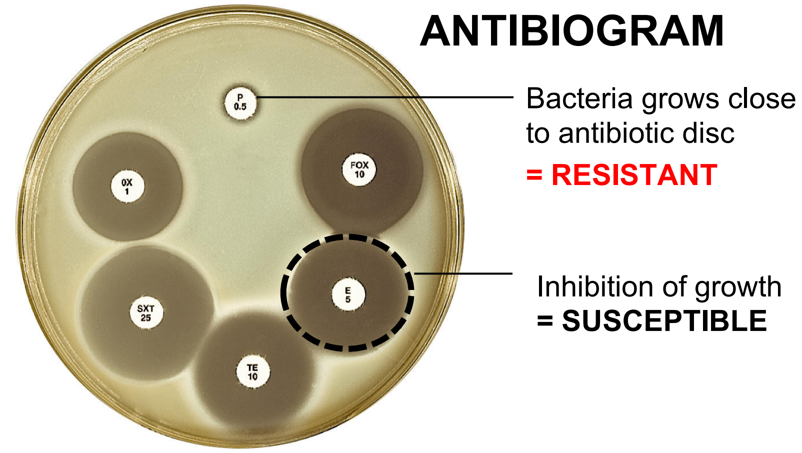
EPFL iGH intelligent GLOBAL HEALTH

Federated Prototypical Learning for Automated Antibiogram Interpretation in Ultra-Low-Resource Settings



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1 INTRODUCTION

Antibiogram

- determines the effectiveness of antibiotics
- minimizing the risk of antibiotic resistance
- MSF developed Antibiogo [4] to automate procedure

PROBLEM

- Antibiotic discs change, due to new antibiotics and changes in resistance patterns. We need **continuous learning**.
- Sensitive data where **privacy** needs to be preserved.
  Solution: classical **federated learning (FL)**
- *But* FL assumes a large communication budget, communication and client stability. Not interpretable.
- Antibiogo needs to function in **ultralow resource settings**.

AIM

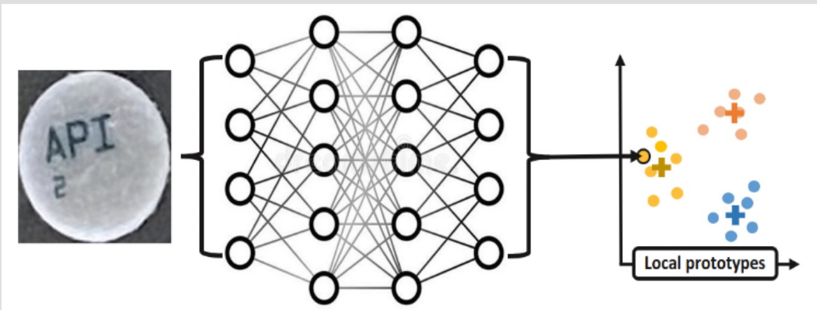
Adapt FL to

- ❑ Continuously learn to improve antibiogram interpretation (few-shot learning)
- ❑ Low communication costs
- ❑ Interpretability
- ❑ Modularity

2 METHOD: PROTOTYPICAL LEARNING

- Prototypical learning involves creating a **representative example** for each class of data points in a given dataset and classifying new data points based on their **similarity to the prototypes** [5].

