Towards Real Unsupervised Anomaly Detection Via Confident Meta-Learning

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Introduction

- We argue that what is commonly referred to as unsupervised anomaly detection is better described as semi-supervised, as it assumes all training data are nominal.
- While this approach alleviates the need for labeled defective samples, it still requires an operator to care fully curate the training dataset to ensure that no anomalous samples are present.
- Manual filtering step introduces a significant limitation: it is time-consuming and susceptible to human error and bias.

Problem Statement

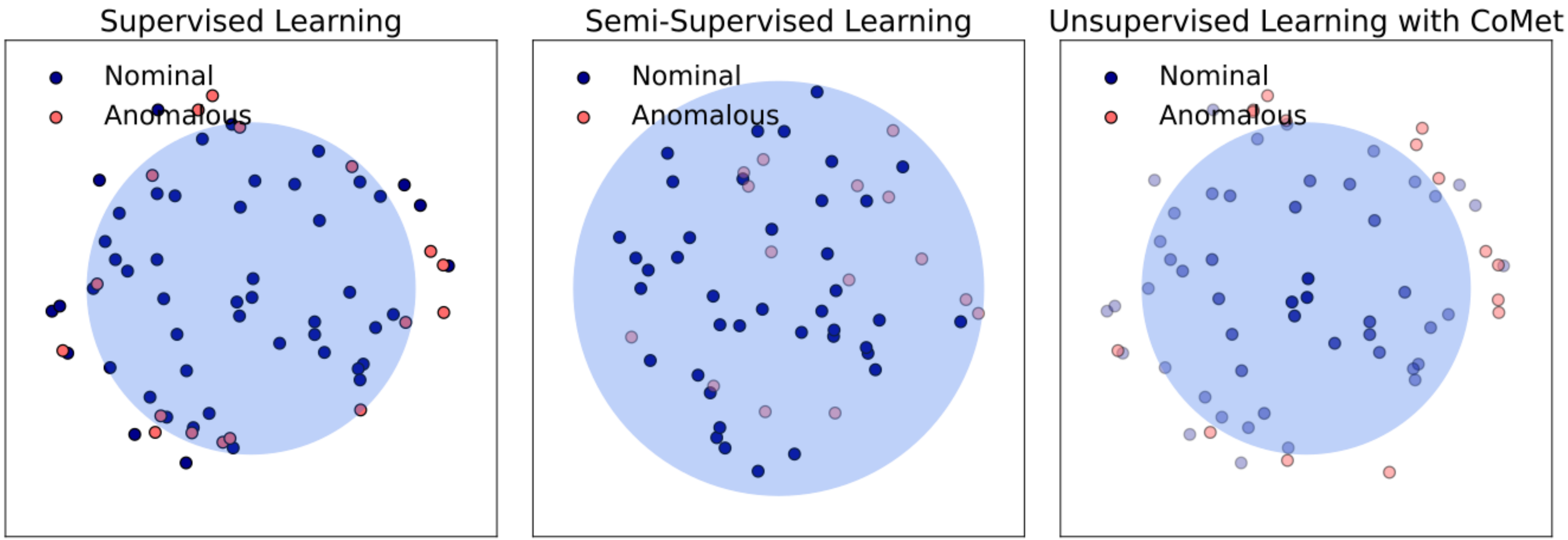

Fig 1: Impact of anomalies and boundary samples in training sets.

Proposed Approach

- We propose a novel **Confident Meta Learning (CoMet)** training strategy that eliminates the need for manually filtering training data.
- Our method enables deep learning models to learn from raw, uncurated datasets where nominal and anomalous samples may coexist, without requiring explicit labels.
- By relaxing the assumption that all training data are nominal, our approach allows anomaly detection models to operate in a truly unsupervised manner.

