Development of an R Toolbox for Near-Infrared Spectroscopy Data Processing and Analysis of Plant Metabolic Phenotypes

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Chapter 1

Introduction

The understanding of interplay between plant physiology and its hidden biochemical process is crucial for the improvement of basic plant science and addressing global challenges such as food security, crop resilience and combating climate change [1]. In recent years, advanced High-throughput analytical techniques such as Near-Infrared Spectroscopy (NIRS) and Liquid Chromatography-Mass Spectrometry (LC-MS) has instigated a paradigm shift in plant biology [2][3]. These High-throughput techniques are mostly used in areas like genomics, imaging and spectroscopy and is known for their ability to collect and analyse the data faster than traditional techniques[3]. High-throughput techniques are widely used since they enable the efficient collection of vast amount of data at various scales, from molecular to field level over significant time periods[4]. The big data generated by these high throughput procedures present both opportunities and challenges at the same time. It requires efficient processing to extract maximum useful results and this is where Machine Learning (ML) or Deep Learning (DL) becomes indispensable [4][5]. ML as a part of Artificial Intelligence (AI) refers to the ability of computers to find patterns and learn from the existing data which can be employed in processing high dimensional data [6][4]. The ML algorithms are powerful enough to analyse complex, high dimensional datasets, enabling accurate predictions of plant traits or other features based on the input data. Additionally, integrating these big data with ML could help the researchers to optimize data processing pipelines, enhance predictive accuracy and thereby enter into a new era of data-driven decision-making [4][5]. This project employs linear models, non-linear models and neural networks to predict various plant features and compare their performances.

Chapter 2

Background

The background of this study include

2.1 Related Work

2.2 Near Infrared Spectroscopy (NIRS)

2.3 R Programming

2.4 Machine Learning

2.4.1 Partial Least Square Regression (PLSR)

2.4.2 Random Forest (RF)

2.4.3 Convolutional Neural Network (CNN)

2.5 Mass Spectrometry and Liquid Chromatography

Chapter 3

Implementation

3.1 Packages

Github, testing, actions

3.2 Contributions elsewhere

3.3 HPC runs

Chapter 4

Results and Discussion

4.1 Data charecterestics

histogram, spectra

4.2 Baseline Machine Learning Models Pablo

PLS, RF, CNN

4.2.1 Variable importance

4.3 Variations in Baseline systems

4.3.1 modifying the Test and Training split

4.3.2 input data length

4.4 Sues

Chapter 5

Reference

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