

Federated Learning for Mechanical Equipment Diagnostics: Applications to Image Segmentation and Tabular Data Anomaly Detection*

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Abstract— Federated learning (FL) has emerged as a promising paradigm for collaborative model training while preserving data confidentiality. This paradigm is particularly relevant in industrial environments where strong confidentiality constraints limit data sharing between production sites or industrial partners. This study investigates the applicability of FL in the context of mechanical equipment diagnostics using two complementary data modalities:

First, an infrared thermography image segmentation framework based on the SegFormer architecture is evaluated for detecting defects in mechanical connecting rods. A distributed training framework is implemented in which local models are trained independently and aggregated using a modified Federated Averaging strategy applied to encoder parameters [1], [2].

Second, a federated anomaly detection framework based on One-Class Support Vector Machines (OC-SVM) is proposed for tabular sensor data originating from a centrifugal pump demonstrator. To address confidentiality issues related to support vector sharing, a novel pseudo-support vector generation method is introduced.

Experimental results demonstrate that federated aggregation improves local model performance for image segmentation while preserving data privacy. For tabular data, the proposed pseudo-support vector mechanism enables federated aggregation while maintaining confidentiality and producing meaningful global models.

I. INTRODUCTION

Condition monitoring and predictive maintenance have become key components of modern industrial systems. Traditional approaches for machine diagnosis and monitoring generally rely on correlating signal-processing results from sensors with models of the machine kinematic chain to extract diagnostic indicators commonly referred to as features. Using large volume of data and deep learning approaches alleviate the need for manual feature engineering. However, in industrial environments, data are often distributed across multiple sites and cannot be shared due to confidentiality constraints. This limitation restricts the development of robust diagnostic models that require large and diverse datasets.

Federated learning addresses this challenge by allowing multiple participants to collaboratively train a model without sharing raw data. In this paradigm, each participant trains a local model using its own dataset and shares only model

parameters or updates with a central aggregation server. The server computes a global model that integrates knowledge from all participants.

The objective of this paper is to evaluate the applicability of federated learning in mechanical diagnostics scenarios involving heterogeneous data sources. Two complementary use cases are investigated: image-based defect detection using infrared thermography and tabular sensor-based anomaly detection in a fluidic benchmark.

The main contributions of this work are:

- 1- Construction of two industrial datasets derived from mechanical test benches
- 2- Development of federated learning strategies adapted to image segmentation and anomaly detection tasks.
- 3- Proposal of a privacy-preserving pseudo-support vector aggregation mechanism for OC-SVM models.
- 4- Evaluation of the proposed methods under IID and non-IID data distribution scenarios.

II. FEDERATED IMAGE SEGMENTATION FOR DEFECT DETECTION

A. Thermography Dataset

An infrared thermography dataset composed of 854 images of defective connecting rods was used to investigate federated learning for image-based defect detection. Thermographic inspection is widely used in industrial inspection processes because temperature variations can reveal structural defects or material discontinuities.

The images include both front and rear views of the components. Each image is associated with a manually annotated mask representing the defective location. Figure 1 presents an example of the two types of images from the database representing the front (left) and the rear (right) parts of a mechanical connecting rod.

*Resrach supported by CETIM Foundation.

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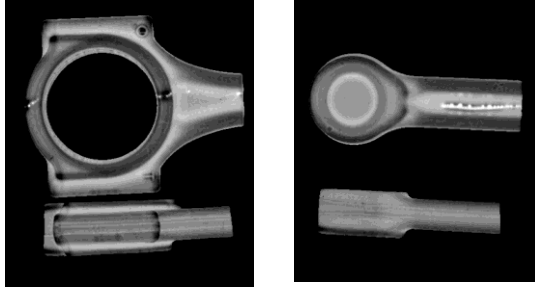


Figure 1. Example of the two types of images from the database representing the front (left) and the rear (right) parts of a mechanical connecting rod

These images were annotated. In another words each image is associated with a mask indicating the position of the defects on the image (see Figure 2)

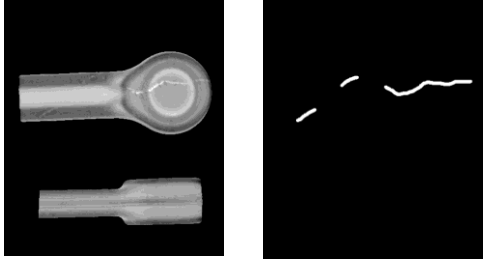


Figure 2. Image of the front part of a mechanical connecting rod (left) and its associated mask (right).

