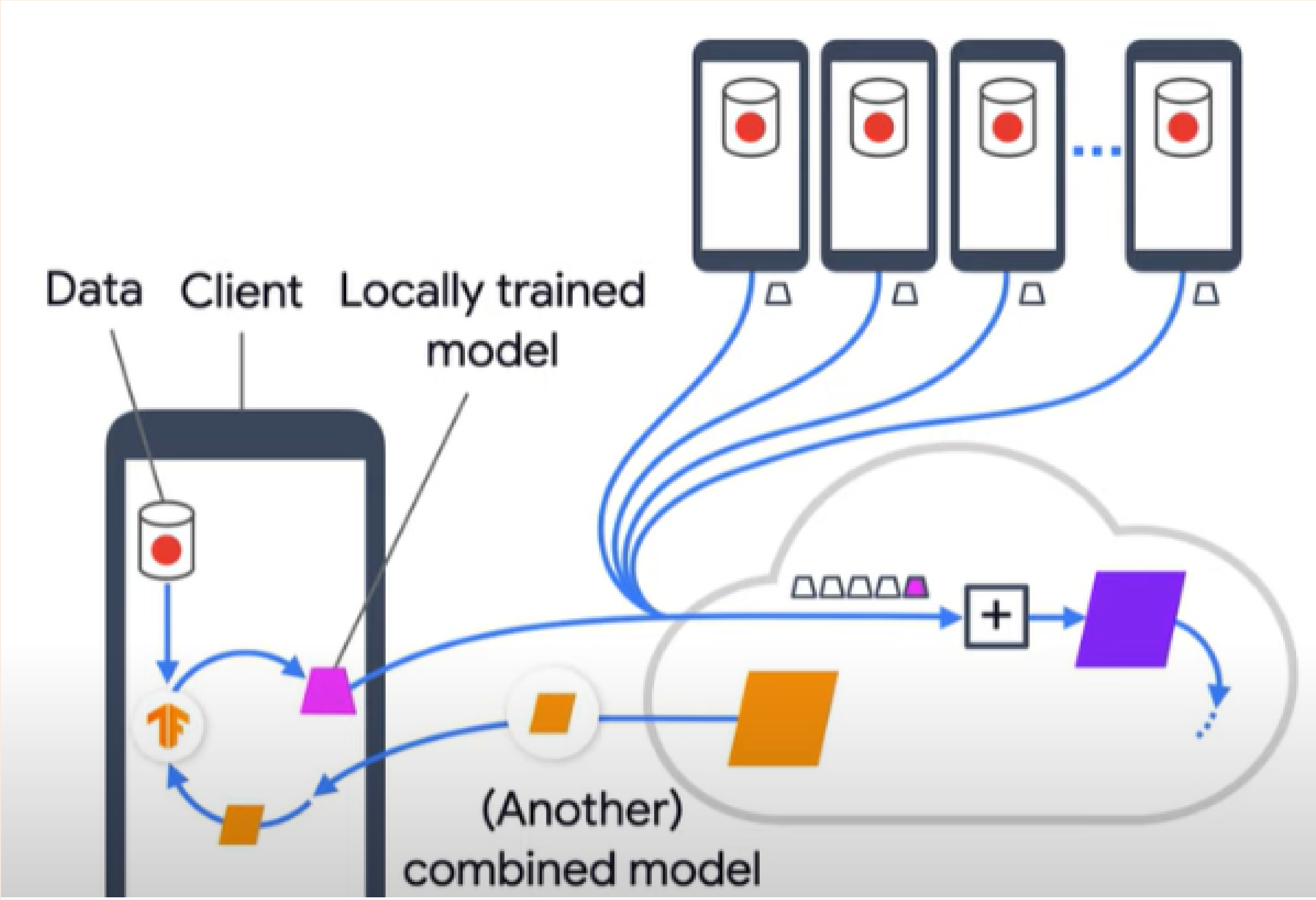


How it works?

