

**Deep Leaf Phenotyping: Multi-level Leaf Phenotyping based on Novel
Computer Vision Frameworks**

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**DEPARTMENT OF ELECTRICAL ENGINEERING
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**Deep Leaf Phenotyping: Multi-level Leaf Phenotyping based on Novel
Computer Vision Frameworks**

by

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DEPARTMENT OF ELECTRICAL ENGINEERING

Submitted

*in fulfillment of the requirements of the degree of Doctor of Philosophy
to the*



INDIAN INSTITUTE OF TECHNOLOGY DELHI
MAY 2023

This is for you maa, paa, nonu
& anu

Certificate

This is to certify that the thesis entitled “**Deep Leaf Phenotyping: Multi-level Leaf Phenotyping based on Novel Computer Vision Frameworks**” being submitted by **SWATI BHUGRA** to the Department of Electrical Engineering, Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** is the record of the bona-fide research work carried out by her under my supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted either in part or in full to any other university or institute for the award of any degree or diploma.

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Abstract

Quantification of plant traits (leaf area, leaf count etc.) is a key component of precision agriculture. In this context, the utilisation of robust imaging equipment (microscopic visible, thermal, hyperspectral etc.) permits non-invasive monitoring of plants resulting in multi-modal plant image data. Thus, the development of computer vision methods for precise quantification of plant traits is gaining momentum. However, due to the complex structure of plant traits such as small size, low contrast with respect to the background and limited multi-trait image data has led to the investigation of only few plant traits. Thus, there exists scope for the development of robust and automated analysis algorithms for the extraction of plant traits at multiple levels (such as cell, organ and plant) from images acquired in controlled lab-settings and field environments. For instance, due to the dynamic feature rich background, low contrast and occlusion, stomata study using microscopic images is less prevalent in contrast to its counterparts such as root traits. Since, stomata are pores on leaf surface that plays a key role in regulating the temperature of the plants through gas exchange, stomata study is crucial with respect to precision agriculture. Thus, in this thesis we propose a novel convolutional neural networks (CNNs) based framework for stomata detection and segmentation and the generalisability of the framework is shown in terms of its applicability on different plants.

Another gap is that the majority of image analysis algorithms to extract leaf-

level traits have been proposed for model plants such as Arabidopsis (<https://plant-image-analysis.org>). Since leaf exhibits large shape variance, the current methods proposed for leaf-level analysis are limited in terms of their applicability to different plants. In this thesis, we propose a novel graph based formulation to extract leaf shape knowledge independent of plant variety. We demonstrate its broad utility on multiple plant datasets.

It is to be noted that the leaf-level analysis of model plants (such as Arabidopsis) can be reliably studied using 2D visible images due to their small size and short growth cycle. But for classical plants such as rice, wheat etc. high self-occlusions results in information loss based on 2D images. In this context, we present a novel deep convolutional neural networks based framework that utilises prior on the leaf shape for a robust and dense 3D plant reconstruction. To summarise, in thesis we explore leaf at microscopic level (stomata detection and segmentation), organ level (leaf segmentation) and plant level (3D plant reconstruction) from images acquired in lab settings.

The aforementioned frameworks have been proposed for images acquired in controlled environments i.e greenhouses and high-throughput phenotyping platforms. However, images acquired in field environments suffers from additional challenges such as high illumination variation, background noise, visual field variation to name a few. Thus, to overcome these challenges, we also propose a novel deep learning framework for leaf-level analysis based on field images.

