Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

SEMI-SUPERVISED CONTRASTIVE LEARNING FROM SEMICONDUCTOR MANUFACTURING TO TFT-LCD DEFECT MAP

Chia-Yen Lee[1], I-Kai Lai[1], and Yen-Wen Chen[1]

[1] Department of Information Management, National Taiwan University, Taipei City, TAIWAN

ABSTRACT

Defect pattern detection and classification present significant challenges in thin-film transistor liquid-crystal display (TFT-LCD) manufacturing. Traditional machine learning approaches struggle with data scarcity, insufficient labeling, and class imbalance. To address these limitations, this study proposes a two-stage defect classification framework for Test for Open/Short (TOS) maps, which measure electrical defects by using contrastive pre-training on semiconductor manufacturing wafer bin maps to enhance classification with limited TOS data, followed by a novel dual-branch open-world semi-supervised learning that robustly handles both class imbalance and novel pattern discovery.

1 INTRODUCTION

During TFT-LCD manufacturing, electrical defects disrupt signal transmission and cause visible panels defects. Test for Open/Short (TOS) maps provide reliable identification of electrical defects. TOS faces three challenges: (1) insufficient labeling, as manual inspection is time-consuming and costly; (2) inherent data imbalance; and (3) emergence of novel defect patterns during production. Most existing studies focus on classification using traditional machine learning techniques under the assumption that all defect patterns are known in advance, which rarely holds true in real settings. While open-world semi-supervised learning (SSL) (Cao et al. 2022) has emerged as a promising approach for addressing scenarios where unlabeled data may contain novel classes not present in the labeled dataset, current open-world SSL typically assume class balance, limiting their effectiveness in imbalanced manufacturing settings. To address these challenges, we propose a two-stage framework that combines contrastive representation learning with open-world SSL for classification within TOS maps in a transductive manner. The framework first leverages contrastive pre-training for knowledge transfer from wafer bin maps, which share similar defect patterns with TOS maps, to enhance feature extraction despite limited TOS data. Second, the framework employs a dual-branch open-world SSL that integrates a contrastive learning for distribution estimation to classify both known and new defect patterns under imbalanced conditions.

2 METHODOLOGY

The proposed two stages framework is shown in Figure 1. In the contrastive learning pre-training stage, we pretrain the feature extractor on a wafer bin maps dataset using SimCLR (Chen et al. 2020) to generate transferable feature representations. In the open-world SSL stage, we transfer the pretrained weights and implement our dual-branch open-world SSL. The two branches guide each other iteratively during training, creating a mutually beneficial feedback loop. The contrastive learning branch performs contrastive learning based on self-supervision and guidance from pseudo-labels provided by the open-world SSL branch. This estimated distribution is subsequently used to regularize the predictions of the open-world SSL branch to address challenges posed by imbalanced data. The open-world SSL branch extends the ORCA (Cao et al. 2022) framework. The supervised objective implements cross-entropy loss with an uncertainty adaptive margin mechanism to balance known and novel class learning speed. The pairwise objective transforms cluster learning into a similarity prediction task, encouraging similar patterns to cluster together using a modified binary cross-entropy loss. Distribution regularization aligns model predictions with the estimated distribution using KL divergence.

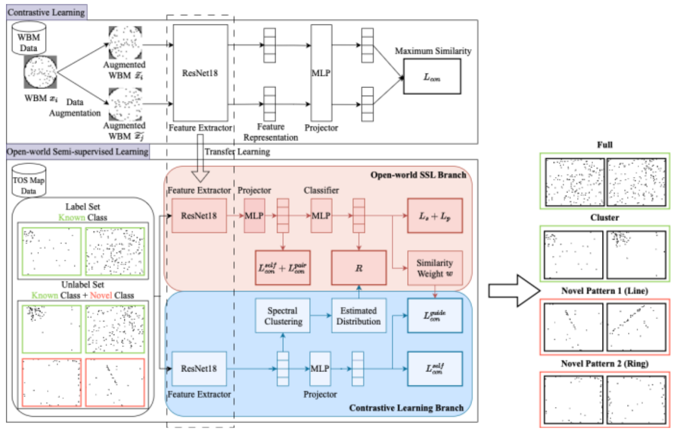

Figure 1: The proposed two-stage SSL framework.

3 EMPIRICAL STUDY

We collect four defects types of TOS map with 521 synthetic data based on real settings. To validate the proposed framework, two experimental scenarios were constructed. In the first scenario, a setting was created where known pattern datasets are relatively larger than novel pattern datasets, simulating the typical class imbalance in manufacturing environments. In the second scenario, this relationship was reversed to simulate the emergence of large quantities of novel pattern data resulting from production environment changes. The classification results are averaged over ten repeated experiments. The proposed framework demonstrates significant advantages over other methods across both scenarios. Specifically, our framework achieves superior classification accuracy while maintaining competitive or lower variance in most cases. In contrast, ORCA exhibited higher performance variability due to its frequent failure to identify novel patterns effectively. The comparison between methods with and without pre-training confirms the necessity of our knowledge transfer strategy. Without pre-training, ORCA failed to recognize novel patterns, and the proposed method also experienced notable performance degradation. Furthermore, a t-SNE visualization of the learned representation shows that our proposed framework enables more compact and well-separated feature clusters, particularly for novel classes. These results validate our dual-branch method and pre-training strategy for robust defect classification in imbalanced and novel pattern scenarios.

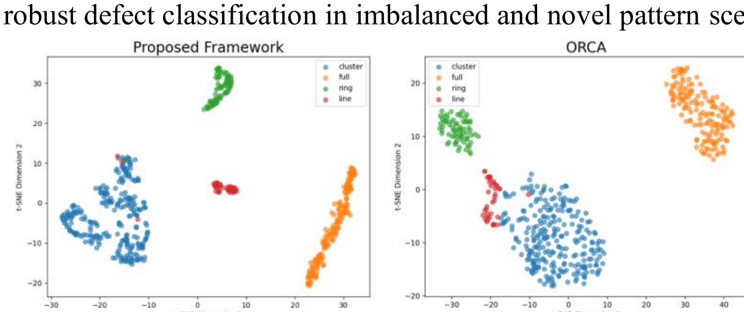

Figure 2: Comparing representations of ORCA, and proposed framework using t-SNE.

REFERENCES

Cao, K., Brbic, M., & Leskovec, J. 2022. Open-World Semi-Supervised Learning. Proceedings of the International Conference on Learning Representations.

Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. 2020. A Simple Framework for Contrastive Learning of Visual Representations. Proceedings of the 37th International Conference on Machine Learning, 1597–1607.