

COMPUTER VISION BASED PLANT PHENOTYPING

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COMPUTER VISION BASED PLANT PHENOTYPING

by

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*We have not succeeded in
answering all our problems. The
answers we have found only serve
to raise a whole set of new
questions. In some ways we feel we
are as confused as ever, but we
believe we are confused on a
higher level and about more
important things.*

Posted outside the mathematics
reading room,
Tromsø University

Certificate

This is to certify that the work contained in the thesis entitled “**Computer Vision based Plant Phenotyping**” is being submitted by **Ms. Shiva Azimi** 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 bonafide research work carried out by her under our supervision. In our 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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[Shiva Azimi]

Abstract

In last two decades, the biggest challenge to the whole world is to make sure the food security for the people. Increasing world population and the loss of arable land due to various climatic and man made factors have necessitated the development of modern tools and techniques for increasing crop yield. The modern farming, also referred to as precision farming, is not only more efficient, but also more sustainable than the traditional farming methods that are prevalent today. Precision farming combines remote sensing, IoT devices, robotics, big data analytics, artificial intelligence, and other emerging technologies into an integrated crop production infrastructure.

Computer vision and image processing can play a crucial role in precision farming, enabling increased crop outputs to meet the demands of a rising world population. The extensive computer vision applications such as image retrieval, stereo reconstruction, object tracking and recognition, etc., play an essential role in imaging based plant phenotyping. Imaging based plant phenomics that deals with measuring some observable traits of the plants such as color, leaf density, overall shape, volume, etc., can be employed to monitor plant health and growth. Compared to the traditional phenotyping methods that are destructive and time-consuming, imaging based methods offer smart and automated alternatives that measure stress levels in plants in less time without disturbing the plant.

Using traits of plants for detecting physiological changes in response to abiotic stresses such as lack of water, nutrients, poor lightning condition, etc., has a significant role in plant and crop management. After moisture induced stress, nutrient induced stress in plants is the most critical factor and can significantly reduce the agricultural yield. These Stresses in plants can significantly lower the agricultural yield. The stress due to water deficiency can affect many visible plant traits such as size and surface area, the number of leaves and their color, etc. Nitrogen, an essential nutrient, is a crucial growth-limiting factor and is the prime component of amino acids, proteins, nucleic acids, and chlorophyll. Nitrogen deficiency affects certain visible traits in plant such as area, color, the total number of leaves and plant height, etc. Pulses like chickpeas play an important role towards ensuring food security in poor countries owing to their high protein and

nutrition content.

Therefore, in this dissertation, we present computer vision along with image processing techniques to monitor plant health and diseases. To the best of authors' knowledge, there is no work present in literature that deals specifically with the performance evaluation of the keypoints detectors and the local feature descriptors as applied to 3D point cloud data in the context of plant health classification and plant growth analysis. Therefore, we quantitatively compare the performance of different keypoint detectors and local feature descriptors for plant health and growth monitoring. As a second contribution, we compared the performance of different 3D correspondence grouping algorithms, viz, Nearest Neighbor Similarity Ratio, Random Sample Consensus, Geometric Consistency, and 3D Hough Voting in context of 3D plant point clouds. We have also extended 2D maximum likelihood matching to 3D Maximum Likelihood Estimation Sample Consensus.

As the third contribution, we have considered automated phenotyping of stress level classification from Sorghum plant shoots due to nitrogen deficiency using a 23-layered CNN architecture. Since there is no publicly available digital image dataset of chickpea plant shoots under different moisture stress conditions. To fill this gap, the fourth contribution is we have construction of dataset of chickpea plant shoot images that are common in India. The next contribution is comparative analysis of Deep Learning techniques with different classical Machine Learning approaches using different performance measures. Also, we contrast the performance of the conventional DL with the sophisticated 71-layer ResNet-18 model. We have also proposed a BAT optimized ResNet-18 model that automatically identifies the best value of the mini-batch size to be used for training. Training the model with the optimized parameters has resulted in the ceiling level of the classification performance over the chickpea data.

The last contribution, is proposing an LSTM-CNN architecture to learn visual-temporal patterns from the chickpea plant dataset. we also conducted a comparative analysis of the CNN architecture used in the proposed model with the other CNN techniques used for time-invariant classification of water stress.

