# Poster: mmLeaf: Versatile Leaf Wetness Detection via mmWave Sensing

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## ABSTRACT

Leaf wetness detection is one of the key technologies for preventing plant diseases in agriculture. In this poster, we propose mmLeaf, leveraging a commercial off-the-shelf millimeter-wave (mmWave) radar to detect actual leaf wetness in diverse environments and lighting conditions. mmLeaf captures mmWave signals reflected by monitored leaves with a two-dimensional (2D) scanning system. Then, we use a multiple-input multiple-output (MIMO) array and synthetic aperture radar (SAR) to reconstruct the signal distribution of different planes of the leaves. A deep learning model takes the fused signal distribution as inputs to classify the leaf wetness. We implement mmLeaf using a frequency-modulated continuous-wave (FMCW) radar and evaluate its performance with a potted plant indoors. By exploring the use of mmWave signals, mmLeaf delivers an end-to-end detection framework that achieves up to 90% accuracy in classifying leaf wetness under different distances.

## CCS CONCEPTS

• **Computer systems organization** → **Sensors and actuators**;
• **Computing methodologies** → **Machine learning**.

## KEYWORDS

mmWave sensing, Leaf Wetness, Near-field Radar Imaging, SAR, Deep Learning

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## 1 INTRODUCTION

Leaf wetness brought by dew, precipitation, fog, or irrigation is a key parameter in agriculture, as leaf wetness duration (LWD) is inextricably linked to plant diseases. Specifically, free water on leaves provides a venue for phytopathogenic fungi and bacteria to grow and spread [1]. Once free water has been present on the leaf surface for a certain period at a suitable temperature, different pathogens (e.g., Venturia inaequalis) can survive. Empirical simulation models take numerous agrometeorological variables as inputs

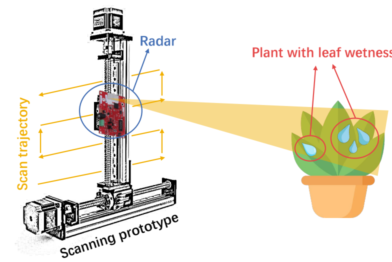


**Figure 1: Leaf wetness detection with mmLeaf**

to estimate leaf wetness. For example, a leaf tends to be wet or dry when the weather is heavily rainy or completely dry/windy. However, measuring leaf wetness becomes challenging facing abrupt temperature changes, windless humid weather, various crop structures, and diverse leaf surface properties [2]. Therefore, fine-grained leaf wetness detection is preferred for crop disease control.

Currently, camera-based methods and electronic leaf wetness sensors (LWSs) are available to determine leaf wetness in real deployments. Since water can change how a leaf reflects light, and the temperature of wet leaves is different from dry leaves, infrared or RGB cameras capture the leaf images, which are fed to deep learning models for leaf wetness analysis [3]. However, camera-based approaches suffer from environmental and lighting changes. For example, RGB cameras do not work in darkness, and infrared cameras work poorly in hot environments. On the other hand, electronic LWSs [4] are widely deployed in practice. With different wetness levels on a sensor's surface, the sensor obtains different resistance or electrical impedance readings of the electronic circuits on its surface [4]. However, the sensor's surface materials are very different from those of a leaf's surface. The detection results only represent sensor wetness but not the actual wetness of the leaf surface. Besides, commercial electronic LWSs with an average price of approximately \$160 per unit, are challenging for farmers to afford and utilize effectively [5].

In this poster, we present mmLeaf, a versatile millimeter-wave (mmWave) based sensing system for wetness detection on real leaves in diverse environments. As illustrated in Figure 1, we use a commercial off-the-shelf (COTS) mmWave radar to build a two-dimensional (2D) scanning system, which emits frequency-modulated continuous-wave (FMCW) signals and records the reflected signals from the target leaves. Since the water on the leaves can influence the reflected signals, we analyze these signals to infer the wetness of the leaves. First, with the multiple-input multiple-output (MIMO) antenna array and synthetic aperture radar (SAR), we use the range migration algorithm [6] to reconstruct the fine-grained signal distribution images for different planes of the plant. Moreover, we use segment fusion to combine signal distributions at different planes


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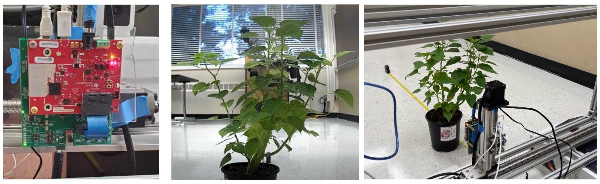

(a) mmWave radar (b) Potted plant. (c) Experiment scenario

**Figure 2: mmLeaf implementation for detecting the leaf wetness of a potted plant in indoor environment.**

of the plant and deal with the depth information to achieve the effect of data enhancement and output the fused reconstruction results. Finally, we develop a deep learning model, which takes the fused reconstruction results as input to classify leaf wetness.