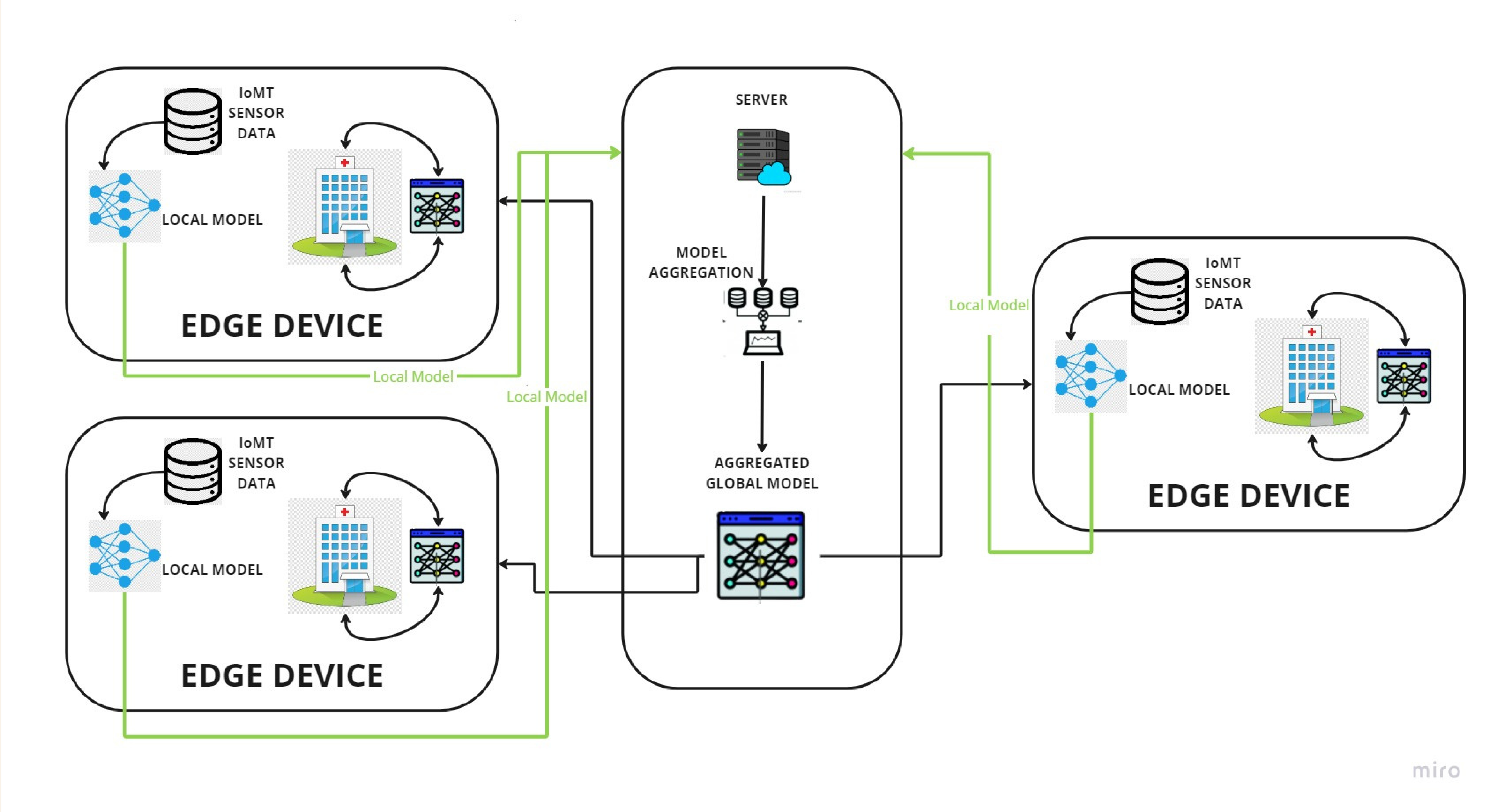

Data
Client
Locally trained model
Initial model
Combined model

But this done once can't assure a good model, thus we need to do it again and again so that the combined model becomes the initial model for the next round, and it gets better round by round.

How it works?



Federated Learning in IoMt System Architecture?



Simulation

Datasets

- The dataset used contains images related to COVID-19 and Viral Pneumonia.
- The images are loaded and processed for further analysis, including resizing to 100x100 pixels.
- The datasets (covid and pnemo) are created for COVID and Viral Pneumonia images, respectively.
- In total, we are taking 3616 COVID data images with 1205 Viral Pneumonia images.

- The data is automatically split among the different clients based on randomness.

Simulation

- The Python software platform called Kaggle is used to simulate the suggested federated learning model.

- The features of federated averaging, local training, and client creation are implemented in a federated SVM class.

- The required number of customers can be changed and adjusted according to the user.

