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Data Science for Economics

Cultivating insights: Prediction models for plant growth

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## Abstract

Accurately predicting plant growth is critical to optimizing agricultural productivity in an era of growing food demand and climate challenges. This thesis, titled **"Cultivating Insights: Prediction Models for Plant Growth"**, explores advanced techniques for plant phenotyping, leveraging digital image processing and time-series models to provide deeper insights into plant growth patterns. The focus is on automating leaf detection and surface area estimation using computer vision algorithms and improving the predictive capacity of plant growth models through statistical and machine learning approaches.

The research begins by addressing the limitations of traditional phenotyping methods and highlighting the role of modern data-driven approaches in improving the precision and efficiency of plant growth monitoring. A key contribution of the thesis is the development of an enhanced leaf detection algorithm, which addresses challenges like leaf occlusion and varying lighting conditions, improving the accuracy and robustness of existing methods. Additionally, a new approach for calculating plant surface area is introduced, providing an alternative metric for growth analysis alongside traditional leaf count techniques.

This thesis also presents the implementation of two time-series models—ARIMA and Bayesian approaches—for forecasting plant growth based on hourly data collected through controlled experiments. These models are compared in terms of accuracy, computational efficiency, and applicability to real-time plant monitoring systems.

The results demonstrate that, while surface area estimation is a robust alternative, leaf detection remains the most precise metric for monitoring growth. Time-series models provide strong predictive capabilities, with the Bayesian model outperforming in terms of accuracy. This work not only advances the current state of plant phenotyping but also offers practical applications for precision agriculture, where the integration of predictive models can lead to optimized farming practices and resource management.

# Introduction

## Background and motivation

The global challenge of food security has placed unprecedented importance on the study of plant growth. As climate change, population growth, and sustainability concerns intensify, the agricultural sector is facing increasing pressure to optimize crop yields and manage resources efficiently. Traditional agricultural methods, while effective, are limited in their ability to predict and analyze plant growth in real-time. This has led to the integration of modern technologies, particularly data-driven models, into plant phenotyping and growth prediction efforts.

Phenotyping—the measurement of observable characteristics such as leaf count, surface area, and overall plant size—provides critical insights into the health and development of plants. However, manual methods for acquiring this information are often labor-intensive, time-consuming, and prone to human error. With advances in computer vision and machine learning, researchers are now equipped with powerful tools to automate the collection and analysis of plant growth data. These tools enable the extraction of detailed phenotypic information from images, providing a more accurate and scalable approach to monitoring plant development.

In this context, the current research focuses on developing predictive models for plant growth using digital image processing and time-series analysis. By leveraging data from controlled experiments, this work aims to contribute to the broader goal of improving agricultural practices through data-driven insights.

## Plant growth prediction

Predicting plant growth is a complex task that requires an understanding of numerous factors, including environmental conditions, plant genetics, and developmental stages. Traditional approaches rely heavily on empirical data gathered through manual observation. However, modern data-driven methods are increasingly gaining traction due to their ability to analyze large datasets and uncover patterns that would otherwise go unnoticed.

The ability to predict plant growth accurately has numerous applications in agriculture. For instance, it can help optimize water and nutrient use, predict harvest times, and even detect early signs of stress or disease. The integration of time-series models and machine learning algorithms into plant growth analysis allows for more precise predictions, enhancing decision-making processes for farmers and researchers alike.

## Problem statement

Despite significant advancements in computer vision and machine learning, the accurate prediction of plant growth remains a challenging problem. One of the primary difficulties lies in the variability of plant phenotypes, which can be influenced by both genetic and environmental factors. Furthermore, the occlusion of leaves in densely packed plant structures and varying lighting conditions complicate the task of accurately detecting and quantifying leaves in images. While several algorithms exist for leaf detection, their accuracy and robustness vary across different plant species and conditions.

Another challenge arises in predicting the growth trajectory of plants based on historical data. Time-series models, such as ARIMA and Bayesian approaches, offer promising methods for forecasting plant growth. However, the accuracy of these models depends heavily on the quality of the input data and the tuning of model parameters. Thus, developing an effective pipeline for data acquisition, image processing, and growth prediction remains a critical research objective.