सार

पौधों के लक्षणों (पत्ती क्षेत्र, पत्ती गिनती आदि) की मात्रा का निर्धारण सटीक कृषि का एक प्रमुख घटक है। इस संदर्भ में, मजबूत इमेजिंग उपकरण (सूक्ष्म दृश्यमान, थर्मल, हाइपरस्पेक्ट्रल इत्यादि) का उपयोग पौधों की गैर-आक्रामक निगरानी की अनुमति देता है जिसके परिणामस्वरूप मल्टी-मोडल प्लांट छवि डेटा प्राप्त होता है। इस प्रकार, पौधों के लक्षणों की सटीक मात्रा निर्धारित करने के लिए कंप्यूटर विज्ञान विधियों का विकास गति पकड़ रहा है। हालाँकि, पौधों के लक्षणों की जटिल संरचना जैसे छोटे आकार, पृष्ठभूमि के संबंध में कम कंट्रास्ट और सीमित बहु-विशेषता छवि डेटा के कारण केवल कुछ पौधों के लक्षणों की जांच हुई है। इस प्रकार, नियंत्रित प्रयोगशाला-सेटिंग्स और फ़ील्ड वातावरण में प्राप्त छवियों से कई स्तरों (जैसे सेल, अंग और पौधे) पर पौधों के लक्षणों के निष्कर्षण के लिए मजबूत और स्वचालित विश्लेषण एल्गोरिदम के विकास की गुंजाइश मौजूद है। उदाहरण के लिए, गतिशील सुविधा समृद्ध पृष्ठभूमि, कम कंट्रास्ट और रोड़ा के कारण, सूक्ष्म छवियों का उपयोग करके रंध्र अध्ययन जड़ लक्षणों जैसे इसके समकक्षों के विपरीत कम प्रचलित है। चूँकि, स्टोमेटा पत्ती की सतह पर छिद्र होते हैं जो गैस विनिमय के माध्यम से पौधों के तापमान को विनियमित करने में महत्वपूर्ण भूमिका निभाते हैं, सटीक कृषि के संबंध में स्टोमेटा का अध्ययन महत्वपूर्ण है। इस प्रकार, इस थीसिस में हम स्टोमेटा का पता लगाने और विभाजन के लिए एक उपन्यास कन्वेन्शनल न्यूरल नेटवर्क (सीएनएन) आधारित ढांचे का प्रस्ताव करते हैं और ढांचे की सामान्यता को विभिन्न पौधों पर इसकी प्रयोज्यता के संदर्भ में दिखाया गया है।

एक और अंतर यह है कि पत्ती-स्तरीय लक्षण निकालने के लिए अधिकांश छवि विश्लेषण एल्गोरिदम को अरेबिडोप्सिस [\url{\(https://प्लांट-इमेज-एनालिसिस.org\)}](https://प्लांट-इमेज-एनालिसिस.org) जैसे मॉडल पौधों के लिए प्रस्तावित किया गया है। चूँकि पत्ती बड़े आकार में भिन्नता प्रदर्शित करती है, पत्ती-स्तरीय विश्लेषण के लिए प्रस्तावित वर्तमान विधियाँ विभिन्न पौधों पर उनकी प्रयोज्यता के संदर्भ में सीमित हैं। इस थीसिस में, हम पौधों की विविधता से स्वतंत्र पत्ती के आकार का ज्ञान निकालने के लिए एक नवीन ग्राफ आधारित सूत्रीकरण का प्रस्ताव करते हैं। हम कई प्लांट डेटासेट पर इसकी व्यापक उपयोगिता प्रदर्शित करते हैं।

यह ध्यान दिया जाना चाहिए कि मॉडल पौधों (जैसे कि एराबिडोप्सिस) के पत्ती-स्तरीय विश्लेषण का उनके छोटे आकार और छोटे विकास चक्र के कारण 2डी दृश्य छवियों का उपयोग करके विश्वसनीय रूप से अध्ययन किया जा सकता है। लेकिन चावल, गेहूं आदि जैसे शास्त्रीय पौधों के लिए उच्च आत्म-समाधान के परिणामस्वरूप 2डी छवियों के आधार पर जानकारी का नुकसान होता है। इस संदर्भ में, हम एक नवीन गहन दृढ़ तंत्रिका नेटवर्क आधारित ढांचा प्रस्तुत करते हैं जो एक मजबूत और घने 3डी संयंत्र पुनर्निर्माण के लिए पत्ती के आकार पर पूर्व का उपयोग करता है। संक्षेप में, थीसिस में हम प्रयोगशाला सेटिंग्स में प्राप्त छवियों से सूक्ष्म स्तर (रंध्र का पता लगाने और विभाजन), अंग स्तर (पत्ती विभाजन) और पौधे के स्तर (3 डी संयंत्र पुनर्निर्माण) पर पत्ती का पता लगाते हैं।

नियंत्रित वातावरण यानी ग्रीनहाउस और उच्च-थ्रूपुट फेनोटाइपिंग प्लेटफार्मों में प्राप्त छवियों के लिए उपरोक्त रूपरेखा प्रस्तावित की गई है। हालाँकि, फ़ील्ड वातावरण में प्राप्त छवियां अतिरिक्त चुनौतियों से ग्रस्त हैं जैसे कि उच्च रोशनी भिन्नता, पृष्ठभूमि शोर, दृश्य क्षेत्र भिन्नता आदि। इस प्रकार, इन चुनौतियों पर काबू पाने के लिए, हम फ़ील्ड छवियों के आधार पर पत्ती-स्तरीय विश्लेषण के लिए एक उपन्यास गहन शिक्षण ढांचे का भी प्रस्ताव करते हैं।

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