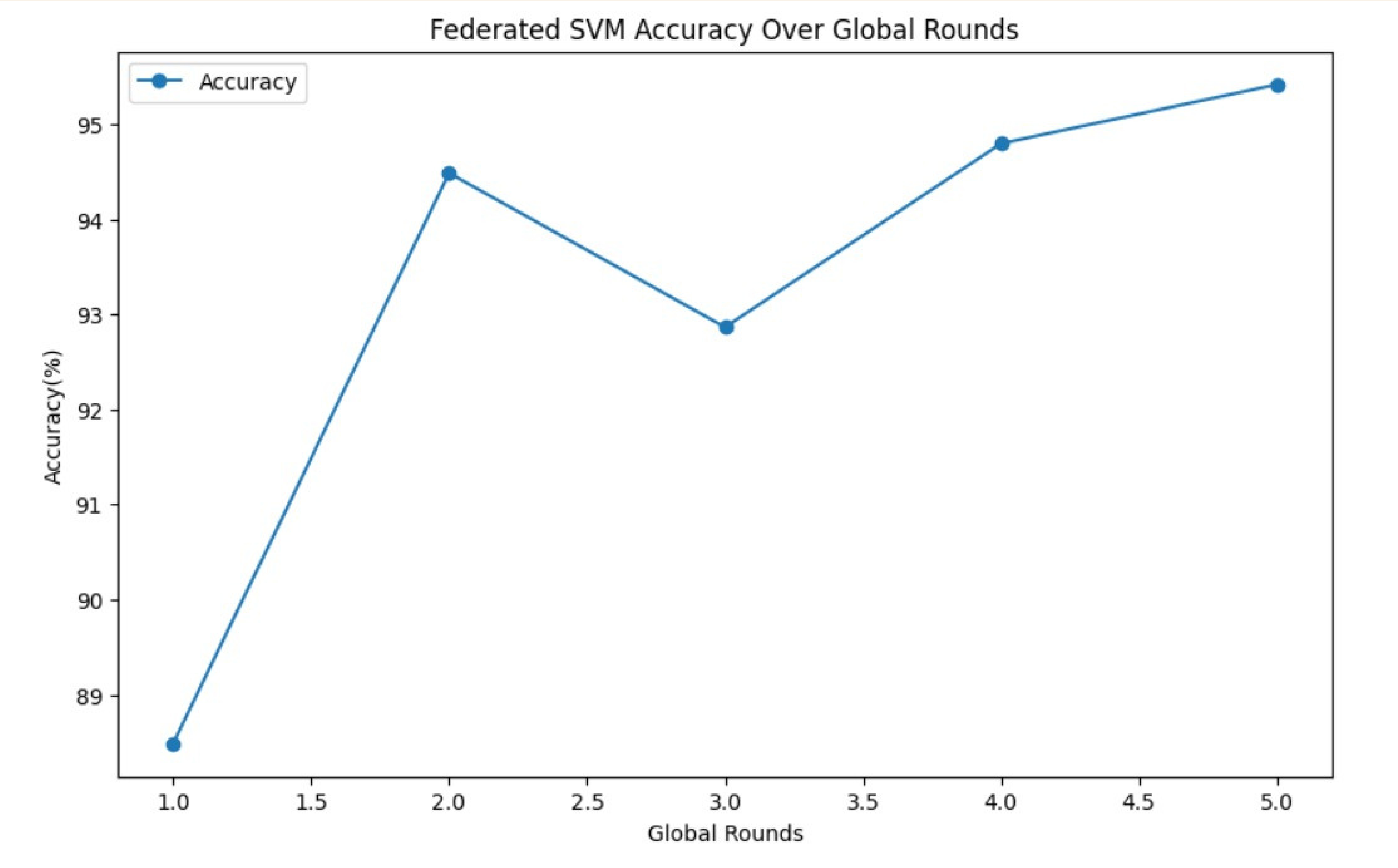
- The data is automatically split into segments for the experiment based on randomness and then sent to clients for testing, validation, and training.

