Explainable Droplet Recognition System for Precision Sprayer Applications

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***Abstract*—AI-driven detection systems are playing an increasingly important role in the advancement of precision agriculture. In this paper, we have implemented a transfer learning pipeline for water droplet detection with the intent to develop quantifiable and real-time detection of post-spray areas for precision spraying applications. The object detection pipeline effectively identified multiple features for water droplet detection from the three curated datasets. We have used two pre-trained convolutional backbones as the feature extractor and achieved an overall detection mean average precision across the three curated datasets of 0.409 and 0.277 for the ResNet50, and MobileNetV3-Large backbones respectively. Additionally, for visual explanations and interpretation, we implemented EigenCAM class activation mapping techniques to highlight the regions of the input images that are important for predictions.**

I. Introduction

In the present-day world, precision agriculture is of vital importance and many precise data-driven AI components are being used extensively as technological advancements occur. In this paper, we explore water droplet recognition for precision spraying that will help quantify the aftereffect of spraying. The current requirements for precision spraying systems are changing to fall in line with the new EU green deal [1]. According to the regulations, precision sprayers need to be evaluated to ensure each system can achieve suitable accuracy in spraying applications with an aim to minimise the usage of chemicals. Therefore, the evaluation must rely upon what has been sprayed and what has happened following the usage of the sprayer. There have been some attempts on spraying aftereffect measurement attempts in recent years [2]. However, we are formulating a methodology based on water droplet detection on plant surfaces as a measure of efficacy in spraying applications. We have used state-of-the-art deep learning methods to detect each droplet formed on plant surfaces after spraying. For this paper, we have used pseudo realistic experimental data generated in a lab setting as there are no other available datasets as this has not been attempted before. We will use transfer learning to aid accuracy and to see if we can find any transferable features.

The remaining sections of this paper are organised as follows. In section II, we provide a description of the dataset used and further detail on the droplet detection network. Following this, we have presented results with Saliency Class Activation Maps (CAMs) to illustrate what features the network is looking at. The influence of model backbones on the model accuracy are also discussed in this section. Finally, conclusions are drawn in Section IV.

II. Methodology

A. Dataset Description

We have collected three datasets (discussed in following subsections) to capture properties of droplets to investigate the efficacy of the usage of deep learning approaches to identify useful features for droplets. We have named the datasets as Drying, High Magnification, and High Resolution in table I. The columns Max and Min in table I indicate the maximum and minimum number of instances per image.

TABLE I
Statistics on Dataset instances

Dataset	Instances	Dataset Name	Max	Min
Drying Droplets	311	Dataset-1	26	2
High Magnification	200	Dataset-2	1	1
High Resolution	2891	Dataset-3	475	4

1) Drying Droplets: This dataset was collected using a high magnification camera pointed at a leaf that was sprayed and recorded over time to observe the spray pattern as the droplets wither away. This dataset is labeled as 'Drying' in table I. These images would provide ideal exposure to the temporal features of droplets changing over time.

2) High Magnification: We have a second set of data with a camera that tracks a single droplet using a high magnification camera to highlight the shape and the curvature of the droplets. The second row in table I relates to this set and this dataset would aid a Deep Neural Network (DNN) to learn droplet shape related features.

3) High Resolution: This dataset was collected manually by gathering images including droplets on plant surfaces from Flickr as a way of augmenting the previous two datasets. Our hypothesis with this dataset is the addition of instances from this dataset will increase the detection accuracy of the droplets in general.

B. Droplet Detection Network

To develop the object detection pipeline for this task, have used a Faster RCNN [3] architecture. We have experimented with two backbones so far; namely, ResNet50, and

MobileNetV3-Large. These are available for transfer learning from PyTorch. Each network had comparable parameters during training. Once model training was done, we generated CAMs for test images using the recently proposed EigenCAM [4] for providing further insight to the model.

III. Results

In this section, we have presented results for each dataset. Shown in table II are the mean average precision (mAP) scores for both backbones across the datasets.