सार

पिछले दो दशकों में, पूरी दुनिया के लिए सबसे बड़ी चुनौती यह सुनिश्चित करना है कि लोगों के लिए खाद्य सुरक्षा। विश्व की बढ़ती जनसंख्या और कृषि योग्य का नुकसान विभिन्न जलवायु और मानव निर्मित कारकों के कारण भूमि ने विकास को आवश्यक बना दिया है फसल की पैदावार बढ़ाने के लिए आधुनिक उपकरणों और तकनीकों की जानकारी। आधुनिक खेती, जिसे सटीक खेती भी कहा जाता है, न केवल अधिक कुशल है, बल्कि पारंपरिक खेती के तरीकों की तुलना में अधिक टिकाऊ है जो आज प्रचलित हैं। सटीक खेती में रिमोट सेंसिंग, IoT डिवाइस, रोबोटिक्स, बिग डेटा एनालिटिक्स, आर्टिफिशियल इंटेलिजेंस, और अन्य उभरती हुई तकनीकों को एक एकीकृत फसल उत्पादन का बुनियादी ढांचा। कंप्यूटर विज्ञान और इमेज प्रोसेसिंग सटीकता में महत्वपूर्ण भूमिका निभा सकते हैं खेती, बढ़ती हुई दुनिया की मांगों को पूरा करने के लिए बढ़ी हुई फसल उत्पादन को सक्षम करना आबादी। छवि पुनर्प्राप्ति जैसे व्यापक कंप्यूटर दृष्टि अनुप्रयोग, स्टीरियो पुनर्निर्माण, वस्तु ट्रैकिंग और मान्यता, आदि, एक आवश्यक भूमिका निभाते हैं इमेजिंग आधारित प्लांट फेनोटाइपिंग में। इमेजिंग आधारित प्लांट फेनोमिक्स जो डील करता है रंग, पत्ती घनत्व जैसे पौधों के कुछ अवलोकन योग्य लक्षणों को मापने के साथ, समग्र आकार, आयतन आदि को पौधों के स्वास्थ्य और वृद्धि की निगरानी के लिए नियोजित किया जा सकता है। पारंपरिक फेनोटाइपिंग विधियों की तुलना में जो विनाशकारी और समय लेने वाली हैं, इमेजिंग आधारित विधियां स्मार्ट और स्वचालित विकल्प प्रदान करती हैं जो पौधे को परेशान किए बिना कम समय में पौधों में तनाव के स्तर को मापें। अजैविक की प्रतिक्रिया में शारीरिक परिवर्तनों का पता लगाने के लिए पौधों के लक्षणों का उपयोग करना पानी की कमी, पोषक तत्वों, बिजली की खराब स्थिति, आदि जैसे तनावों ने पौधे और फसल प्रबंधन में महत्वपूर्ण भूमिका। नमी प्रेरित तनाव के बाद, पौधों में पोषक तत्व प्रेरित तनाव सबसे महत्वपूर्ण कारक है और महत्वपूर्ण रूप से हो सकता है कृषि उपज को कम करना। पौधों में ये तनाव काफी कम कर सकते हैं कृषि उपज। पानी की कमी के कारण तनाव कई दृश्यमान पौधों को प्रभावित कर सकता है आकार और सतह क्षेत्र, पत्तियों की संख्या और उनके रंग आदि जैसे लक्षण। नाइट्रोजन, एक आवश्यक पोषक तत्व, एक महत्वपूर्ण वृद्धि-सीमित कारक है और प्रमुख है अमीनो एसिड, प्रोटीन, न्यूक्लिक एसिड और क्लोरोफिल के घटक। नाइट्रोजन की कमी पौधे में कुछ दृश्य लक्षणों जैसे क्षेत्र, रंग, कुल संख्या को प्रभावित करता है