## Objectives

The primary objective of this thesis is to develop and evaluate a comprehensive pipeline for predicting plant growth using image-based phenotyping and time-series analysis. Specifically, the research aims to:

* **Develop an improved leaf detection algorithm** that enhances accuracy and robustness in different environmental conditions.
* **Design a method for calculating plant surface area** from images, providing an alternative metric for growth analysis.
* **Implement time-series models**, including ARIMA and Bayesian approaches, for predicting plant growth over time.
* **Compare and evaluate the performance** of different predictive models to determine the most effective approach for plant growth forecasting.

## Thesis contributions

This thesis builds on existing research in the field of plant phenotyping while introducing several novel contributions:

* **Enhanced Leaf Detection Algorithm**: A refined version of the existing leaf detection algorithm that improves accuracy under challenging conditions such as occlusion and varying lighting. This algorithm extends the work from previous research, particularly in its application to densely packed plant structures.
* **Surface Area Calculation**: A new approach for estimating plant surface area based on image data, offering a complementary metric to leaf count for analyzing plant growth. This method, while less precise than leaf counting, provides a robust measure that can be used in cases where leaf detection is unreliable.
* **Time-Series Growth Prediction Models**: The integration of ARIMA and Bayesian models for predicting plant growth, using hourly data collected from controlled experiments. These models offer insights into the temporal dynamics of plant development and provide a foundation for future work in real-time plant monitoring systems.

## Thesis structure

The remainder of this thesis is organized as follows:

* **Chapter 2** presents a comprehensive review of the literature on plant growth models, leaf detection techniques, and time-series analysis. The chapter highlights the current state of the art in these areas and identifies key gaps that this research addresses.
* **Chapter 3** provides an in-depth discussion of digital image processing techniques used in plant phenotyping, with a particular focus on leaf detection and surface area calculation.
* **Chapter 4** describes the experimental setup and data collection process, including the use of Raspberry Pi and Pi3 camera systems for image acquisition and the sensors used for environmental data collection.
* **Chapter 5** details the development and implementation of the improved leaf detection and surface area calculation algorithms, with a focus on their accuracy and robustness under different conditions.
* **Chapter 6** introduces the time-series models used for plant growth prediction, including ARIMA and Bayesian approaches, and presents a comparison of their performance.
* **Chapter 7** presents the results of the experiments and discusses their implications for plant growth prediction, as well as the limitations and challenges encountered during the research.
* **Chapter 8** concludes the thesis by summarizing the key contributions and suggesting directions for future research.

# Literature overview

## Overview of plant growth models

Plant growth modeling has progressed from traditional empirical methods toward more sophisticated data-driven techniques, thanks to advances in machine learning and computer vision. Traditional models, such as logistic growth models, rely on equations to describe plant growth patterns, often based on a few input variables like time and environmental conditions. These models are helpful but inherently limited in handling complex, multi-dimensional data, such as images that reveal detailed structural information about plants【1】【2】.

The evolution of phenotyping practices began with the adoption of image-based techniques. Using digital images captured through advanced imaging systems, researchers can measure phenotypic traits such as plant height, leaf count, surface area, and biomass in a non-invasive, efficient manner【1】. Deep learning models, such as Convolutional Neural Networks (CNNs), enable automated analysis of these images by learning complex features that distinguish various traits【3】【5】.

Recently, machine learning algorithms, particularly CNN-based architectures, have demonstrated remarkable accuracy in plant phenotyping. These models can handle large-scale data and complex plant structures, outperforming traditional models in scalability and precision. For instance, deep learning architectures like U-Net and Mask R-CNN provide not only the ability to detect individual leaves but also to accurately segment them from cluttered backgrounds【5】【6】.

## Leaf counting and surface area estimation

### Leaf counting approaches

Leaf counting plays a fundamental role in plant phenotyping as it correlates strongly with plant health and yield potential. Manually counting leaves is labor-intensive and prone to human error, especially for large datasets. Deep learning approaches automate this task by using models that can accurately estimate the number of leaves from a single image【2】【5】.