B. Segmentation algorithm

The “SegFormer” architecture [3] and [4] was selected as the baseline segmentation model. It follows a transformer-based encoder-decoder design in which hierarchical visual features are extracted by the encoder while a lightweight decoder reconstructs the segmentation map.

In the federated learning configuration, the dataset is partitioned into N subsets representing N clients. Each client trains a local SegFormer model using its own dataset. The training dataset was partitioned into ten subsets, each representing a local client, see Figure 3.

In the proposed implementation, only encoder parameters are aggregated, while decoder layers remain client-specific. This strategy allows the sharing of generic visual representations while preserving local specialization [2].

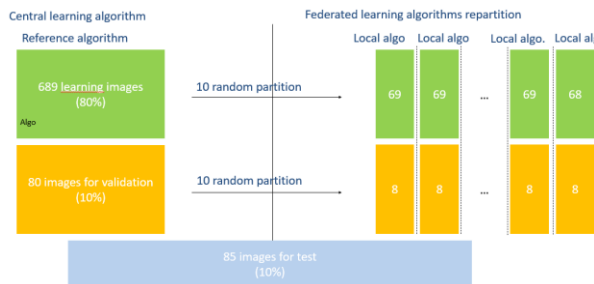


Figure 3. Database partition for federated learning

B. Evaluation Metric

Segmentation performance is evaluated using the Intersection over Union (IoU) metric also called Jaccard index. It consists of dividing the intersection of the pixels between the mask and the prediction by the union of these pixels (Figure 4).

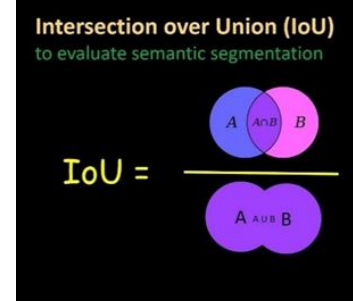


Figure 4. The IOU metric index

C. Experimental results of applying FL for image segmentation

Experimental results show that nine out of ten aggregated models were capable of correctly detecting defects in the thermography images. For seven of these models, the aggregated version outperformed the corresponding local model. On average, the aggregation process improved the Intersection over Union (IoU) metric by approximately 1.2%, see TABLE 1.

TABLE I. FIRST AND SECOND CYCLE MODEL AGREGATION PERFORMANCE USING THE IOU INDEX

	Local C1	Agregated C1	Local C2	Agregated C2	Reference
Model 1	52,9%	53,6%	56,6%	55,5%	60,7%
Model 2	52,1%	49,0%	55,5%	55,3%	60,7%
Model 3	49,7%	52,8%	57,0%	55,7%	60,7%
Model 4	48,1%	50,0%	56,2%	55,9%	60,7%
Model 5	49,2%	52,6%	55,9%	55,2%	60,7%
Model 6	52,0%	52,2%	55,5%	56,3%	60,7%
Model 7	51,3%	49,9%	56,1%	38,6%	60,7%
Model 8	49,3%	52,8%	56,8%	56,7%	60,7%
Model 9	48,7%	51,2%	56,2%	55,7%	60,7%
Model 10	50,4%	0%	56,7%	7,8%	60,7%

A second federated training cycle further improved model performance and moved the aggregated models closer to the centralized reference model.

Additional experiments also investigated the impact of non-IID data distributions by training models using only rear-view images and testing them on mixed datasets.

When models were trained only on rear-view images and evaluated on mixed datasets, segmentation accuracy decreased, highlighting the importance of dataset diversity in federated environments., see TABLE II.

TABLE II. TEST RESULTS USING THE MODEL TRAINED ONLY WITH THE REAR-VIEW IMAGES

	Reference model	Model trained only using the rear-view images
Test using front-view Images	57,2%	39,7%
Test using rear-view images	61,7%	61,6%

III. FEDERATED ANOMALY DETECTION FOR TABULAR DATA

The second use case focuses on anomaly detection in a fluidic test bench composed of a centrifugal pump instrumented with vibration, pressure, temperature, and flow sensors. see Figure 5. The system is integrated into an Industrial Internet of Things (IIoT) architecture that enables continuous monitoring, see Figure 6.

