Deep Learning Methods for Tassel Count Time-Series

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Abstract

ABSTRACT Counting maize tassels in field conditions is predominantly done manually. Recently, computer-vision based methods have been utilized to detect tassels from images captured by UAV transects or poled-mounted cameras [1], [2], [3]. Once tassels are detected, deep-learning based local regression methods, Tasselnet, have been used to estimate in-field tassel counts [4]. However, field images are mostly captured over a period of time. Consequently, the input images in the foregoing Tasselnet technique are not independent but often form unequal sequences of correlated images. As such, the temporal sequence of images offers information about the growth trajectory of the plants. We propose a hybrid model that (a) utilizes convolutional neural network-based tassel localization in images, and (b) drives the local count of tassels utilizing the plant growth trajectory learned from the time-series of images. The resulting model can also handle important auxiliary information, obtained from in-field sensors (for example: soil moisture, air temperature etc.), that impacts plant growth and tassel counts. We implement our methodology on benchmark dataset [4] and compare our results with the SOTA Tasselnet [5]. Our initial results suggest that our technique is computationally viable and can produce accurate point estimates of tassel counts along with interval estimates capturing the precision of our estimates. Keywords: Computer vision, Convolutional neural networks, Deep learning, Maize tassels, Time-series. REFERENCES [1] Shi, Y., Alzadjali, A., Alali, M., Veeranampalayam-Sivakumar, A. N., Deogun, J., Scott, S., & Schnable, J. (2021). Maize tassel detection from UAV imagery using deep learning. Dryad. https://doi.org/10.5061/dryad.r2280gbcg. [2] Mirnezami, S. V., Srinivasan, S., Zhou, Y., Schnable, P. S., & Ganapathysubramanian, B. (2021). Detection of the Progression of Anthesis in Field-Grown Maize Tassels: A Case Study. Plant Phenomics, 2021, 4238701. doi:10.34133/2021/4238701. [3] Shete, S., Srinivasan, S., & Gonsalves, T. A. (2020). TasselGAN: An Application of the Generative Adversarial Model for Creating Field-Based Maize Tassel Data. Plant Phenomics, 2020, 8309605. doi:10.34133/2020/8309605. [4] Lu, H., Cao, Z., Xiao, Y., Zhuang, B., & Shen, C. (2017). TasselNet: counting maize tassels in the wild via local counts regression network. Plant Methods, 13(1), 79. doi:10.1186/s13007-017-0224-0. [5] Xiong, H., Cao, Z., Lu, H., Madec, S., Liu, L., & Shen, C. (2019). TasselNetv2: in-field counting of wheat spikes with context-augmented local regression networks. Plant Methods, 15(1), 150. doi:10.1186/s13007-019-0537-2.

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Counting maize tassels in field conditions is predominantly done manually. Recently, computer-vision based methods have been utilized to detect tassels from images captured by UAV transects or poled-mounted cameras [1], [2], [3]. Once tassels are detected, deep-learning based local regression methods, *Tasselnet*, have been used to estimate in-field tassel counts [4]. However, field images are mostly captured over a period of time. Consequently, the input images in the foregoing *Tasselnet* technique are not independent but often form unequal sequences of correlated images. As such, the temporal sequence of images offers information about the growth trajectory of the plants.

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REFERENCES

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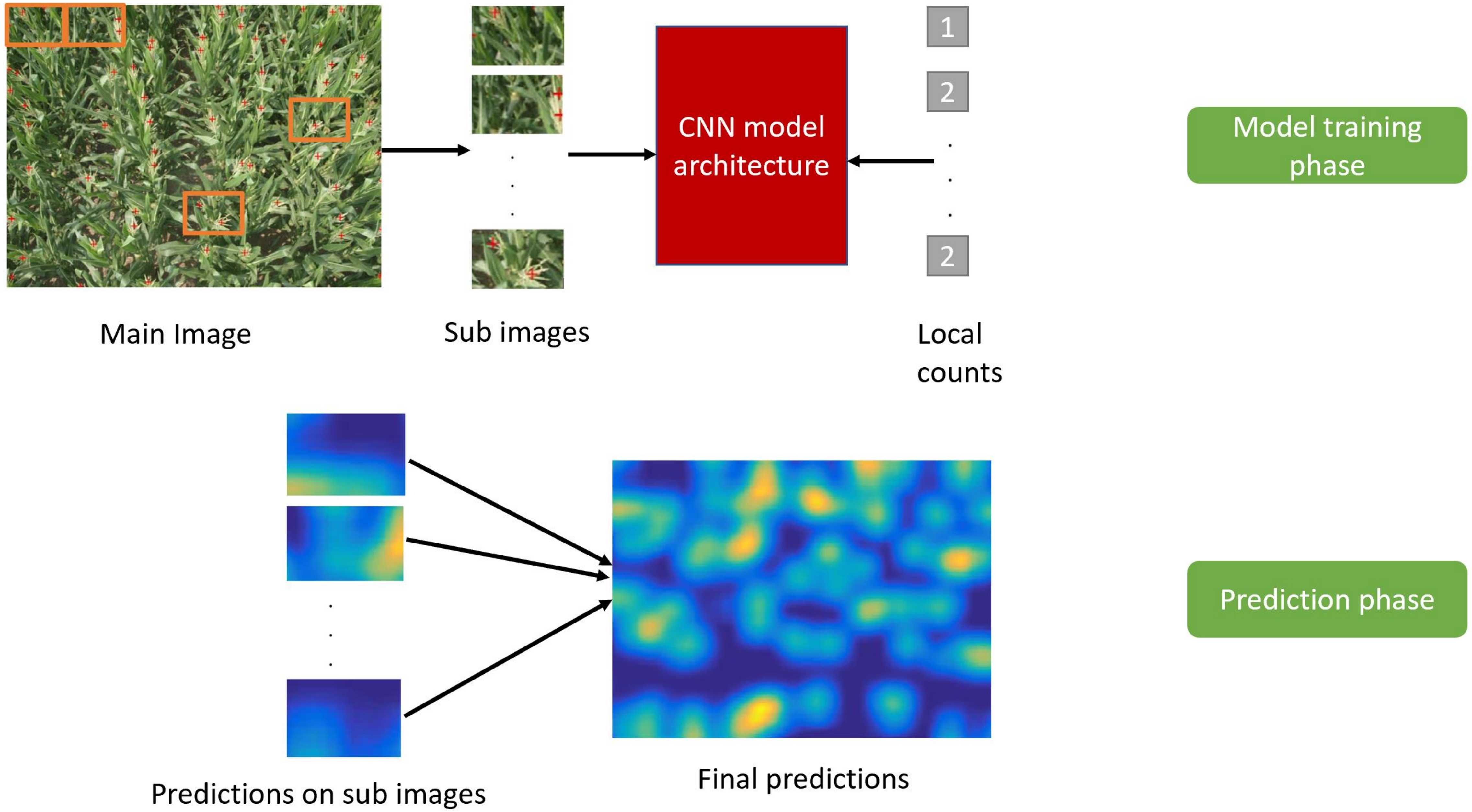
Objective:

Automating the process of crop monitoring and yield forecasting for the maize farmer using AI.



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