पत्तियों और पौधों की ऊंचाई आदि की। दालें जैसे छोले एक महत्वपूर्ण भूमिका निभाते हैं गरीब देशों में उनके उच्च प्रोटीन के कारण खाद्य सुरक्षा सुनिश्चित करना और पोषण सामग्री। अतः इस शोध प्रबंध में हम चित्र के साथ-साथ कम्प्यूटर दृष्टि को भी प्रस्तुत करते हैं पौधों के स्वास्थ्य और रोगों की निगरानी के लिए प्रसंस्करण तकनीकें। सर्वश्रेष्ठ लेखकों के लिए ज्ञान, साहित्य में कोई कार्य मौजूद नहीं है जो विशेष रूप से संबंधित है कीपाइंट डिटेक्टरों और स्थानीय फीचर डिस्क्रिप्टर का प्रदर्शन मूल्यांकन जैसा कि पादप स्वास्थ्य वर्गीकरण के संदर्भ में 3डी पाइंट क्लाउड डेटा पर लागू होता है और पौधों की वृद्धि का विश्लेषण। इसलिए, हम मात्रात्मक रूप से प्रदर्शन की तुलना करते हैं पौधों के स्वास्थ्य के लिए विभिन्न मुख्य बिंदु डिटेक्टरों और स्थानीय फीचर डिस्क्रिप्टर की और विकास निगरानी। दूसरे योगदान के रूप में, हमने के प्रदर्शन की तुलना की विभिन्न 3D पत्राचार समूहीकरण एल्गोरिदम, जैसे, निकटतम पड़ोसी समानता अनुपात, यादृच्छिक नमूना सहमति,, ज्यामितीय संगति, और 3डी हफ़ 3डी प्लांट पाइंट क्लाउड के संदर्भ में मतदान। हमने 2डी मैक्सिमम भी बढ़ाया है 3D अधिकतम संभावना अनुमान नमूना सहमति से मेल खाने की संभावना। तीसरे योगदान के रूप में, हमने तनाव के स्वचालित फेनोटाइपिंग पर विचार किया है नाइट्रोजन की कमी के कारण ज्वार के पौधे के अंकुरों का स्तर वर्गीकरण a . का उपयोग करके 23-स्तरित सीएनएन वास्तुकला। चूंकि कोई सार्वजनिक रूप से उपलब्ध डिजिटल छवि नहीं है विभिन्न नमी तनाव स्थितियों के तहत छोले के पौधे की शूटिंग का डेटासेट। प्रति इस अंतर को भरें, चौथा योगदान यह है कि हमारे पास छोले के डेटासेट का निर्माण है प्लांट शूट इमेज जो भारत में आम हैं। अगला योगदान तुलनात्मक है विभिन्न शास्त्रीय मशीनों के साथ गहन शिक्षण तकनीकों का विश्लेषण विभिन्न प्रदर्शन उपायों का उपयोग करके सीखने के दृष्टिकोण। इसके अलावा, हम इसके विपरीत परिष्कृत 71-परत ResNet-18 . के साथ पारंपरिक DL का प्रदर्शन आदर्श। हमने एक BAT अनुकूलित ResNet-18 मॉडल भी प्रस्तावित किया है जो स्वचालित रूप से प्रशिक्षण के लिए उपयोग किए जाने वाले मिनी-बैच आकार के सर्वोत्तम मूल्य की पहचान करता है। अंतिम योगदान, विज़ुअल टेम्पोरल सीखने के लिए LSTM-CNN आर्किटेक्चर का प्रस्ताव कर रहा है छोले के पौधे के डेटासेट से पैटर्न। हमने एक तुलना भी की अन्य के साथ प्रस्तावित मॉडल में प्रयुक्त सीएनएन वास्तुकला का विश्लेषण पानी के तनाव के समय-अपरिवर्तनीय वर्गीकरण के लिए उपयोग की जाने वाली सीएनएन तकनीकें।

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Abbreviations

ANN	artificial neural networks
BF	Before Flowering
B3R	Bologna 3D retrieval
C	Control
CART	classification and regression
CG	correspondence grouping
CNN	Convolutional Neural Network
DA	Discriminant Analysis
DCNN	deep convolutional neural network
DL	Deep Learning
DN	Deconvolutional Network
DT	Decision trees
DOG	Difference-of-Gaussians
DT	Decision Trees
EVD	Eigen Value Decomposition
FV	Fisher Vector
GC	Geometric Consistency
GIMP	GNU Image Manipulation Program
GMM	Gaussian Mixture Model
GRF	global reference frame
HOG	Histogram of oriented gradients
HV	Hough Voting
IOT	Internet of Things
ISS	intrinsic shape signatures
KNN	K-Nearest Neighbors
LIDAR	Light Detection and Ranging laser systems
LRF	local reference frame
LSTM	Long Short Term Memory
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MLESAC	Maximum Likelihood Estimation Sample Consensus

NB	Naive Bayes
NIPGR	National Institute of Plant Genome Research
NIR@	Near Infrared
NNSR	Nearest Neighbor Similarity Ratio
MVS	Multi-View Stereo
OHP	Optimization of hyper-parameter phase
PCL	point cloud library
RANSAC	random sample consensus
RNN	Recurrent Neural Networks
SIFT	Scale-Invariant feature transform
SHOT	Signatures of Histograms of Orientations
SVM	Support Vector Machines
TOF	Time-of-Flight
2D	Two Dimensional
3D	Tree Dimensional
U3M	UWA 3D modeling
VLAD	Vector of Linearly Aggregated Descriptors
YS	Young Seedling