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A SELF-SUPERVISED LEARNING BASED FRAMEWORK FOR TFT-LCD DEFECT CLASSIFICATION

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ABSTRACT

This study presents a self-supervised learning based framework for TFT-LCD defect classification in semiconductor smart manufacturing. Utilizing the Swapping Assignments between Views (SwAV) model trained on 1,000,000 unlabeled TFT-LCD images, the framework achieves an overall top-1 accuracy of 0.709 and precision of 0.7812 in downstream task of classifying 13 types of TFT-LCD defects. Compared to using SwAV pre-trained weighs on ImageNet, proposed domain-specific self-supervised learning model significantly outperforms, emphasizing the importance of domain-specific training. The framework offers manufacturers a cost-efficient decision support system, enhancing TFT-LCD defect classification quality.

1 INTRODUCTION

Within semiconductor smart manufacturing, defect classification heavily relies on labeled data, resulting in significant costs associated with expert annotation. However, the adoption of self-supervised learning significantly reduces the need for labeled data as the model learns the representation directly from unlabeled data (Kahng and Kim, 2020). Moreover, the learned representations from self-supervised learning yield more robust and generalizable models, leading to improve the defect classification performance under large amount of unlabeled data, even when confronted with unseen or novel defects.

This study proposes a self-supervised learning based framework for TFT-LCD defect classification, which provides an novel solution to address the challenges associated with TFT-LCD defect classification in semiconductor manufacturing. By capitalizing on self-supervised learning techniques, it mitigates the need for expensive and time-consuming manual labeling of defects, reducing the label cost burden.

2 SELF-SUPERVISED LEARNING BASED FRAMEWORK FOR TFT-LCD DEFECT CLASSIFICATION

This study utilizes a dataset of 1,000,000 unlabeled TFT-LCD images to train a Swapping Assignments between Views (SwAV) self-supervised learning model as pretext tasks. The SwAV provides strong performance in image classification task and improvement of computational efficiency (Caron *et al.*, 2020). Subsequently, the trained SwAV model is used for defect classification downstream, focusing on 13 types of TFT-LCD defects, with each defect type comprising 1,000 data. The results demonstrate an overall top 1 accuracy of 0.709 and a precision of 0.7812. These findings highlight the efficacy of the self-supervised learning approach for defect classification in the TFT-LCD manufacturing process. Indeed, offers domain experts a decision support system that enhances the quality of defect classification shown as Figure 1.

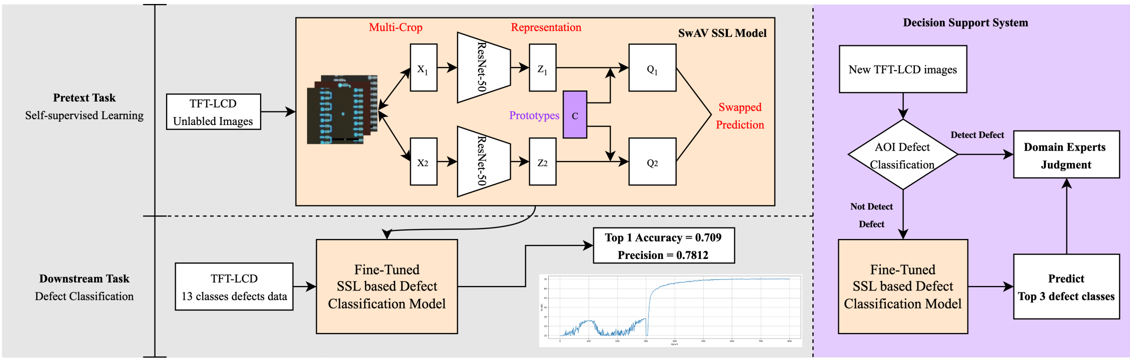

Figure 1: Self-supervised learning based framework for TFT-LCD defect classification

In this study, proposed framework is compared to an approach that does not involve training on domain-specific TFT-LCD defects dataset. The comparison involves loading SwAV model weights pre-trained on ImageNet as pretext tasks and fine-tuning it with same 13 classes of TFT-LCD defect dataset. The results indicate that the approach without training on TFT-LCD defects dataset performs poorly in the TFT-LCD defect classification task, achieving only an overall top 1 accuracy of 31% and a precision of 0.33. Despite the SwAV model pre-trained on ImageNet have strong generalization capabilities, the domain-specific self-supervised learning model outperforms it significantly in the task of TFT-LCD defect classification.

3 CONCLUSION AND FUTURE WORK

In conclusion, this study proposes a self-supervised learning based framework for TFT-LCD defect classification, which provides two main contributions. Firstly, the SwAV self-supervised learning model can learn representations from a large amount of unlabeled data and only uses a few labeled data to fine-tune itself. This approach reduces the time-consuming and costly labeling efforts required from domain experts. Secondly, proposed domain-specific SwAV self-supervised learning model proves to be a more precise and appropriate solution for TFT-LCD defect classification compared to one applying a pre-trained model on ImageNet dataset. Accordingly, this study emphasizes the importance of task-specific training for achieving optimal performance in defect classification tasks within semiconductor smart manufacturing.

The future work will focus on improving the performance of framework by adding domain-specific data augmentation and modifying the structure of SwAV model. Besides, multi-modal data fusion will be applied to add comprehensive information to proposed model such as textual descriptions of defects, which leading to improved accuracy and reliability. (Gaw *et al.*, 2022).

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