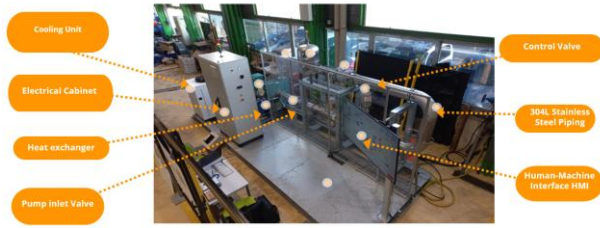


Figure 5. The fluidic circuit test bench

Normal operating data were used to train a One-Class Support Vector Machine (OC-SVM) model that learns the boundary of healthy system behavior. Principal Component Analysis was used to visualize the data distribution and confirm the presence of both stable regimes and transient operating phases.

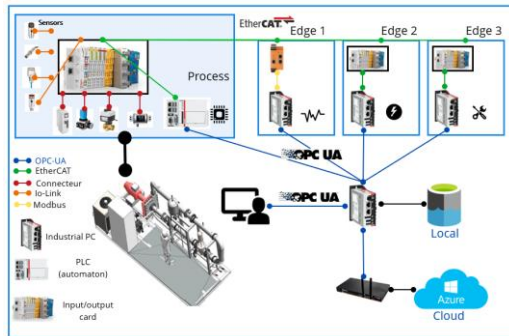


Figure 6. The Benchmark IIoT architecture

A. Dataset Characteristics

The dataset includes several operating conditions. The healthy operation with 65042 samples. Pump mechanical seal leakage (5593 samples), pump blade unbalance (235 samples), cavitation (52 samples) and process faults clogging (12930 samples).

Obviously, the data collected shows a strong dominance in healthy mode. For more details on the demonstrator and the database used, the reader can refer to the reference report [5]

B. Privacy-Preserving Aggregation using Pseudo Support Vectors

In standard OC-SVM models, support vectors correspond to real training samples and cannot be shared without compromising data confidentiality. To address this issue, a pseudo-support vector (pseudoSV) approach was developed. Instead of transmitting real support vectors, each client generates artificial vectors using geometric transformations applied to the original vectors. These pseudo-vectors lie close to the same decision boundary but do not correspond to real observations, see Figure 7.

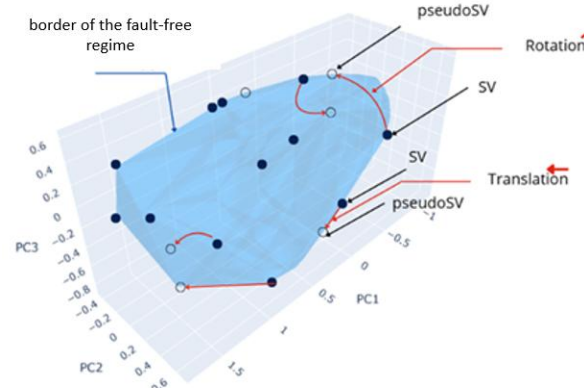


Figure 7. The pseudoSVs generation

The central server aggregates pseudo-support vectors from all clients and trains a second OC-SVM model to produce the global model. This innovative method, preserves privacy while enabling meaningful federated model aggregation, see Figure 8.

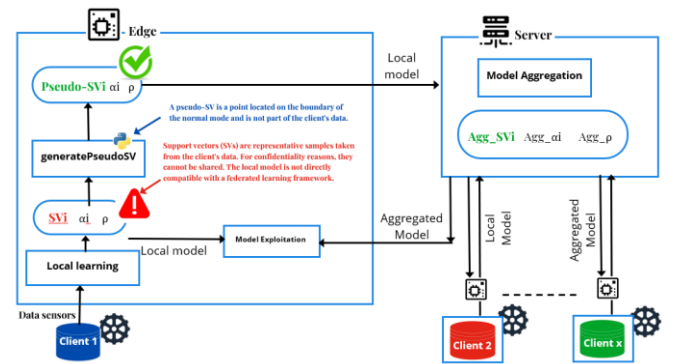


Figure 8. The Benchmark data collection architecture

This method provides a response to the aggregation challenge. It is based on two essential principles:

- Clients never transmit their real SVs, but generate pseudo-SVs, i.e. artificial points reproducing the geometry of the local boundary without corresponding to real data.

