Federated Transfer Learning Scalability in IoT with Communication and Accuracy Trade-offs

Assignee Research

May 30, 2026

Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: How does federated transfer learning scale with varying numbers of IoT device clients in terms of communication efficiency and detection accuracy trade-offs, as measured by convergence speed and F1. Federated learning has attracted growing interest as it preserves the clients' privacy. As a variant of federated learning, federated transfer learning utilizes the knowledge from similar tasks and thus has also been intensively studied. 12 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Communication-Efficient and Privacy-Preserving Feature-based Federated Transfer Learning. Research question: How does federated transfer learning scale with varying numbers of IoT device clients in terms of communication efficiency and detection accuracy trade-offs, as measured by convergence speed and F1 scores?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.4/10.

3 Results

4 papers retrieved. 12 claims extracted; 0 independently verified. Quality review score: 3.4/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The uplink payload of FbFTL is significantly less than that of FTL and FL (P_FbFTL « P_FTL_c < P_FTL_f < P_FL).	×	0.07
FbFTL has the least downlink broadcast payload compared to FL and FTL.	×	0.04
FbFTL requires the least local computation compared to FL and FTL.	×	0.05
In FL and FTL, each client must complete one full forward pass and one backward pass of the parameters for each sample a	×	0.03
In FbFTL, each client only needs to complete the forward pass of the feature extraction sub-model once for each sample.	×	0.02
In FbFTL, all computations other than the feature extraction forward pass are transferred to the Parameter Server (PS).	×	0.03
The intermediate output z (smashed data) cannot be transformed back to the input x due to the non-linearity of activatio	×	0.02
The output y potentially conveys clients' private information to a minor extent.	×	0.03
The proposed system design conceals the relationship between the client's address and uploaded content to eliminate priv	×	0.05
In the FbFTL architecture, the Parameter Server contains a pre-trained source model and a new target model with randomly	×	0.02
In the FbFTL client model, layers 1 through 3 are fixed or updated as part of the feature extraction sub-model, while la	×	0.01
The FbFTL process involves broadcasting fixed parameters and iterative communication for updating task-specific target s	×	0.03

References

- http://arxiv.org/abs/2207.02337v1
- http://arxiv.org/abs/2209.05395v1
- http://arxiv.org/abs/2007.06081v1