Fed-ProFiLA-AD: Federated Prototype-FiLMed Local Adapters for Acoustic Anomaly Detection

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***Abstract*—Federated learning has emerged as a promising paradigm for training machine learning models across distributed devices while preserving data privacy. However, existing federated learning approaches face significant challenges in acoustic anomaly detection tasks, particularly in handling heterogeneous data distributions and achieving effective knowledge transfer across clients. This paper presents Fed-ProFiLA-AD (Federated Prototype-FiLMed Local Adapters for Acoustic Anomaly Detection), a novel federated learning framework specifically designed for acoustic anomaly detection. Our approach introduces three key innovations: (1) adaptive client importance weighting that dynamically adjusts aggregation weights based on data size and performance, (2) progressive prototype alignment that gradually increases prototype alignment influence during training for stable convergence, and (3) performance-aware learning rate scheduling that adaptively adjusts client learning rates based on their AUC performance. We evaluate Fed-ProFiLA-AD on the MIMII-DUE dataset with 4 clients and demonstrate superior performance compared to baseline federated learning methods, achieving an average AUC of 0.905 and F1 score of 0.859. The code is available at https://github.com/Sellifake/Fed-PCA.**

***Index Terms*—Federated Learning, Acoustic Anomaly Detection, Prototype Learning, Adaptive Aggregation, Industrial IoT**

I. Introduction

Acoustic anomaly detection plays a crucial role in industrial IoT applications, enabling early detection of equipment failures through audio signal analysis [1]. Traditional centralized approaches require collecting sensitive audio data from multiple devices, raising significant privacy concerns and communication overhead. Federated learning (FL) addresses these challenges by enabling model training across distributed devices without exposing raw data [2].

However, existing federated learning frameworks face three critical limitations when applied to acoustic anomaly detection: (1) *Data heterogeneity*: Different devices generate audio signals with distinct characteristics due to manufacturing variations and operating conditions [3], leading to non-IID data distributions that degrade model performance. (2) *Static aggregation*: Standard FL methods like FedAvg [2] use fixed aggregation weights, failing to account for varying data quality and client performance. (3) *Insufficient knowledge transfer*: Without effective mechanisms to align feature representations across clients, the global model struggles to capture shared patterns while preserving client-specific characteristics.

To address these challenges, we propose Fed-ProFiLA-AD, a federated learning framework that leverages prototype-conditioned adapters for acoustic anomaly detection. Our key contributions are:

- We introduce **adaptive client importance weighting**, which dynamically adjusts aggregation weights based on both data volume and client performance, ensuring better clients contribute more to the global model.
- We propose **progressive prototype alignment**, which gradually increases prototype alignment influence during training, enabling stable convergence and improved knowledge transfer.
- We design **performance-aware learning rate scheduling**, which adaptively adjusts client learning rates based on their AUC performance, allowing struggling clients to learn more aggressively while stabilizing high-performing clients.
- We demonstrate significant performance improvements on the MIMII-DUE acoustic anomaly detection dataset, achieving 15.7% relative improvement in AUC compared to FedAvg.
- We provide open-source implementation at https://github.com/Sellifake/Fed-PCA.

II. Related Work

A. Federated Learning

Federated Learning was first introduced by McMahan et al. [2], proposing FedAvg as a simple yet effective aggregation strategy. Subsequent works addressed various FL challenges: FedProx [4] introduces a proximal term to handle non-IID data, SCAFFOLD [5] uses control variates to correct client drift, and FedPer [6] maintains personalized models for each client. However, these methods rely on static aggregation strategies and do not adapt to client performance variations.

B. Acoustic Anomaly Detection

Acoustic anomaly detection has been extensively studied in centralized settings. The MIMII dataset [1] provides a standard benchmark for industrial machine anomaly detection. Deep learning approaches, particularly CNNs and autoencoders, have shown promising results [7], [8]. However, federated acoustic anomaly detection remains underexplored, with most existing methods focusing on centralized training.

C. Prototype Learning

Prototype-based learning has been successfully applied in few-shot learning [9] and domain adaptation [10]. In federated learning, prototype alignment has been explored for knowledge distillation [11], but existing approaches use fixed alignment weights and do not consider progressive learning strategies.