Results

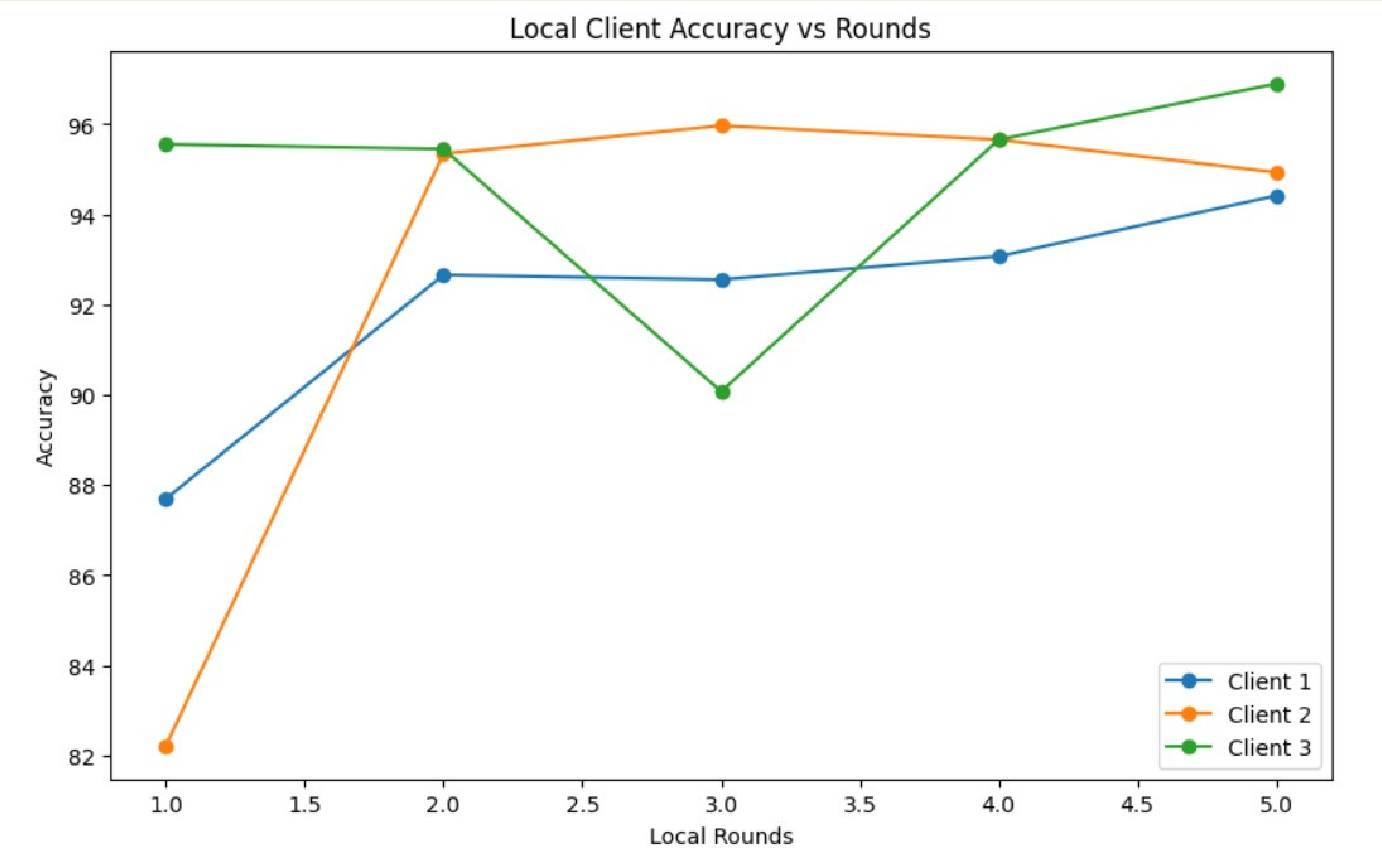
Accuracy and Precision Values at Local and Global Level of one random test

```
global round 1
client 1 acc pr 87.69389865563598 67.32394366197182
client 2 acc pr 82.21302998965874 58.45410628019324
client 3 acc pr 95.55325749741469 98.53658536585365
global test acc pr 88.48672871423646 74.7715451026729
global round 2
client 1 acc pr 92.65770423991727 77.85016286644951
client 2 acc pr 95.34643226473631 94.5701357466063
client 3 acc pr 95.44984488107549 98.52941176470588
global test acc pr 94.48466046190968 90.31657012592056
global round 3
client 1 acc pr 92.55429162357808 77.77777777777779
client 2 acc pr 95.96690796277146 92.46861924686193
client 3 acc pr 90.07238883143744 98.66666666666667
global test acc pr 92.86452947259566 89.63768789710213
global round 4
client 1 acc pr 93.07135470527405 78.87788778877888
client 2 acc pr 95.65667011375389 90.0
client 3 acc pr 95.65667011375389 98.54368932038835
global test acc pr 94.79489831092728 89.14052570305574
global round 5
client 1 acc pr 94.41571871768356 82.86713286713287
client 2 acc pr 94.93278179937953 95.30516431924883
client 3 acc pr 96.89762150982419 94.53781512605042
global test acc pr 95.41537400896243 90.903370708107
```