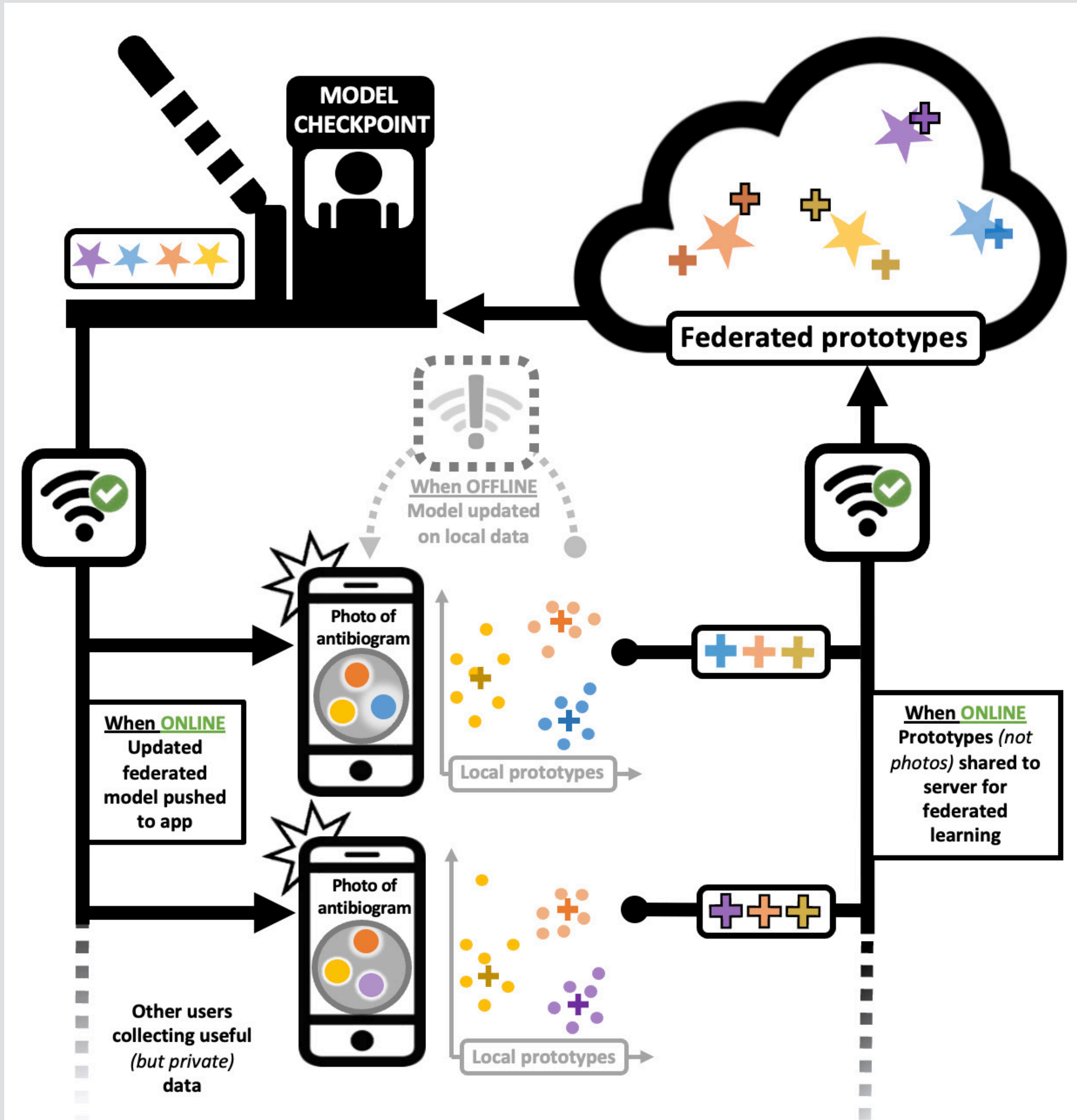
OUR TASK: to recognize the text of an antibiogram disc.



3 METHOD: FEDERATED PROTOTYPICAL LEARNING

- **Federated learning** involves training a model on decentralized data that remains on local devices, rather than being transferred to a central server, thereby providing **data privacy**.

Here we adapt it to only communicate the **prototypes** of each class.



4 RESULTS

AIM ACHIEVED using prototypical learning

- ✓ Ultra low communication cost (we only need to communicate the prototype once)
- ✓ Modularity

AIM ACHIEVED using FEDERATED prototypical learning

- ✓ Continuous learning
- ✓ Interpretability
- ✓ Data Privacy

- ✓ Federated prototypical learning generalizes as least as well as standard supervised learning to **unseen** classes: **71.2** (+-0.8) vs. **69.6** (+-2.5) on EMNIST.
- ✓ Since only the prototypes need to be communicated, the communication costs are reduced by **>10.000%** compared to classical FL.
- ✓ 3 datapoints per class are sufficient to approximate the prototype of a class.

5 CONCLUSION

- Novel and impactful problem setting for FL.
- Few-shot learning is possible but improvable.
- Our work is a first step toward ultralow resource -efficient FL able to handle intermittent updates and continual learning.

REFERENCES

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