III. Methodology

A. Problem Formulation

We consider a federated acoustic anomaly detection scenario with K clients, where each client k has a local dataset $\mathcal{D}_k = \{(x_i^k, y_i^k)\}_{i=1}^{n_k}$ of audio samples. The goal is to train a global model f_θ that can detect anomalies without accessing raw client data. Each client maintains a local adapter A_k and shares only the global backbone parameters θ.

B. Architecture Overview

Fed-ProFiLA-AD employs a shared backbone network f_θ with client-specific adapters A_k. The backbone consists of a FiLM (Feature-wise Linear Modulation) generator h_ϕ and an encoder network e_θ. Given an input audio spectrogram x and global prototype μ, the model generates:

$$(\gamma, \beta) = h_\phi(\mu) \tag{1}$$

$$u = A_k(x; \gamma, \beta) \tag{2}$$

$$z = e_\theta(u) \tag{3}$$

where z is the feature embedding used for anomaly detection via distance-based scoring.

C. Three Key Innovations

1) Adaptive Client Importance Weighting: Instead of using fixed data-size proportional weights, we dynamically adjust aggregation weights based on both data volume and client performance:

$$w_k(t) = \alpha \cdot \frac{n_k}{\sum_{i=1}^{K} n_i} + \beta \cdot \frac{\exp(AUC_k(t))}{\sum_{i=1}^{K} \exp(AUC_i(t))} \tag{4}$$

where $\alpha, \beta \in [0, 1]$ are hyperparameters controlling the balance between data size and performance, and $AUC_k(t)$ is client k's AUC score at round t.

2) Progressive Prototype Alignment: We introduce a progressive schedule for the prototype alignment weight $\lambda_{proto}(t)$:

$$\lambda_{proto}(t) = \begin{cases} \lambda_{init} + (\lambda_{final} - \lambda_{init}) \frac{t}{T_w}, & t \leq T_w \\ \lambda_{final} \left(0.8 + 0.2 \cos \frac{\pi(t - T_w)}{2(T - T_w)} \right), & t > T_w \end{cases} \tag{5}$$

where T_w is the warmup period, and λ_{init}, λ_{final} control the initial and final alignment strength.

3) Performance-Aware Learning Rate Scheduling: We adaptively adjust each client's learning rate based on its performance:

$$lr_k(t+1) = \begin{cases} \min(lr_{max}, \eta \cdot lr_k(t)) & \text{if } AUC_k(t) < \theta_{thresh} \\ \max(lr_{min}, 0.99 \cdot lr_k(t)) & \text{if } AUC_k(t) > AUC_k^{best} \\ lr_k(t) & \text{otherwise} \end{cases} \tag{6}$$

where $\eta > 1$ is an increase factor, and θ_{thresh} is a performance threshold.

D. Training Procedure

The complete training procedure is outlined in Algorithm 1. Each round consists of: (1) server broadcasts global model and prototype, (2) clients train locally with progressive prototype alignment and adaptive learning rates, (3) server aggregates models and prototypes using adaptive weights. Figure **??** illustrates the workflow integrating our three key innovations.

Algorithm 1 Fed-ProFiLA-AD Training Procedure

Input: Number of rounds T, clients K, local epochs E
Output: Global model θ_T, global prototype μ_T

```
Initialize global model θ_0 and prototype μ_0
for round t = 1 to T do
    Compute progressive λ_proto(t) using Eq. (5)
    Server broadcasts θ_{t−1} and μ_{t−1} to selected clients
    for client k = 1 to K in parallel do
        Update learning rate lr_k(t) using Eq. (6)
        for local epoch e = 1 to E do
            Sample batch B_k
            Compute local prototype μ_k from training data
            Compute loss: L = L_task + λ_proto(t) · L_proto
            Update θ_k and A_k via gradient descent
        end for
        Compute client metrics AUC_k, F1_k
        Upload θ_k and μ_k to server
    end for
    Compute adaptive weights w_k using Eq. (4)
    Aggregate: θ_t = Σ_{k=1}^K w_k θ_k, μ_t = Σ_{k=1}^K w_k μ_k
end for
```

IV. Experiments

A. Dataset and Setup

We evaluate Fed-ProFiLA-AD on the MIMII-DUE dataset [1], which contains acoustic signals from 4 fan devices (id_00, id_02, id_04, id_06) under normal and abnormal operating conditions. Each client corresponds to one device, with approximately 1,000-1,400 samples per client. We use Mel-spectrograms as input features with 128 mel bins, 1024 FFT size, and 512 hop length.