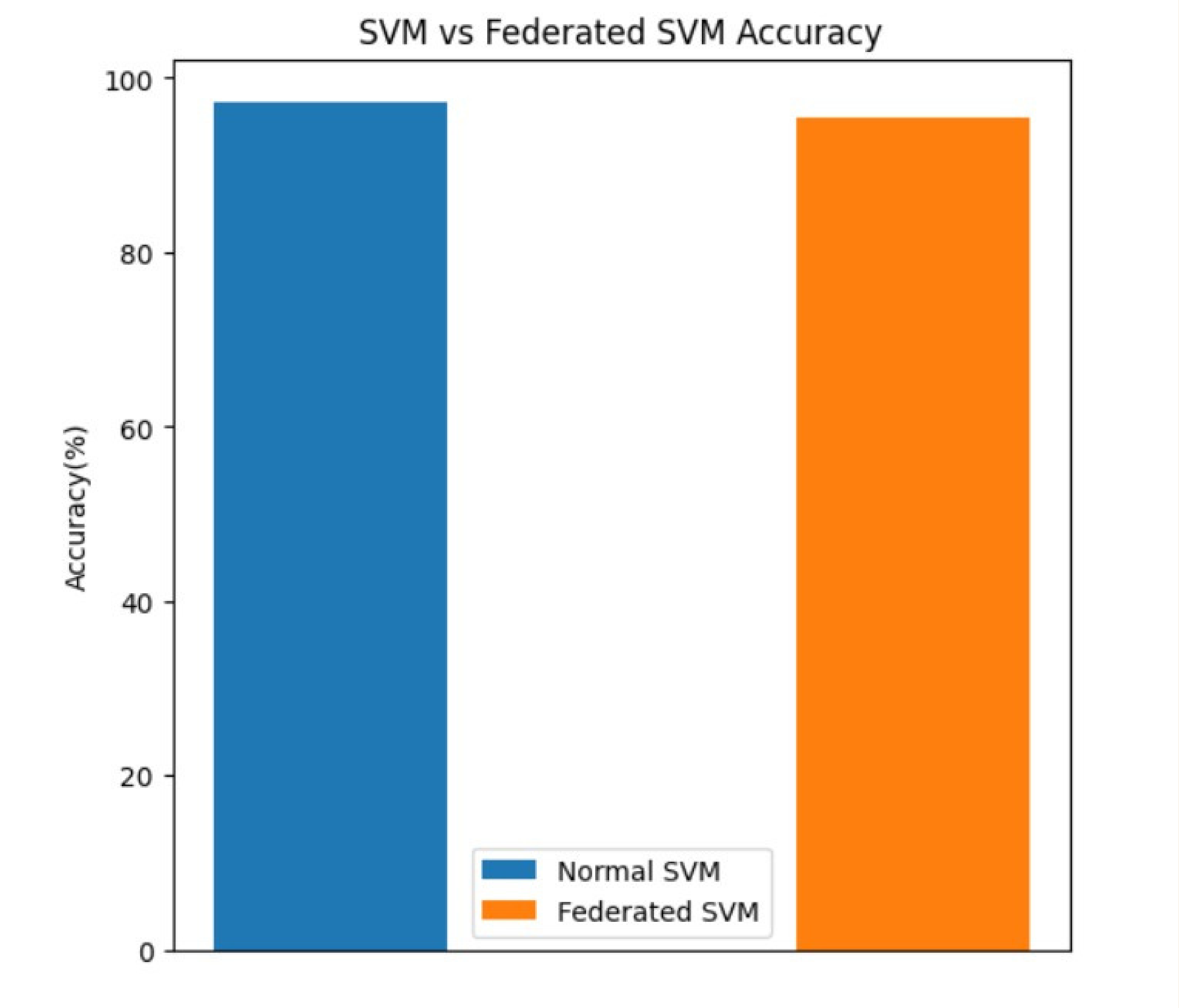
Federated SVM Accuracy



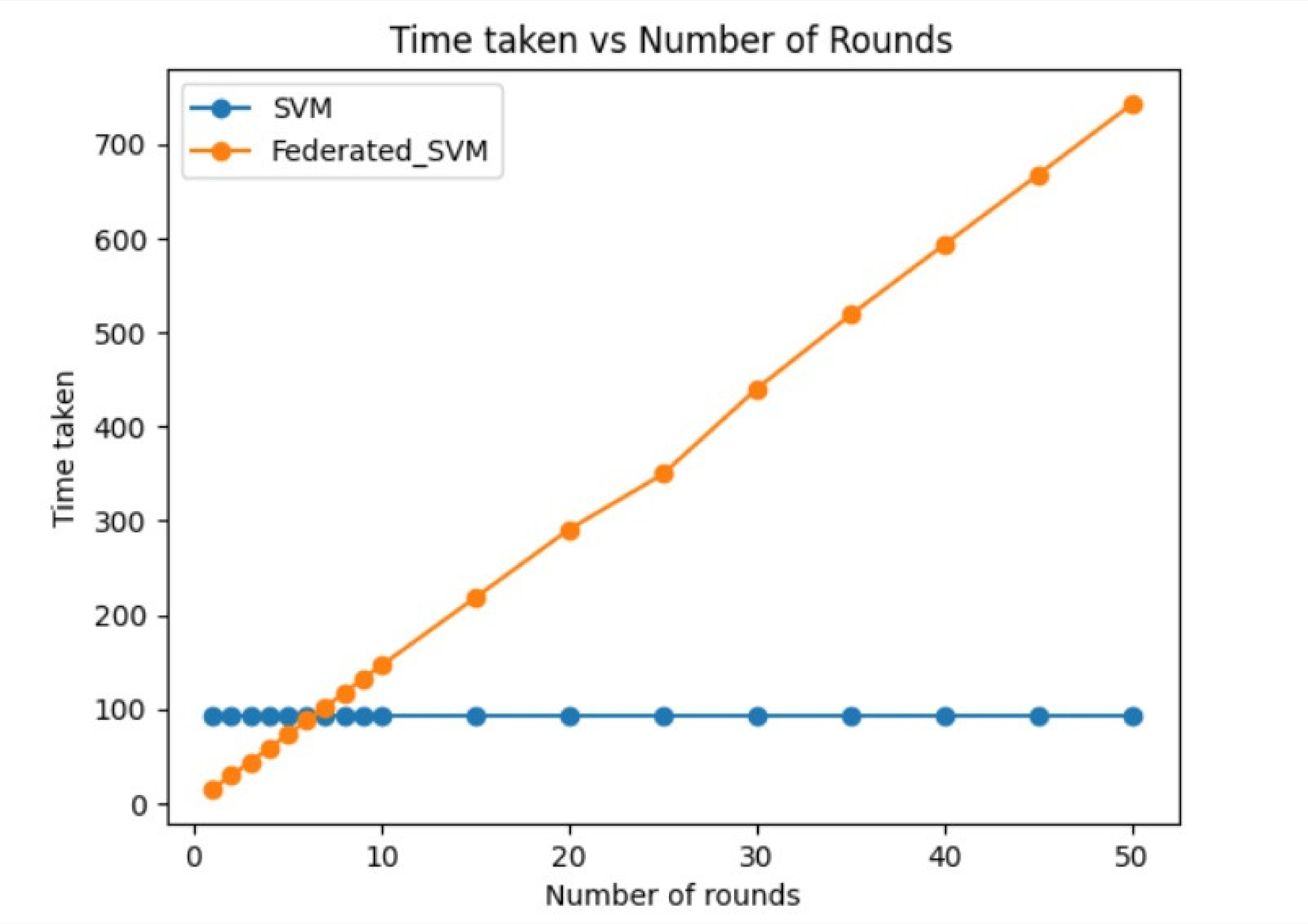
Local Client's Accuracy



SVM vs Federated SVM Accuracy



Computation time plot between SVM and FL SVM



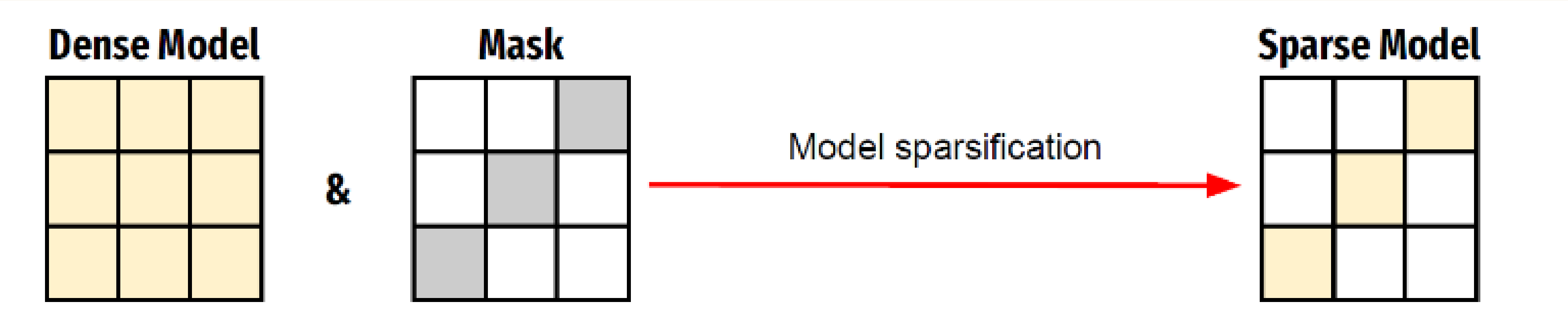
Conclusion

- The core aim of the algorithm is to evaluate the effectiveness of the federated algorithm, with a focus on privacy and security considerations.
- This evaluation is carried out using a well-established dataset and the experimentation involves three distinct clients, each equipped with its unique dataset distribution.
- An intriguing observation emerges when the model is tested exclusively on the local data of each client, the accuracy is notably lower.
- Remarkably, the accuracy achieved through federated learning is more or equal to that obtained through conventional centralized training methods.

It’s not an end…

Sparsed Federated Learning

- Transfer sparse models instead of dense models to reduce the communication cost in federated learning.
- The proposed method in sparse FL Communication constructs a sparse model by selecting only parameters that have been updated significantly.
- How it works? : We compute the absolute difference between the parameters of the local model before and after training, and exchange only the upper quantile of the updated parameters between the server and the clients.