TABLE II
MEAN AVERAGE PRECISION (MAP) RESULTS

Backbone	Dataset	mAP
ResNet50	Dataset-1	0.646
MobileNetV3	Dataset-1	0.569
ResNet50	Dataset-2	0.910
MobileNetV3	Dataset-2	0.902
ResNet50	Dataset-1,2,3	0.409
MobileNetV3	Dataset-1,2,3	0.277
ResNet50	Augmented Dataset-1	0.640
MobileNetV3	Augmented Dataset-1	0.587
ResNet50	Augmented Dataset-2	0.898
MobileNetV3	Augmented Dataset-2	0.870

A. Dataset-1,2 Results

As can be seen from the first two rows in table II, for the Drying dataset, the ResNet50 achieved an mAP of 0.646 whilst the MobileNetV3-Large achieved an mAP of 0.569. From table II the results for the High Magnification dataset are optimal. The ResNet50 achieved an mAP of 0.910 whilst the MobileNetV3-Large achieved an mAP of 0.902.

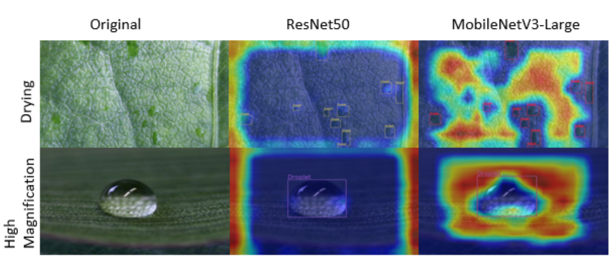

Fig. 1. Class Activation Maps from the final layers of ResNet50 and MobileNetV3-Large backbone for an instance from Dataset-1 (first row) and Dataset-2 (bottom row).

B. Augmentation using the High Resolution Dataset

The hypothesis, as previously mentioned, requires us to compare the mAP from the Drying and High Magnification datasets to the augmented dataset results. These are shown in table II, unfortunately the only results that have improved are the MobileNetV3-Large with the Drying dataset. This is reinforced with figure 2 which shows the CAMs for both backbones. From figure 2 it can be seen that a temporal feature has been used for the MobileNetV3-Large when considering the High Resolution image. It could be suggested that this feature could also be used for other images in the test set for the Drying dataset and improve the mAP. Interestingly, when comparing results from figure 1 and 2 it can be shown that the ResNet50 finds different features for the Drying dataset using a pattern when mixing with the other datasets instead of a temporal one. Yet the ResNet50 still uses temporal features to identify the High Magnification droplet.

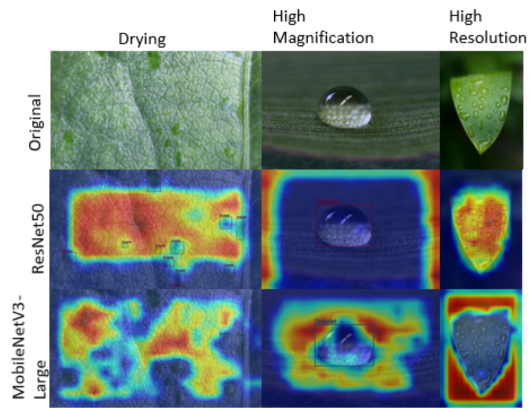

Fig. 2. Class Activation Maps from the final layers of ResNet50 (middle row) and MobileNetV3-Large (bottom row).

IV. Conclusion

To conclude, we have presented an explainable AI approach for droplet detection using CAMs, allowing us to gain further understanding of features for water droplet detection. When considering different backbones, this provides a visual clue on which network is more effective along with the values given by the accuracy indicators. The usage of multiple datasets allowed for different features to be found for each dataset. When considering the Drying dataset and the High Magnification dataset, temporal features were captured by the ResNet50 backbone, but not by the MobileNetV3 backbone. The future work for this paper is to use more realistic datasets to identify droplet features that can be used for monitoring purposes in a real-world precision spraying setup. We are aiming to develop and fine-tune an accurate droplet detection network by utilising the findings from our exploration.

V. Acknowledgement

This work is supported by the Engineering and Physical Sciences Research Council [EP/S023917/1]. This work is also supported by Syngenta as the Industrial partner.

References

[1] E. Commission, "The european green deal," in *European Commission*, 2019. [Online]. Available: https://bit.ly/3fje1au

[2] V. Partel, S. Charan Kakarla, and Y. Ampatzidis, "Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence," *Computers and Electronics in Agriculture*, vol. 157, pp. 339–350, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169918316612

[3] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," 2015. [Online]. Available: https://arxiv.org/abs/1506.01497

[4] M. B. Muhammad and M. Yeasin, "Eigen-cam: Class activation map using principal components," in *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2020, pp. 1–7.