A Representative Sampling Approach to Few-Shot Transfer Learning

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1 Introduction

Plant growth estimation is crucial in controlled environment agriculture (CEA). Traditional manual measurements and conventional image processing techniques are inefficient for large-scale monitoring, and deep learning models often require large datasets. In this study, we propose a representative sampling approach in few-shot regression context for cucumber plant height estimation to address data scarcity and improve generalization. In few-shot learning settings, recent research has shown that representative samples help in better performance. Xu and Lu selected the most representative samples from the training set and used them to train a conditional VAE to generate more representative features [3]. Axiotis et al. used k-means clustering and sensitivity sampling to select representative samples [1].

2 Method Overview

The dataset included 464 side-view images captured daily over 16 days for 29 cucumber plants and their height measurements. Images were resized to 224 $\times$ 224 pixels, and normalized using ImageNet statistics [2]. We extracted 768-dimensional features using Vision Transformer (ViT-B/16) model pre-trained on the ImageNet dataset. Model development was conducted on the training set (371 images), with hyperparameters optimized using 10-fold cross-validation (334 training and 37 validation images per fold). Fuzzy C-Means clustering was applied to each training fold with two clusters, determined based on partition entropy values. The top-N high-confidence samples were proportionally selected (e.g., three from each cluster for $N = 6$). The predictive performance of linear regression, decision tree regression, support vector regression (SVR), random forest regression, and artificial neural network (ANN) models was evaluated using representative and randomly selected samples for comparative analysis.

3 Key Results & Analysis

	Representative Sampling		Random Sampling	
Model	RMSE	R^2	RMSE	R^2
Linear regression	28.21 ± 11.24	0.66 ± 0.12	36.53 ± 16.37	0.31 ± 0.76
Decision tree	40.92 ± 7.69	0.21 ± 0.24	56.74 ± 13.72	-0.71 ± 1.25
SVR	28.21 ± 10.66	0.66 ± 0.12	36.20 ± 14.79	0.36 ± 0.57
Random forest	38.05 ± 13.61	0.40 ± 0.15	44.73 ± 17.67	-0.01 ± 0.95
ANN	32.28 ± 12.10	0.56 ± 0.15	33.78 ± 9.13	0.48 ± 0.16

Table 1. Mean RMSE and R^2 with standard deviations from 10-fold cross-validation of regression models trained on 6 samples ($N = 6$).

Our results, in Table 1, suggest that representative sampling outperforms random sampling and considering the dataset spanned heights from 40 mm to 300 mm, this indicates reliable predictive performance even with very few samples. Standard deviations were consistently smaller with representative samples, indicating more stable performance. Across all models, gains diminished with incresing N, suggesting that the advantage of representative sampling is strongest in data-limited scenarios.

4 Conclusion

In this study, we demonstrated that the proposed approach can effectively estimate cucumber plant height using a minimal number of representative samples. In practice, this strategy can be applied by selecting plants at representative growth stages without requiring large annotated datasets. While our dataset was limited in size and collected under controlled conditions, future work will extend this framework to test its robustness beyond controlled setups.

References

1. Axiotis, K., Cohen-Addad, V., Henzinger, M., Jerome, S., Mirrokni, V., Saulpic, D., Woodruff, D., Wunder, M.: Data-efficient learning via clustering-based sensitivity sampling: Foundation models and beyond. arXiv preprint arXiv:2402.17327 (2024)
2. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: Imagenet: A large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. pp. 248–255. Ieee (2009)
3. Xu, J., Le, H.: Generating representative samples for few-shot classification. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 9003–9013 (June 2022)