Sparsed Federated Learning

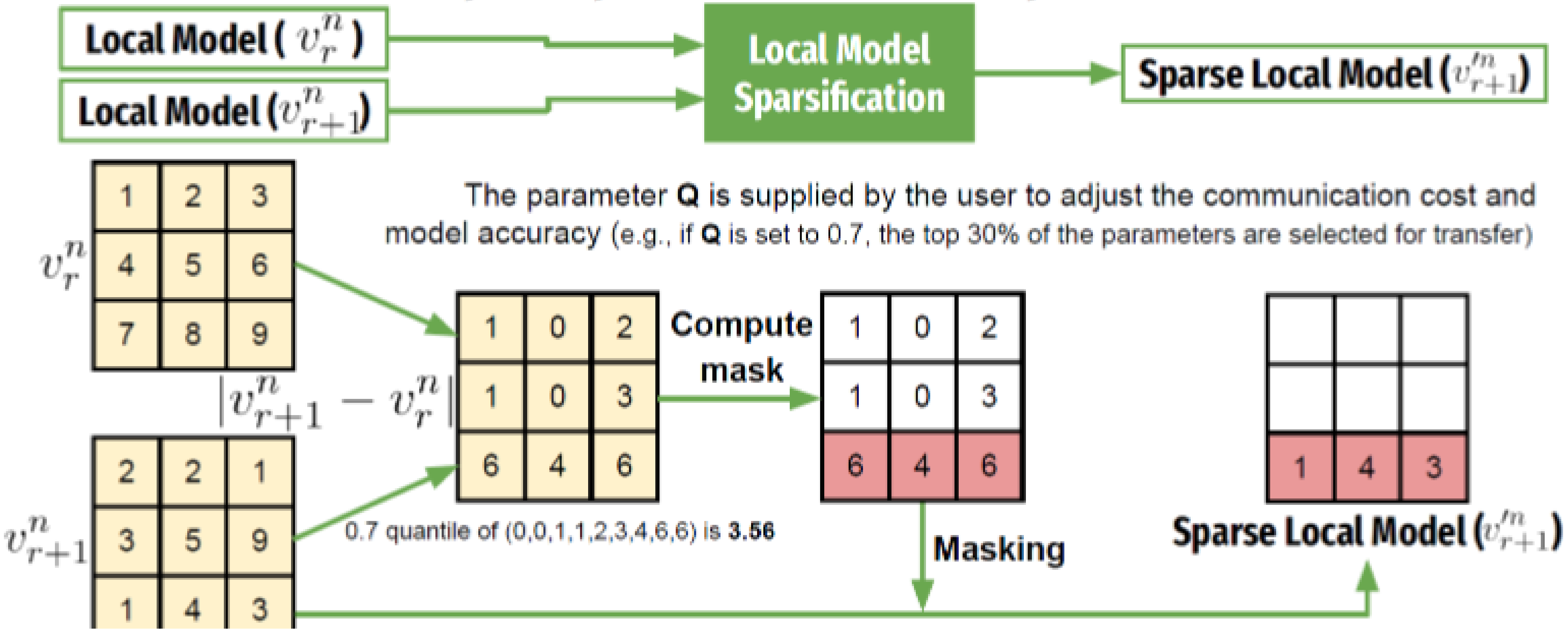
- This parameter-wise selection approach increases the opportunity to reduce communication costs since it omits unnecessary parameters and keeps the necessary parameters for the transfer.

- Justification: It is reasonable not to transfer the parameters that do not have significant updates in the local model, since they may not have much impact on the global model update.

- The tradeoff between the model accuracy and the communication cost is adjusted with a hyperparameter. This hyperparameter controls the level of sparsification, i.e. what fraction of the model is exchanged between the server and clients.

