Plant Disease Detection Using an Electronic Nose

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***Abstract*—This paper presents experimental results on differentiating between healthy wheat plants and plants infected with Fusarium Head Blight (FHB) based on sensing the ambient gases in the plant environment using a gravimetric electronic nose enabled by a functionalized capacitive micromachined ultrasonic transducer (CMUT) array and machine learning (ML) algorithms. The CMUT sensor array is functionalized with organic/inorganic materials to capture disease-related volatile signals. The sensor data is processed and analyzed using ML algorithms for accurate plant classification. Experimental results demonstrate the effectiveness of the proposed approach in achieving high accuracy for plant disease detection at the end of the 11th day after plant inoculation.**

Keywords—VOCs; plants; infection; disease; e-nose; machine learning.

I. Introduction

Plant diseases cause significant threats to agricultural productivity and global food security. Timely and accurate detection of plant diseases is crucial for effective disease management, prevention of crop losses, and sustainable agricultural practices, which will result in reducing economic losses [1].

Various technologies are currently employed in the diagnosis of plant diseases [2]–[6]. Although these techniques exhibit efficacy and sensitivity in detection, their implementation predominantly occurs within laboratory settings, necessitating the utilization of intricate instrumentation that mandates specialized proficiency for operation. Traditional methods of plant disease diagnosis primarily rely on visual inspection, which often results in delayed detection and ineffective control measures [7]. However, recent advancements in sensor technologies, particularly gas sensors, have opened up new avenues for early disease detection and precision agriculture [8].

Gas sensors offer the advantage of non-destructive and real-time monitoring, enabling rapid detection of plant diseases even at the earliest stages, when symptoms may not be visually apparent. By detecting the volatile organic compounds (VOCs) emitted by plants, gas sensors provide valuable insight into the biochemical and physiological changes occurring in plants affected by the disease [9]. Gas sensors enable the identification of specific diseases or disease patterns, facilitating targeted intervention strategies for disease management and control. Furthermore, integrating sensor technologies with precision agriculture could revolutionize plant disease management practices [10]. By continuously monitoring the VOC emissions from crops, gas sensors can provide real-time data on disease dynamics within a field or greenhouse environment. This information enables farmers to make data-driven decisions regarding disease control measures, such as targeted pesticide applications or optimized storage strategies, thus minimizing the use of agrochemicals and reducing the environmental impact [11].

Gas sensors for plant disease detection are undergoing rapid development and refinement, with advancements in sensor design, sensitivity, selectivity, and data analysis techniques. Researchers explore various sensor types, each with advantages and limitations. Additionally, integrating gas sensors with machine learning algorithms holds immense potential for enhancing disease detection accuracy and automation [12].

This paper aims to present functionalized CMUT sensor array results for plant disease detection in growth chambers using ML-based classification algorithms. This work attained a precision level of over 85% within an adequate dataset. The successful validation of a notable accuracy during the proof-of-concept phase promises the prospective efficacy of the device in the actual application. Details of sensor preparation, experimental setup, gas testing, and results from plant experiments are provided in the following sections.

II. Experimental Work

A. Preparation of Sensors

Capacitive micromachined ultrasonic transducer (CMUT) arrays used for sensor implementation in this study were fabricated on a 100-mm glass wafer using standard microfabrication techniques [13]. The array consists of 8 elements (**Fig. 1a)**. The top surface of the CMUT elements was coated with gold. In addition to one unfunctionalized (gold) channel, Polyisobutylene (PIB), Polydimethylsiloxane (PDMS), Copper (II) Phthalocyanine (CuPc), and silver nanoparticles (Ag) were used as sensing layers on other channels. Each element in the array was functionalized with 0.1-wt% diluted solutions by using the

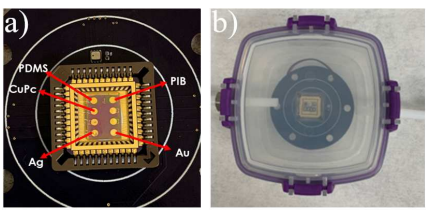

Fig. 1. a) E-nose sensor array, b) Test chamber.

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drop coating technique [14], [15]. The array elements were wire-bonded on a chip carrier connected to the supporting electronics. The whole system was powered by a 3.7-V lithium-ion battery and placed in a small chamber to perform the gas tests (**Fig. 1b)**.

B. Plants Inoculation

The Perigee wheat plants provided by BASF were grown in Cone-tainers containing a soil-less mix in an air-conditioned greenhouse with a 50% shade curtain for 25 days (four days for emergence plus three weeks post-emergence). Greenhouse temperatures were set to 25°C during the day and 17°C during the night. Relative humidity was 65% and day length was 16 hours. Plants were then selected for uniformity and moved to a growth chamber before treatment.