Segmentation-based approaches, such as U-Net, focus on extracting leaf regions by identifying pixel-level boundaries between leaves and their surroundings. The Mask R-CNN model further enhances this by using region proposal networks to locate objects and segment them simultaneously, allowing for leaf counting even in complex plant structures where leaves may overlap each other【5】【6】.

An alternative to segmentation is direct leaf counting, which bypasses the need to detect and segment each leaf. For instance, multi-scale regression approaches leverage varying image resolutions to estimate leaf counts without pixel-level annotations. The multi-scale fusion technique proposed by Itzhaky et al. (2018) has been particularly useful for counting leaves in densely populated images where traditional detection methods may fail【3】.

Moreover, YOLO-based detection algorithms have been shown to be highly effective in real-time leaf counting tasks. YOLO (You Only Look Once) is a high-speed object detection model that divides an image into a grid and predicts bounding boxes and confidence scores for each object. This model is particularly efficient for leaf counting in dynamic environments, as it processes the entire image in a single pass, making it suitable for real-time applications【2】【9】.

### Surface area estimation

While leaf counting provides discrete information about plant growth, surface area estimation offers a continuous metric, giving a better sense of the plant’s overall health and photosynthetic potential. Surface area estimation techniques rely on accurate segmentation of leaf regions, followed by calculations of pixel-based measurements that are then converted into real-world units【3】.

Deep learning models like ResNet50 have been employed for estimating surface area from segmented leaf images. By combining convolutional layers that capture hierarchical image features with fully connected layers, these models achieve high accuracy in surface area estimation across various plant species. Additionally, methods that employ region proposals, like Faster R-CNN, can be adapted to measure surface area by detecting leaf boundaries and extracting spatial dimensions of the plant canopy【6】【7】.

## Image processing techniques in agriculture

The accuracy of automated plant phenotyping heavily relies on the quality of image processing techniques. Here, segmentation and object detection are crucial in ensuring that the extracted features accurately represent plant traits such as leaf number and surface area.

* **Segmentation**: Accurate segmentation is essential for isolating individual leaves from their background. U-Net and Mask R-CNN are two popular models in this domain, providing state-of-the-art performance for tasks such as leaf segmentation. U-Net’s encoder-decoder architecture allows for precise delineation of leaf edges, even in challenging conditions like shadowing or occlusion【5】【6】. In parallel, Mask R-CNN enhances object detection by using region-based segmentation, which is beneficial for identifying overlapping or hidden leaves【5】【6】.
* **Background Removal**: Removing the background noise from images is a critical preprocessing step in leaf detection and surface area estimation. Classical methods, like thresholding and color space transformations, are combined with deep learning techniques to improve accuracy. These methods are especially important in greenhouse environments where lighting conditions may vary【6】【8】.
* **Object Detection**: YOLOv3 and its variants are widely used in real-time leaf counting applications. YOLOv3’s ability to simultaneously detect multiple leaves in a dense arrangement makes it a preferred choice for fast and accurate phenotyping. The model’s grid-based detection strategy allows it to handle complex scenarios, where traditional methods might struggle to separate overlapping leaves【9】【8】.

## Time series analysis in agriculture

### Overview of ARIMA models

Time-series models, such as ARIMA (Auto-Regressive Integrated Moving Average), have long been employed to predict plant growth by analyzing historical data trends. ARIMA models are particularly effective for short-term forecasting, such as daily or weekly growth increments, because they model temporal dependencies in the data. In agricultural contexts, ARIMA is widely used to model growth patterns over time. It’s extension to ARIMAX can also provide insights into how external variables such as temperature, humidity, and light intensity influence plant development【4】【8】.

Moreover, ARIMA models have been combined with other techniques to improve accuracy in forecasting plant phenotypes under fluctuating environmental conditions. For example, hybrid ARIMA models, which integrate machine learning techniques like support vector regression (SVR), have been explored to handle more complex, non-linear growth patterns. This hybrid approach has shown improved performance in agricultural forecasting by accounting for seasonal variations and external factors【10】.