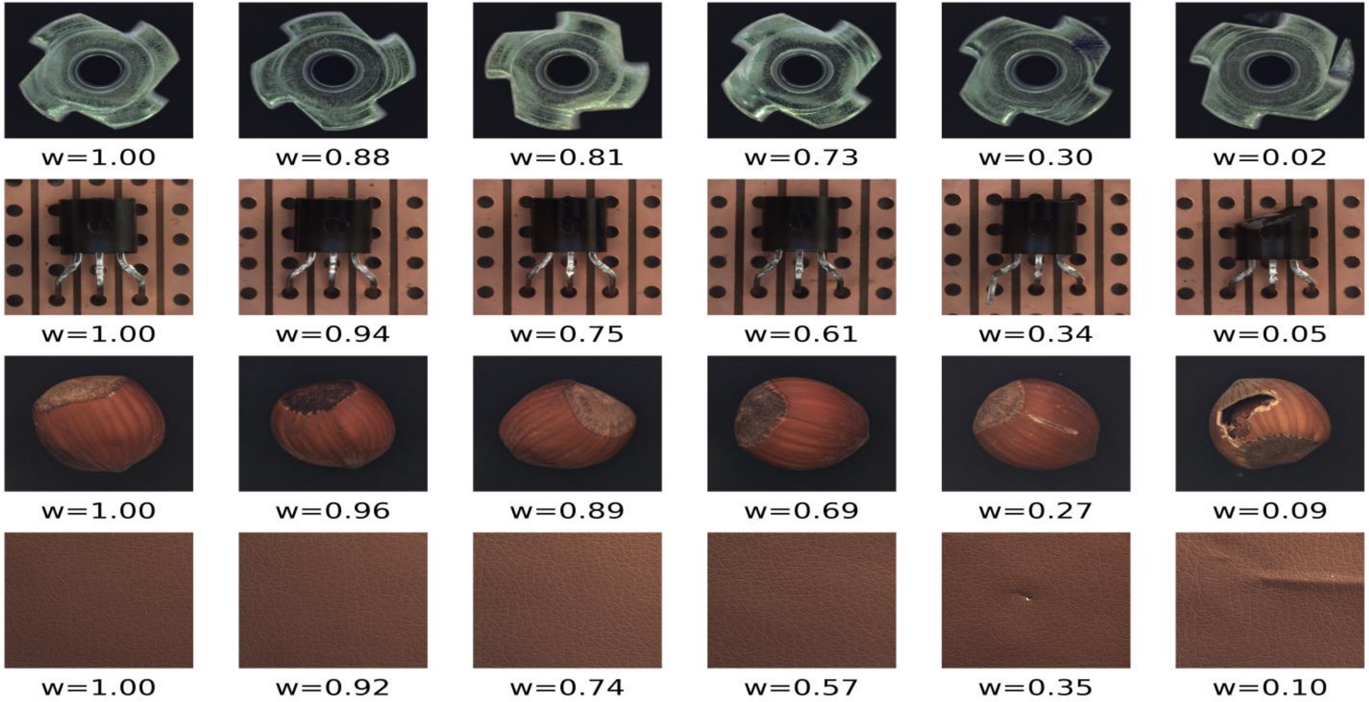

Fig 2: Training samples (nominal and anomalous) for some classes of the MVTec-AD dataset with the associated confidence weight w estimated by CoMet. Weights close to 1 indicate prototypical samples, while lower weights suggest samples close to (or beyond) the decision boundary.

Main Contributions

- A novel training framework that allows anomaly detection models to learn more robust models by assigning low confidence scores to ambiguous samples near the decision boundary.
- Models trained with CoMet achieve higher performance in anomaly detection by significantly reducing undetected anomalies (false negatives) at the cost of slightly increasing false positives.
- Extensive experiments on three public benchmarks demonstrate that CoMet achieves state-of-the-art performances, effectively handling the presence of anomalous samples in the training set.