An aerosol sprayer was used to spray the head of plants (around Feekes 10.5) with fungal inoculum (10,000 spores/ml) or sterile water (mock) from top to bottom until liquid was dripping from plants. The plants were moved to dark dew chambers set at 25°C with 95-98% relative humidity for 24 hours. Then placed back into the growth chambers. As a secondary control and to test method related plant stress volatiles, untreated (healthy) plants that were not exposed to the dew chamber were used to collect volatile compounds.

C. Experimental Setup

The infected and mock treated plants were grown and placed in the growth chambers for testing. **Fig. 2** shows a schematic sensor setup. As the first step of the testing procedure, a sensor baseline was obtained by using ambient air filtered by desiccants. Plant gas samples were collected through each growth chamber using a vacuum pump. Only one solenoid valve was active at a time, while the rest were off. The described sampling process was repeated many times to have adequate data for implementing the machine learning algorithms for classification. Moreover, the data were collected on the 6th day and 11th day after the inoculation of the plants.

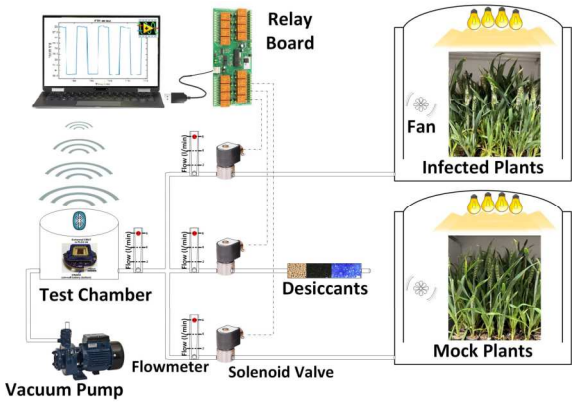

Fig. 2. Experimental setup.

D. Data Processing

MATLAB 2021a was utilized for all data processing (**Fig. 3**). The sensor data were collected from the plants on the 6th day and 11th day after inoculation. Initially, a baseline correction was implemented on the raw data to prevent signal drift caused by environmental factors [16]. Subsequently, frequency shift (Δf) features were extracted from the sensor signal, using subtraction of data points between the *gas on* and the *gas off* states, **(Fig. 3)**. For evaluating the classification performance, various machine learning (ML) algorithms, namely Random Forest (RF), k-Nearest Neighbor (k-NN), and Support Vector Machine (SVM) were employed. A k-fold cross-validation technique was utilized, where a model was created using a training set (k-1) and evaluated using the remaining set as the test set. This process was repeated iteratively for k times. The accuracy results were presented as a confusion matrix in k-fold cross-validation, comprehensively explained in a previous study [14].

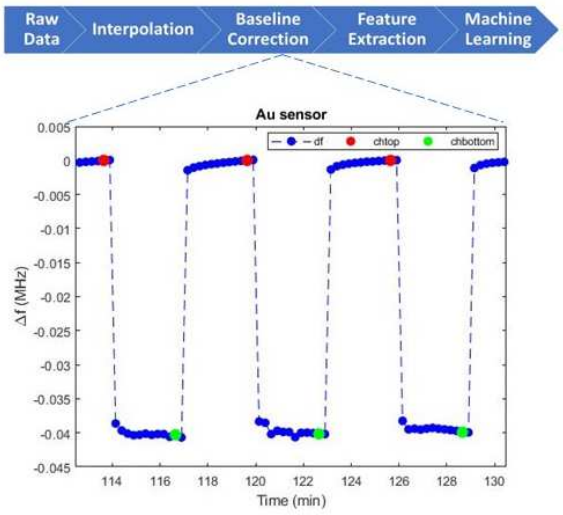

Fig. 3. Data processing flow chart and baseline-corrected signal response of Au sensor.

Machine learning (ML) algorithms often come with default hyperparameters, which are pre-defined settings. This can be a quick and convenient way to start machine learning, especially when exploring a new algorithm or dealing with a small dataset. By performing model tuning, hyperparameter settings that are more suitable for a specific dataset and problem can be obtained. This can lead to improved model performance, accuracy, generalization, and predictions or results. The model tuning was implemented using different hyperparameters for each model to minimize five-fold cross-validation loss in the data using Bayesian optimization of the classifiers. These hyperparameters were found using automatic hyperparameter optimization, which gives the best hyperparameters for each classifier.

III. Results and Discussion

A. Infected and Mock Treated Plants on Different Days

At 6 days after infection, early symptoms (yellowing) were observed in heads of infected plants compared to

mock infected control plants (**Fig. 4**). Clear differences were observed at 11 days. Infected plants showed head bleaching, indicative of FHB symptoms. Mock infected plants showed no bleaching, but some evidence of physiological stress (leaf yellowing) was observed in both mock and infected plants.