### Bayesian models in growth prediction

Bayesian methods provide a flexible framework for predicting plant growth, particularly when dealing with uncertainty or limited data. Bayesian time-series models, such as those implemented using the PyMC3 library, allow for the incorporation of prior knowledge about the system, which can then be updated dynamically as new data becomes available. This is particularly useful in agriculture, where growth patterns are often non-linear and affected by various unpredictable environmental factors【3】【4】.

Bayesian approaches have also been extended to hierarchical models, where the growth of different plants or groups of plants can be modeled together, sharing information across levels of the hierarchy. This type of model improves predictive accuracy, particularly in scenarios where data is sparse or when modeling plants under different environmental conditions. The flexibility of Bayesian models also allows them to handle missing or noisy data more effectively than traditional methods like ARIMA【11】.

### Advanced deep learning technics

Beyond ARIMA and Bayesian methods, newer time-series techniques such as Long Short-Term Memory (LSTM) networks have been introduced to predict plant growth more accurately. LSTMs, a type of recurrent neural network (RNN), are particularly well-suited for time-series forecasting as they capture long-term dependencies in sequential data. LSTMs have shown great promise in predicting agricultural time-series data, especially for long-term growth forecasts where traditional models like ARIMA may struggle【12】.

Another advanced approach is Gaussian Process Regression (GPR), which has been applied to plant growth prediction. GPR models provide a probabilistic framework that can quantify uncertainty in predictions, making them useful for agricultural applications where precise predictions are challenging due to the complexity of biological processes【13】.

# Image analysis in Plant Science

## Introduction to Digital Image Processing

Digital image processing plays a crucial role in modern plant phenotyping, enabling the automated analysis of plant growth and health. The key advantage of digital imaging is its non-invasive nature, allowing researchers to observe phenotypic traits without disturbing the plant's growth process. In agricultural science, image analysis provides tools to extract valuable information, such as leaf count, surface area, and growth dynamics, which are critical for understanding and predicting plant development. Image-based phenotyping systems rely on capturing high-quality images and applying sophisticated processing algorithms to extract meaningful information. The increasing availability of affordable hardware and open-source software has made image processing more accessible to the agricultural community, paving the way for precision farming practices.

### Types of Digital Images

Digital images used in plant phenotyping can be broadly categorized based on the spectral range in which they are captured. The most common image types include:

* **RGB (Red-Green-Blue) Images**: These are standard color images captured using conventional cameras. RGB images are widely used due to their simplicity and ease of processing. They provide enough information for tasks like leaf counting and surface area estimation.
* **Hyperspectral Images**: Hyperspectral imaging captures data across multiple bands of the electromagnetic spectrum, allowing for the detection of subtle changes in plant physiology. These images are particularly useful in identifying stress factors, such as nutrient deficiencies or disease.
* **Thermal Images**: Thermal cameras capture infrared radiation, offering insights into plant transpiration and heat stress. These images are valuable in identifying areas where plants may be experiencing drought stress or irregular water distribution.

### Image Acquisition

Acquiring high-quality images is the foundation of successful plant image analysis. In plant phenotyping, cameras are typically mounted on fixed stations, drones, or robots to capture images at regular intervals. Raspberry Pi-based systems, as used in this research, are gaining popularity due to their affordability and flexibility. Equipped with a Pi camera, these systems can capture time-lapse images at set intervals to monitor plant growth continuously. Additionally, environmental data such as temperature and humidity are often recorded alongside images to provide context for growth variations. High-resolution cameras are essential for ensuring the accuracy of subsequent image analysis steps, such as leaf segmentation and surface area calculation.

## Image pre-processing techniques

Image pre-processing is a critical step in preparing raw images for analysis. It enhances image quality, corrects distortions, and ensures that the plant features are more distinguishable from the background. Common pre-processing steps include background removal and noise reduction.

