Semi-supervised mold differentiation using typical laboratory results as label data

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1 Extended Abstract

1.1 Introduction

Ensuring clean air in offices and production facilities is crucial for employee health and operational efficiency. According to the VDI guideline 6022, air quality from ventilation systems should be maintained[1]. To monitor this, customers provide air samples in petri dishes, which are incubated for 5-7 days to allow mold growth. These molds are then counted and differentiated to assess air quality. Manual differentiation, especially under a microscope, is time-consuming and costly.

The project aimed to reduce the time required for differentiating macromorphologically distinguishable molds using deep neural networks, excluding samples needing microscopic examination. Automating this process could significantly reduce costs, enabling more frequent sampling and early detection of air quality issues.

1.2 Goal of the project

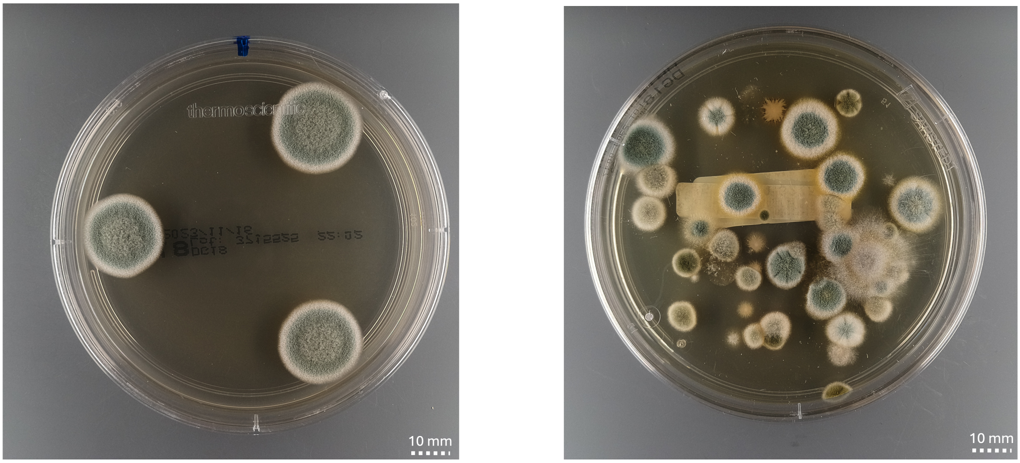
The goal was to train two classification models to differentiate five specific classes of mold using artificially created data. A sixth class, "other," was included to handle unobserved species. The target classification accuracy was set at 60% as a realistic initial target.

1.3 Main steps

Dataset Creation A semi-supervised approach was used to generate a artificial dataset. Images of mold samples on Petri dishes were captured after 5-7 days of incubation. A pre-trained YOLOv7 model detected molds, significantly reducing manual annotation time. Uniform samples allowed for automated annotation, maintaining high-quality labeled data for training the classification models.

Model selection and training EfficientNet V2 [2] and Normalization-Free Net (NFNet) [3] were selected for their ability to handle high data variance and varying input sizes. Both models were pre-trained on ImageNet [4] to leverage transfer learning.

Training included data augmentation to improve robustness. Two training strategies were used:



(a) Artificial sample (b) Real sample

Fig. 1: Comparison of artificial and real samples used for dataset creation.

- **Padded Image Training**: Images were padded to a fixed size for batch processing.
- **Training on Unpadded Images**: Preserved the original size and features, suitable for NFNet.

Explainable AI Grad-CAM (Gradient-weighted Class Activation Mapping) [5, 6] was implemented to ensure that model predictions were interpretable. Grad-CAM generates visual explanations, highlighting regions in the input image most influential in the decision-making process.

Evaluation on real data After training on the artificial dataset, models were evaluated on real laboratory data to assess their performance. Fine-tuning and parameter adjustments ensured they met the target accuracy of 60%. The NFNet model, trained on unpadded images, showed superior performance in handling data variance.

1.4 Summary of results

The NFNet model, trained on unpadded images, achieved 85.9% accuracy, 83.7% precision, and 78.9% recall. EfficientNet V2, with padded images, achieved 81.4% accuracy, 55.3% precision, and 53.6% recall.

Grad-CAM provided valuable insight into the model's decision-making process, ensuring transparency. The semi-supervised approach reduced manual differentiation time by approximately 50%, speeding up the process and reducing costs.

Overall, the results provide a promising foundation for the further development and practical implementation of automated mold differentiation systems in laboratories.

References

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