CoMet Pipeline

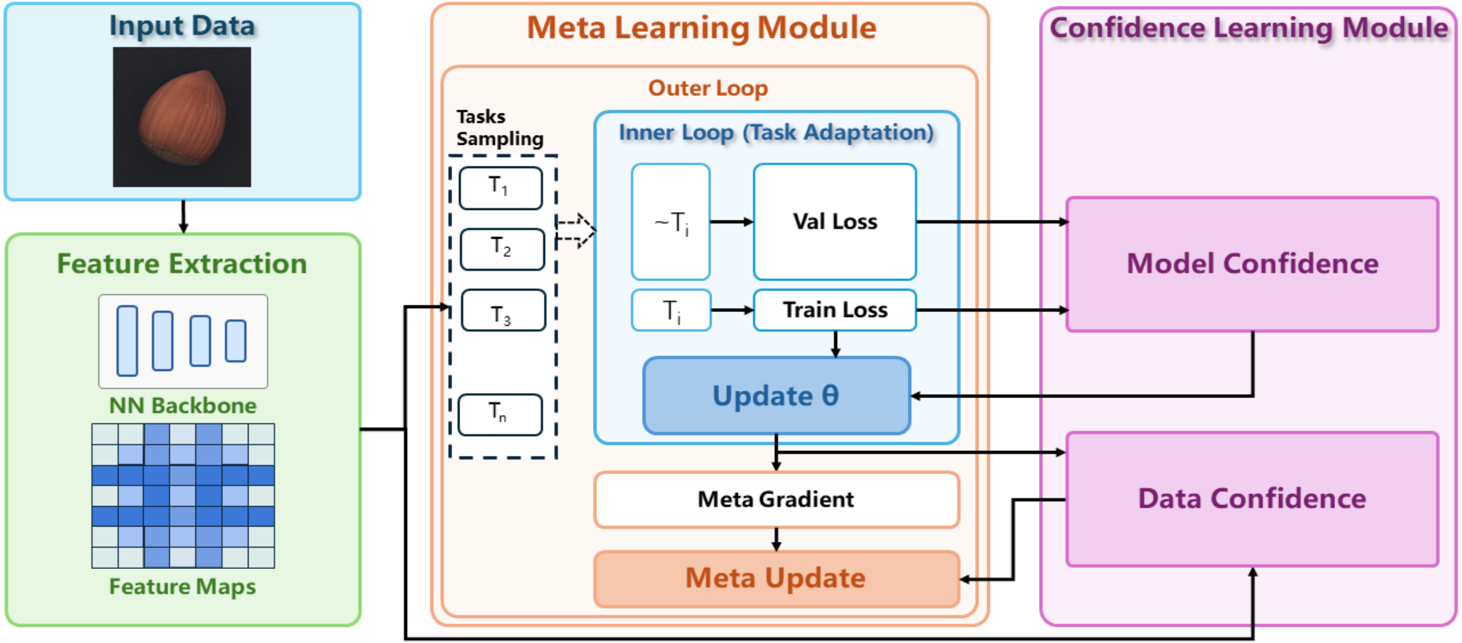

Fig 3: CoMet pipeline.

Confident Learning

- The goal of the confident learning module is to allow the model to rely more on those samples that are more prototypical for the normal class and less on those samples that are anomalous or close to the boundary.
- To this aim, we quantify both **Data Uncertainty** and **Model Uncertainty** within an unsupervised learning framework, where we do not have access to labels.

Quantifying Data Uncertainty

- To quantify data uncertainty, we adapt the concept of the confident joint from the Confident Learning framework to our unsupervised setting. In this context, we consider the relationships between data points and their confidence scores assigned by the model.

$$w_i = \min\left(1, {}^{t}/_{a_\theta(x_i)}\right)$$

$$t = Q3 + \kappa(Q3 - Q1)$$

- We can now define the data weighted loss function as:

$$L_{data}(\theta) = \sum_{i=1}^{N} w_i \, . L_{AD}\left({}^{x_i}/_{\theta}\right)$$

Quantifying Model Uncertainty

- We quantify the model's uncertainty by calculating the determinant of the covariance matrix Σ formed from the training and validation loss distributions.