## 2 SYSTEM DESIGN

mmLeaf consists of three modules as follows:

**MIMO-SAR Sensing.** We design a MIMO-SAR sampling scheme to sense the target plants. Specifically, we use a mmWave radar with multiple transmitters and receivers to transmit FMCW signals and record the reflected signals. Moreover, to achieve a larger antenna aperture of the MIMO array, we use SAR scanning, in which the mmWave radar is moving along a specific trajectory on a 2-axis slide rail.

**MIMO-SAR Imaging.** We pre-process the reflected signals and use the range migration algorithm [6] to reconstruct MIMO-SAR near-field leaf images. We generate several images in different at different depths at a time. Each image contains the distribution of the reflected signals by the reflection plane of the plant at the corresponding depth within a specific area synthesized by the SAR aperture to reduce interferences caused by proximity plants.

**Leaf Wetness Detection.** We consider the overall effect of leaf wetness on the signal distribution and combine the imaging information of the whole plant at different depths. The output of depth information fusion is the input of a deep learning model, which has the structure of VGG-16 [7] combined with a classifier to detect whether the leaves are wet or not.

## 3 SYSTEM IMPLEMENTATION

**Prototype.** We implement a prototype with a TI IWR1642 mmWave radar operating at 77 to 81 GHz frequency band and a DCA 1000EVM for collecting raw mmWave reflected signals. The core chip of the mmWave board only costs $40. The radar is equipped with a two-axis mechanical scanner as shown in Figure 2. The SAR scanning has a horizontal range of 200mm and a vertical range of 100mm. The time required to complete one SAR scanning is approximately six minutes. It is a tradeoff between scanning time and image informativeness.

**Dataset.** We have collected 120 pairs of plant data corresponding to dry and wet placed at different distances from the radar and with different poses, including the placement distances of 200 mm, 300 mm, and 400 mm. The maximum sensing distance is determined by the plant shape and leaf density. Figure 3 shows five generated MIMO-SAR images at different depths. The textures of the images indicate the properties (e.g., wetness, shape) of the plant's reflection planes at those depths.

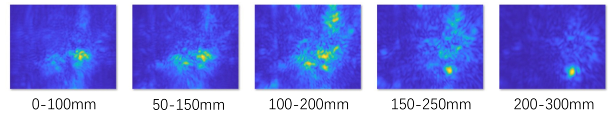


**Figure 3: MIMO-SAR images of a potted plant at different depths.**

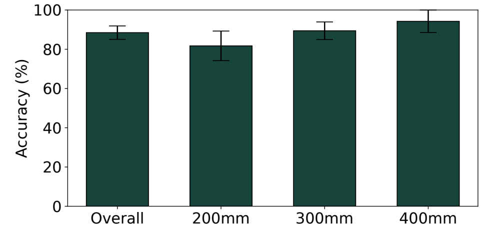


**Figure 4: The overall accuracy of mmLeaf and performance at different placement distances.**

## 4 EVALUATION

We use cross-validation to randomly split the data into training and test sets in a four-to-one ratio, and evaluate the accuracy of our model on the test set. As shown in Figure 4, the overall average accuracy is about 88%, and the highest overall accuracy is 93%. In addition, when the placement distance between the plant and radar is 200 mm, the average accuracy is the lowest, which may be due to insufficient received signal due to the specular reflection at shorter distances. Besides, the placement distance of plants can be increased by enlarging the array aperture.

## 5 CONCLUSION

This poster presents mmLeaf, a versatile mmWave leaf wetness detection system that is light-insensitive, reflecting actual leaf wetness, and non-destructive. Our results show that mmLeaf can achieve up to 90% mean accuracy in different placement distances. With our indoor experiments, we believe that mmLeaf can work in general by training the model with a more comprehensive dataset.

## 6 ACKNOWLEDGMENTS

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