### Background removal

Background removal is essential in plant image analysis as it isolates the plant from the surrounding environment. Without effective background removal, the image analysis algorithms may incorrectly identify non-plant elements, reducing the accuracy of metrics such as leaf count and surface area. Various techniques are employed to remove backgrounds, including thresholding and color-space transformations. For instance, converting an image from RGB to the HSV (Hue-Saturation-Value) color space can make it easier to separate plant material from the background based on color differences. Machine learning methods, such as Mask R-CNN, can also be used to segment plants and remove backgrounds more accurately in complex scenarios【5】【6】.

### Noise reduction and Filtering

Images captured in natural environments often contain noise due to factors like uneven lighting, shadows, and reflections. Noise reduction techniques, such as Gaussian filtering, help in smoothing images while preserving important features like edges. Median filtering is another popular technique used in plant image processing, particularly when dealing with images that contain salt-and-pepper noise. These methods improve the quality of the image, ensuring more accurate leaf detection and surface area estimation【5】【6】.

## Leaf detection algorithms

Leaf detection is a core task in plant phenotyping, as the number of leaves is a key indicator of plant health and growth. Various algorithms have been developed for detecting leaves, ranging from traditional computer vision techniques to advanced deep learning approaches.

### Traditional approaches

Traditional leaf detection approaches primarily rely on edge detection and contour-based methods. Algorithms such as Canny edge detection and Hough Transform are used to identify the boundaries of leaves. Once the edges are detected, further processing, like contour finding, can be applied to count the number of distinct leaves. These methods, although effective in simple scenarios, often struggle in complex images where leaves overlap or have irregular shapes. Additionally, varying lighting conditions and occlusions make traditional methods less reliable.

### Deep Learning Approaches

In recent years, deep learning techniques have revolutionized leaf detection by significantly improving accuracy in complex scenarios. Models like U-Net and Mask R-CNN have been widely adopted in plant phenotyping. U-Net, with its encoder-decoder architecture, excels at segmenting individual leaves from an image, even when they overlap. Mask R-CNN, on the other hand, extends this capability by performing both object detection and instance segmentation, allowing it to accurately detect each leaf in dense foliage. These methods use large labeled datasets for training, which enable them to generalize well across different plant species and environmental conditions【5】【6】.

## Feature extraction for Plant Growth

Feature extraction is the process of identifying and quantifying phenotypic traits that can be used to assess plant growth. Leaf count and surface area are two primary features extracted from plant images.

### Leaf count and surface area

Leaf count is a straightforward but highly informative metric for assessing plant health. Automated leaf counting can be performed using deep learning models like Mask R-CNN or YOLO, which detect individual leaves even in cluttered images. Surface area, on the other hand, provides a more comprehensive measure of plant size and health. After detecting the leaves, surface area is estimated by calculating the number of pixels that correspond to the leaves and converting this value to a real-world measurement using calibration techniques【5】【6】.

### Challenges in Leaf Segmentation

Leaf segmentation presents several challenges, particularly in images where leaves overlap or are partially occluded. In such cases, traditional segmentation methods often fail to distinguish individual leaves. Variations in leaf shape and size also add complexity to the task. To address these challenges, deep learning models like Mask R-CNN and U-Net have been developed to handle dense foliage by learning from large datasets. However, these methods require extensive computational resources and high-quality labeled data for training【6】【7】.

## Image Calibration and Cropping

Image calibration ensures that the measurements extracted from images are accurate and consistent. Calibration typically involves correcting distortions caused by the camera lens and converting pixel-based measurements into real-world units. Calibration is particularly important for tasks like surface area estimation, where accurate scaling is crucial. Cropping, on the other hand, removes unnecessary parts of the image, focusing the analysis on the region of interest, such as the plant canopy.

## Summary

This chapter has outlined the key steps in image processing for plant phenotyping, from image acquisition and pre-processing to leaf detection and feature extraction. The advancements in deep learning techniques, particularly in leaf segmentation and surface area estimation, have significantly improved the accuracy and scalability of plant phenotyping. However, challenges such as occlusion and variability in plant structure continue to present obstacles, highlighting the need for further research and innovation in this field.

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