$$\sum = \begin{bmatrix} Cov\,(L_{train}, \; L_{train}) & Cov(L_{train}, \; L_{val}) \\ Cov\,(L_{val}, \; L_{train}) & Cov(L_{val}, \; L_{val}) \end{bmatrix}$$

- To incorporate this measure into the training procedure, we introduce an adaptive regularization term λ that adjusts dynamically.

$$\lambda(\sum) = \lambda_0 . \left(1 + \gamma \, . \, det(\sum)\right)$$

- Combining both model and data uncertainty, our confident learning loss function becomes:

$$L_{SCL}(\theta) = \sum_{i=1}^{N} w_i \, . \, L_{AD}\left({}^{x_i}/_{\theta}\right) + \lambda(\sum) . \, \|\theta\|_2^2$$

Meta Learning

- Inner Loop Optimization:

$$\theta' = \theta - \alpha \nabla_\theta L_{train}(\theta)$$

- Outer Loop Generalization:

$$\theta = \theta - \beta \nabla_\theta L_{meta}(\theta)$$

- We finally integrate the reweighted loss function from Confident Learning into the meta-objective:

$$L_{meta}(\theta') = \sum_{i=1}^{N} w_i \, . L_{AD}\left({x_i}/{\theta'}\right) + \lambda(\Sigma'). \|\theta'\|_2^2$$

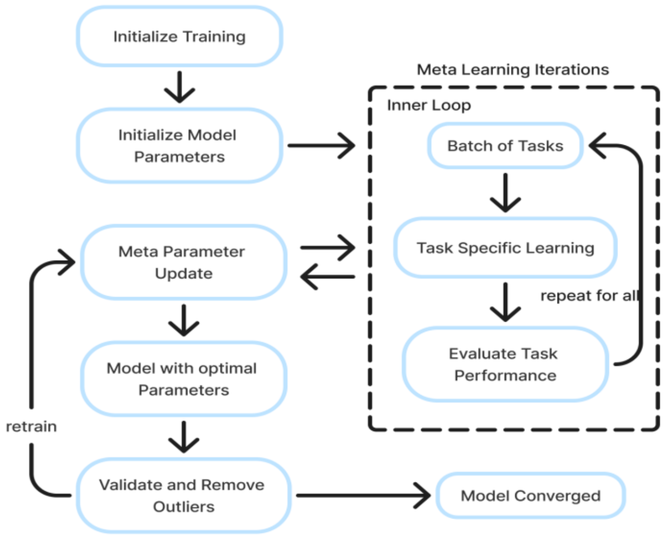

Fig 4: Meta-learning process with outer and inner loops. In the inner loop, each task batch T1 to Tn updates task-specific parameters by optimizing θ'. After completing inner loop updates, the outer loop aggregates these adjustments to refine the global θ, enhancing the model's ability to generalize and adapt quickly to new tasks.

Results

- Three state-of-the-art datasets including **MVTec-AD, VIADUCT** and **KSDD2** were used for experiments.
- **CoMet Implementation with Normalizing Flow**
  - We implemented our strategy to DifferNet and the performance of this model improved 94.9 to **99.2**, 76.2 to **83.5** and 91.5 to **94.9** for **MVTec-AD, VIADUCT** and **KSDD2** respectively.
- **CoMet Implementation with SimpleNet**
  - We implemented our strategy to SimpleNet and the performance of this model improved 99.6 to **99.7**, 87.1 to **90.3** and 91.7 to **92.2** for **MVTec-AD, VIADUCT** and **KSDD2** respectively.