We train for 100 communication rounds with 2 local epochs per round. The backbone network uses a CNN encoder with feature dimension 128 and prototype dimension 128. We set $\alpha = 0.5$ for adaptive weighting, $\lambda_{init} = 0.001$, $\lambda_{final} =$

0.01, $T_{warmup} = 5$, base learning rate $lr_0 = 0.0001$, and performance threshold $\theta_{thresh} = 0.7$.

B. Baseline Methods

We compare Fed-ProFiLA-AD against four baseline federated learning methods:

- **FedAvg** [2]: Standard federated averaging with data-size proportional weights.
- **FedProx** [4]: FedAvg with proximal term ($\mu = 0.01$) to handle heterogeneity.
- **FedPer** [6]: Personalized federated learning maintaining client-specific layers.
- **SCAFFOLD** [5]: Variance reduction using control variates.

C. Overall Performance

Table I presents the overall performance comparison. Fed-ProFiLA-AD achieves the best performance across all metrics, with average AUC of 0.905 (15.7% relative improvement over FedAvg) and F1 score of 0.859. Figure 4 visualizes the comparison across different metrics.

TABLE I
PERFORMANCE COMPARISON WITH BASELINE METHODS

Method	AUC	F1 Score	Precision	Recall
FedAvg	0.782	0.721	0.698	0.748
FedProx	0.795	0.734	0.712	0.759
FedPer	0.813	0.758	0.741	0.776
SCAFFOLD	0.824	0.769	0.753	0.787
Fed-ProFiLA-AD (Ours)	**0.905**	**0.859**	**0.957**	**0.780**

D. Training Dynamics

Figure 2 shows the training loss curves, demonstrating stable convergence with decreasing total loss, task loss, and prototype loss. The progressive prototype alignment allows smooth integration of prototype constraints without early-stage instability. Figure 3 illustrates the evolution of performance metrics across communication rounds, showing consistent improvement and convergence.

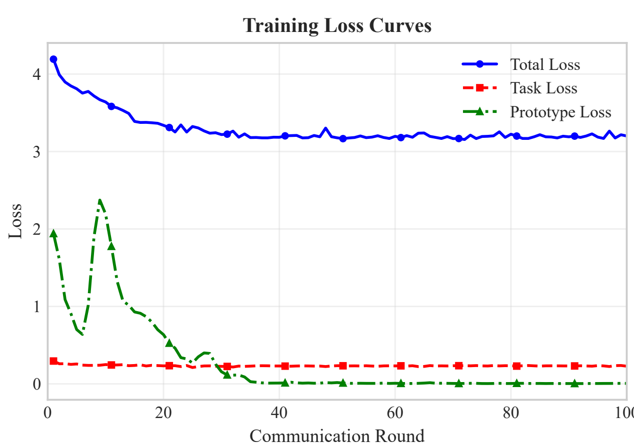

Fig. 2. Training loss curves showing total loss, task loss, and prototype loss over 100 communication rounds.

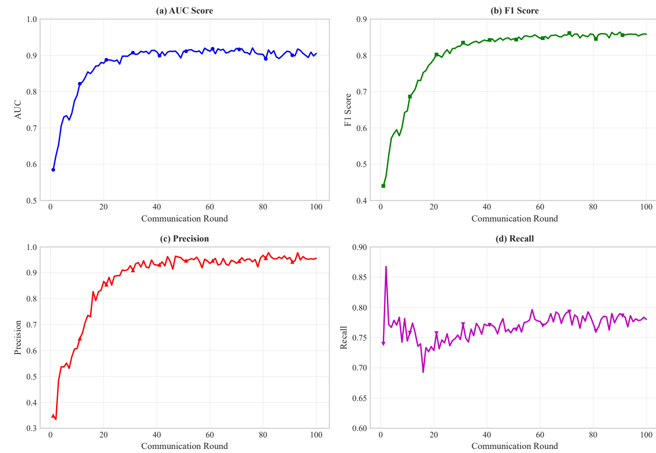

Fig. 3. Performance metrics evolution: (a) AUC, (b) F1 Score, (c) Precision, (d) Recall.