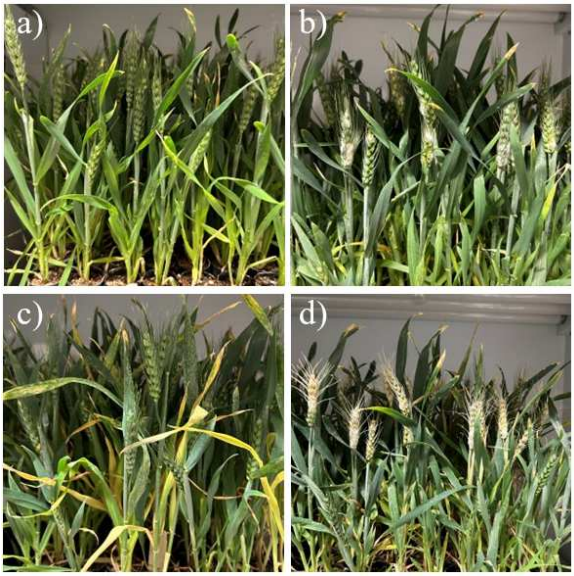

Fig. 4. Mock-treated plants on a) day 6 and c) day 11. Infected plants on b) day 6 and d) day 11.

B. Classification of the Plants by the CMUT E-Nose Technology and Data Analytics

In **Table 1**, the prediction accuracies of several models were shown to analyze the distinction between the mock treated and infected plants on the 6th day (D6) and the 11th day (D11) after inoculation. All ML algorithms had higher classification accuracy on D11 than that on D6. The highest accuracies on both D6 and D11 were obtained by using the SVM classifier (**Fig 5a** and **Fig. 5b)**. It was observed that almost 50% of the time, the plants were mismatched on the D6 data set. However, classification accuracy increased to 85% for the D11 data set, which might be caused by the increasing disease status of the plants.

TABLE 1. CLASSIFICATION ACCURACY RESULTS FOR THE PLANTS ON TWO DIFFERENT DAYS

ML / Feature	k-NN		SVM		RF	
	D6	D11	D6	D11	D6	D11
Δf^1	40	85	45	85	37	82
Δf^2	52	85	50	83	42	87

D6, D11: They refer to the 6th and 11th days after infection of the plants, respectively.
Δf^1: Default hyperparameters of the models were used.
Δf^2: Hyperparameter optimization of the models were done.
All the numbers represent the classification accuracy.
The model tuning was performed on the ML classifiers.

Table 1 also shows that the model tuning increased the classification accuracy, e.g., from 82% to 87% for the RF classifier (**Fig. 5c)**. It was observed that 90% of the infected plant data samples were classified correctly. In comparison, this ratio for the mock plant data set was around 83%, which showed that 25 out of 30 samples were correctly classified as mock plants. The hyperparameters of the RF classifier are optimized using the Bayesian optimization method. For the present dataset, optimum number of "meanleafsize" was calculated as 13, and the optimum method turned out to be the "GentleBoost", which minimizes the exponential loss because of prediction.

Within this work, we have conducted a comparative analysis of classification performance using model tuning on the ML classifiers. Our findings indicate that hyperparameter optimization improves classification performance.

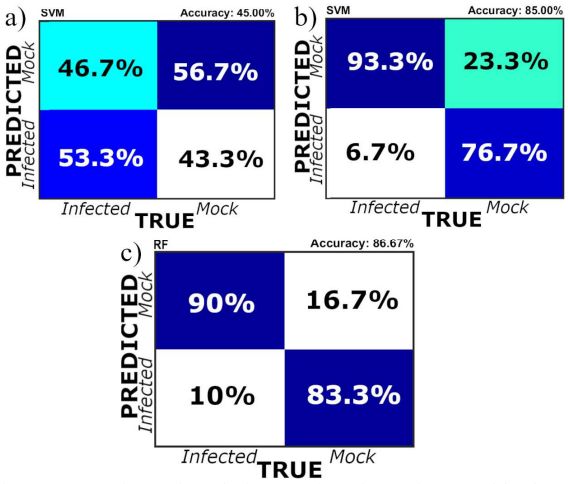

Fig. 5. Comparison of confusion matrices for a) day 6 and b) day 11, c) Confusion matrix resulting from model tuning

IV. CONCLUSION

Previously, we have introduced an e-nose sensor technology and explored its applications for environmental sensing as well as plant volatiles in a laboratory setting [14], [15]. This work has presented that the sensor prototype produces results in the plant environment indicating remote real-time monitoring for crop yield could be feasible. Our primary objective was to demonstrate this technology in a growth chamber environment as a first step for deployment to realistic plant environments. Next, we will test our sensors in more realistic environments, such as larger growth chambers, greenhouses, etc. We also aim to detect differences between the diseased plants and control plants in earlier stages of disease progression by refining our gas sampling procedures, optimizing the chemical functionalization layers in our sensor prototype, and fine-tuning the classification algorithms used.

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