- The server extracts a global OC-SVM model from all of these pseudo-SVs coming from the different clients by applying a second OCSVM classification. In this way, the fundamental parameters of the model (SV, α_i , ρ) are recalculated directly from transformed and secured data.

This strategy has two major advantages:

- Confidentiality is guaranteed, since only artificial and non-traceable samples are exchanged between clients and the server.
- The relevance of the global model is ensured, because the OC-SVM finds its parameters by exploiting an enriched set of pseudo-SVs from all clients.

Note that attention to data uniformity (IID) must always be checked so as not to degrade the performance of the model. Indeed, although the proposed method partially resolves this problem, nevertheless this lock remains significant.

C. Experimental results

Experiments were conducted using several strategies for distributing healthy dataset among four clients, including clustering-based partitioning, quantile-based partitioning, and temporal block partitioning. These strategies introduce different degrees of data heterogeneity (No IID). Figure 9 presents the two-dimensional PCA of healthy data distribution according to the three strategies: A) Characteristic clusters, B) quantile, C) temporal blocks. Blue presents data coming from client 1, Orange for client 2, light blue for client 3 and red for client 4. The objective of this distribution is twofold:

- Reproduce non-independent and non-identically distributed data situations,
- Analyze the impact of this heterogeneity on the learning of local models and, subsequently, on the federated model.

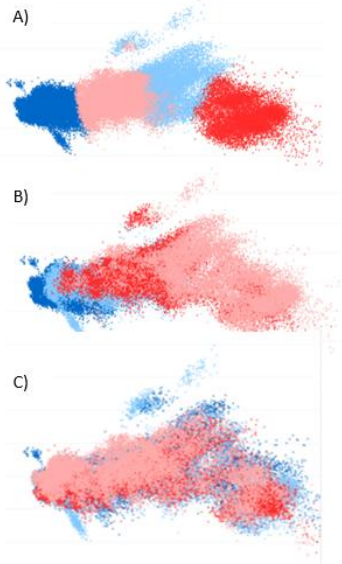


Figure 9. Two dimensional PCA resrepresentation of healthy data distribution according to the three strategies: A) Characteristic clusters, B) quantile, C)temporal blocks. Colors represents the four clients.

D. Results for applying FL for anomaly Detection using Tabular Data

For each distribution strategy (clusters of characteristics, quantiles of a variable, temporal blocks), four local OCSVM models are trained, corresponding to the four simulated clients. Each model is trained exclusively on local healthy data, without access to data from other clients.

In order to evaluate the ability of local OCSVM models to recognize nominal operation, they are tested on an independent healthy dataset, composed of 5854 samples, identical to that used for the evaluation of the global model. This data was not used when training local models and comes from the same processing pipeline.

Table III presents the percentage of healthy observations correctly recognized as normal by each of the local models, for the three data distribution strategies. Each column corresponds to a local OCSVM model (clients 1 to 4), trained on a different subset of data depending on the strategy considered.

TABLE III. RESULTS OF THE APPLICATION OF THE DIFFERENT MODELS ON THE TEST DATA

	Local client 1	Local Client 2	Local client 3	Local client 4	Aggregated	Reference central
Characteristic-clusters distribution	43,91 %	15%	13,07 %	30,99 %	54,89 %	95,46%
Quantile distribution	48,66 %	25,25 %	26,9 %	39,65 %	48,66 %	95,45%
Temporal blocks distribution	89,19 %	93,41 %	90,96 %	92,96 %	99,81 %	95,46%

Results show that strongly non-IID distributions significantly reduce the ability of local models to represent the full normal operating space. The federated model partially improves the coverage of healthy data but still remains below the centralized reference model when the heterogeneity is very strong. Time-based partitioning produced more homogeneous distributions and yielded better local and federated performance

IV. CONCLUSION

This work investigated federated learning approaches for mechanical equipment diagnostics using both image and tabular datasets.

For infrared thermography image segmentation, federated training with encoder-level aggregation improved the performance of several local models and demonstrated the feasibility of collaborative learning in industrial inspection scenarios.

For tabular data anomaly detection, a novel pseudo-support vector mechanism enabled the federated aggregation of OC-SVM models while preserving data confidentiality.

In practice, industrial datasets often exhibit strong temporal or operational variations. Future research should therefore

focus on aggregation strategies that explicitly account for non-IID data distributions, additional contextual information sharing, and real-world deployment on IIoT edge infrastructures connected to cloud-based aggregation servers.

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