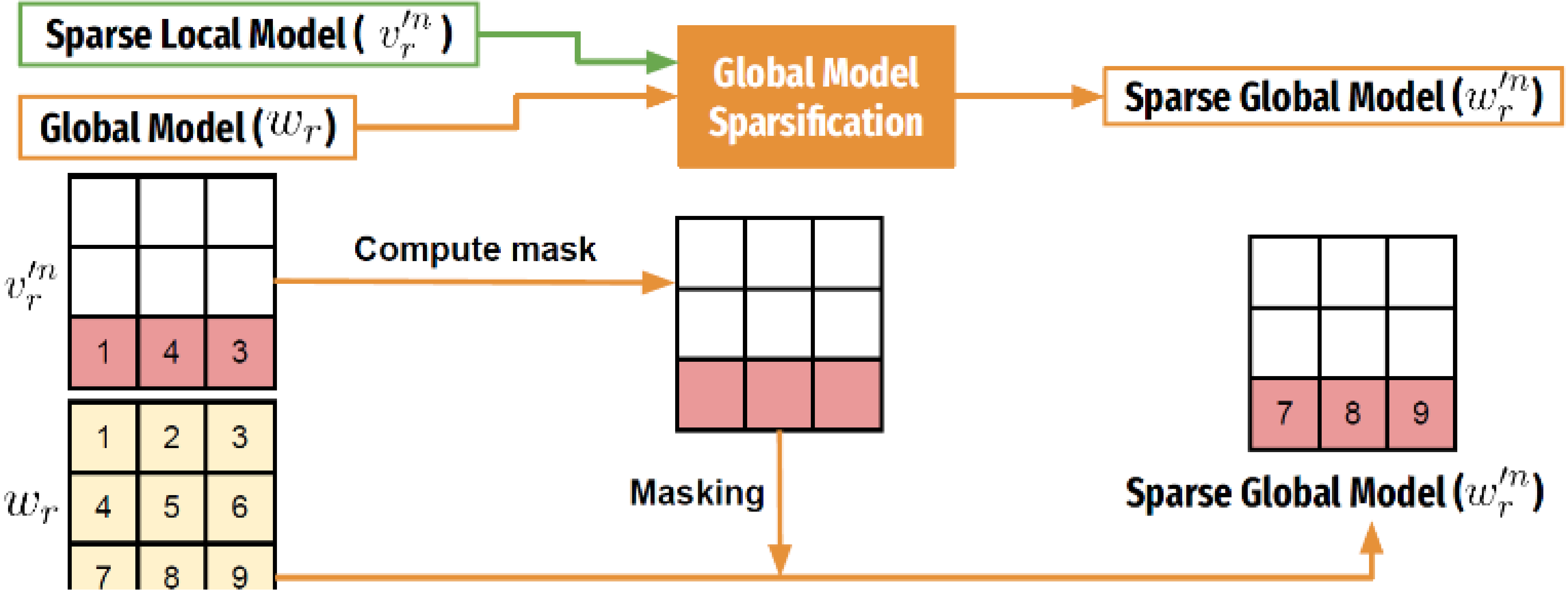
Local model sparsification

Extracts the most updated parameters to construct sparse local model

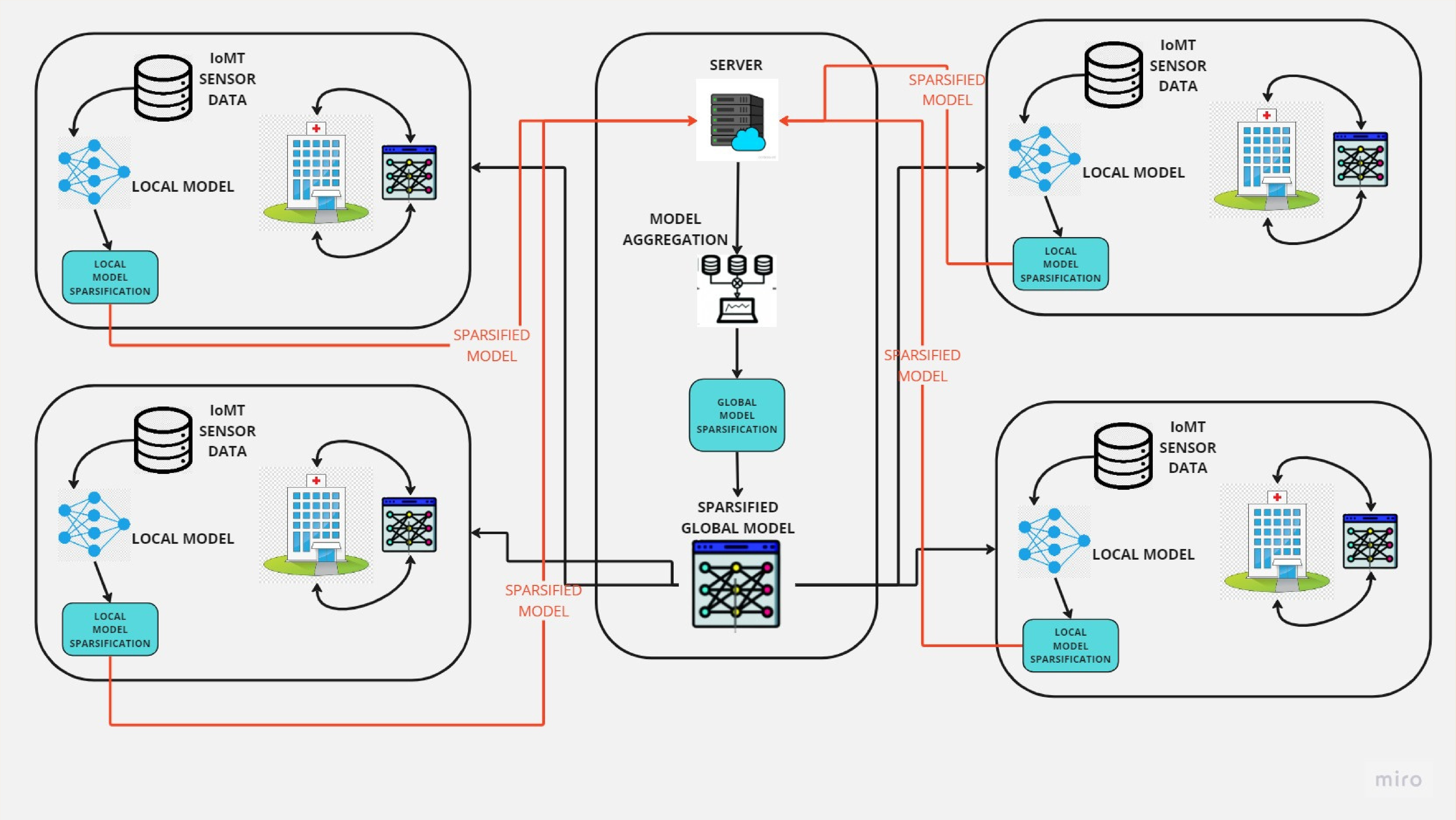


Global model sparsification

Reuse local model mask to construct sparse global model because the parameters in the mask are still not converged yet at client-side and then those parameters have to be updated to converge



Sparsed Federated Learning in IoMt System Architecture?



Conclusion

- A novel method to reduce the communication cost for federated learning by sparsifying local and global models.

- The proposed method utilises exchanging the most updated parameters of neural network models.

- One immediate benefit of sparse Federated Learning is smaller size, given we only need to keep the non-zero connections, which is a huge benefit when trying to fit the networks in edge devices.

Thank You