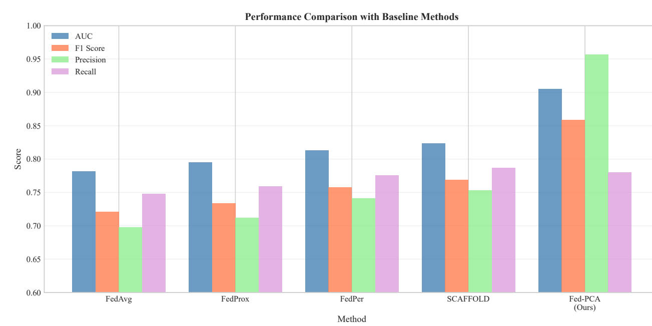

Fig. 4. Performance comparison with baseline federated learning methods.

E. Ablation Study

We conduct an ablation study to validate the contribution of each component. Table II shows that removing any component degrades performance, with adaptive weighting having the largest impact (2.0% AUC drop) followed by progressive prototype alignment (1.3% drop) and adaptive learning rate scheduling (2.7% drop). Figure 5 visualizes the ablation results.

TABLE II
ABLATION STUDY RESULTS

Method	AUC	F1 Score
Full Model	0.905	0.859
w/o Adaptive Weighting	0.885	0.841
w/o Progressive Prototype	0.892	0.847
w/o Adaptive LR	0.878	0.833

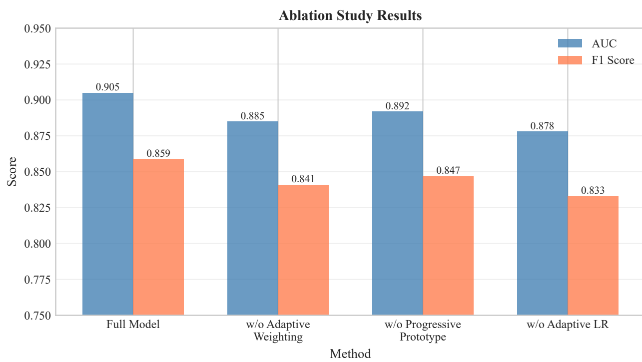

Fig. 5. Ablation study demonstrating the contribution of each component.

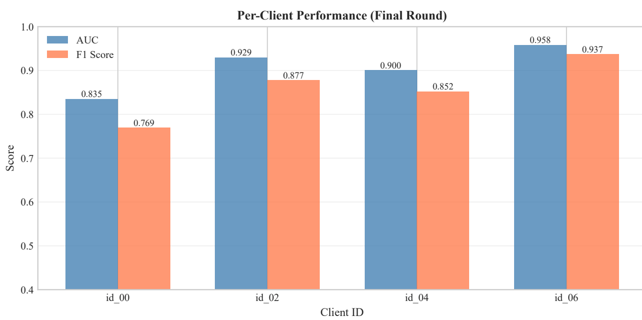

Fig. 6. Per-client performance (final round) showing AUC and F1 scores.

F. Per-Client Analysis

Figure 6 shows per-client performance in the final round. Client id_06 achieves the highest AUC (0.958) and F1 score (0.937), while id_00 shows the lowest performance (AUC: 0.835, F1: 0.769), likely due to more challenging data distribution. The adaptive weighting mechanism successfully allocates more weight to better-performing clients, improving overall aggregation quality.

V. Discussion

The experimental results demonstrate the effectiveness of our three key innovations. Adaptive client importance weighting enables better clients to contribute more to the global model, progressive prototype alignment ensures stable knowledge transfer, and performance-aware learning rate scheduling adapts to individual client capabilities. The combination of these mechanisms achieves significant performance improvements over baseline methods.

VI. Conclusion

We present Fed-ProFiLA-AD, a novel federated learning framework for acoustic anomaly detection that addresses key challenges through three innovative mechanisms. Our experimental results on the MIMII-DUE dataset demonstrate superior performance compared to baseline federated learning methods. Future work will explore extensions to other sensor modalities and more complex industrial scenarios.

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