Dataset	DifferNet [20]			CoMet-NF		
	Precision	Recall	F_1-score	Precision	Recall	F_1-score
MVTec AD	95.6	76.4	84.9	92.5	93.4	92.9
VIADUCT	79.1	70.3	74.4	77.1	90.8	83.4
KSDD2	90.9	87.5	89.2	87.4	94.3	90.7

Dataset	SimpleNet [16]			CoMet-SN		
	Precision	Recall	F_1-score	Precision	Recall	F_1-score
MVTec AD	98.1	98.9	98.5	97.8	99.8	98.8
VIADUCT	84.1	93.6	88.6	83.4	97.5	89.9
KSDD2	96.2	70.0	81.0	96.0	70.3	81.2

Table 1: Average Precision and Recall for baseline and CoMet models on MVTec AD, VIADUCT and KSDD2 datasets.

Noise Robustness

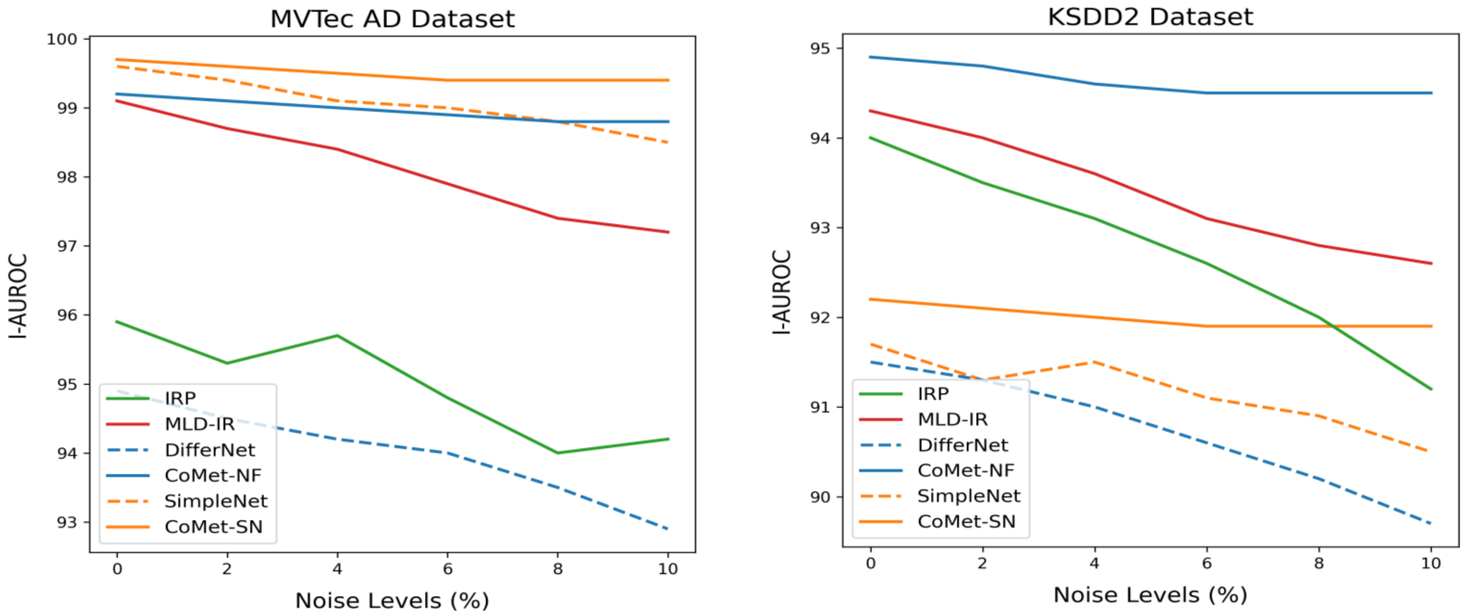

Fig 5: Comparison of anomaly detection methods on the MVtec-AD and KSDD2 datasets, showing I-AUROC values across noise levels from 0% to 10%.

Conclusion

- We targeted the problem of unsupervised anomaly detection, where unlabeled nominal and anomalous samples are available at training time.
- We presented CoMet, an innovative framework for training anomaly detection models that integrates confident learning with meta learning to iteratively refine decision boundaries by dynamically identifying and down weighting ambiguous boundary samples.

Find out more

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