

Supporting Information

Enhancing Pigment Phenotyping and Classification in Lettuce Through the Integration of Reflectance Spectroscopy and AI Algorithms

Renan Falcioni ^{1,*}, João Vitor Ferreira Gonçalves ¹, Karym Mayara de Oliveira ¹, Caio Almeida de Oliveira ¹, José A. M. Demattê ², Werner Camargos Antunes ¹ and Marcos Rafael Nanni ¹

¹ Graduate Program in Agronomy, Department of Agronomy, State University of Maringá, Av. Colombo, 5790, Maringá 87020-900, Paraná, Brazil

² Department of Soil Science, Luiz de Queiroz College of Agriculture, University of São Paulo, Av. Pádua Dias, 11, Piracicaba 13418-260, São Paulo, Brazil

* Correspondence: renanfalcioni@gmail.com; Tel.: +55-44-3011-8940

Table S1. Descriptive analysis parameters of lettuce varieties. Pigment of leaves expressed by leaf area (mg m^{-2}), mass (mg g^{-1}), and volume (mL L^{-1}). ($n = 132$).

Parameters	Count (n)	Mean	Median	Minimum	Maximum	CV (%)
Chla (mg m^{-2})	132	128.3	118.3	63.1	306.4	39.2
Chlb (mg m^{-2})	132	66.5	61.7	39.4	147.3	35.1
Chla+b (mg m^{-2})	132	194.9	182.1	108.0	453.7	37.6
Car (mg m^{-2})	132	45.5	42.3	25.6	101.9	35.5
AnC (nmol cm^{-2})	132	13.1	11.4	0.0	68.6	125.8
Flv (nmol cm^{-2})	132	58.4	49.0	0.0	178.3	62.2
Chla (mg g^{-1})	132	14.8	14.3	8.2	31.4	26.4
Chlb (mg g^{-1})	132	7.7	7.7	4.5	15.1	23.1
Chla+b (mg g^{-1})	132	22.5	21.7	13.2	46.5	24.9
Car (mg g^{-1})	132	5.3	5.1	3.2	10.9	24.2
AnC ($\mu\text{mol g}^{-1}$)	132	16.3	16.4	0.0	83.1	121.3
Flv ($\mu\text{mol g}^{-1}$)	132	74.2	71.0	12.7	203.8	60.1
Phe (mL L^{-1})	132	62.8	66.3	42.7	78.7	16.6
Chla/b ratio	132	1.9	2.0	1.4	2.2	9.4
Car/Chla+b ratio	132	0.2	0.2	0.2	0.3	6.1

Table S2. STEPW and VIPs by wavelengths selected according to classified algorithm-based ANOVA and information gain ratio ($p < 0.001$) by band range spectroscopy from reflectance leaves. Bold underlines show shared wavelengths between the STEPW and VIP.

Band range (nm)	N	Shared	STEPWise selection wavelengths (nm)	Most responsive VIP-rank selection wavelengths (nm)
400-700	34	7	548, 570, 560, 581, 531, 700, 544, 540, 538, 615, 545, 456, 491, 437, 434, 645, 654, 452, 429, 472, 641, 609, 687, 658, 687, 658, 614, 626, 430, 594, 441, 528, 527, 659, 427, 443	549, 548, 550, 547, 551, 546, 552, 545, 544, 553, 543, 542, 554, 555, 559, 535, 560, 533, 573, 522, 524, 574, 570, 589, 599, 606, 608, 500, 497, 510, 700, 610, 693, 491
700-1300	57	3	701, 737, 1034, 915, 703, 1274, 933, 975, 995, 924, 922, 954, 983, 970, 799, 923, 908, 1021, 1027, 992, 911, 885, 798, 1088, 1001, 811, 842, 857, 860, 805, 831, 829, 1033, 935, 832, 845, 879, 928, 801, 780, 787, 807, 986, 847, 994, 806, 907, 846, 995, 810, 1003, 803, 859, 941, 918, 978, 874	986, 965, 960, 954, 958, 700, 711, 754, 757, 707, 766, 749, 762, 748, 767, 1057, 1156, 1295, 1151, 1149, 1445, 1169, 1173, 1284, 789, 1283, 1174, 1131, 1276, 795, 1185, 797, 1115, 1266, 1108, 896, 814, 913, 1423, 1055, 1299, 1047, 861, 1058, 1249, 1109, 743, 867, 1087, 1244, 879, 745, 892, 740, 715, 768, 853
1300-2400	22	2	2245, 1861, 2023, 1310, 1830, 1842, 2220, 1921, 1803, 1806, 1841, 1816, 1941, 2277, 2295, 2296, 1829, 1843, 2013, 1924, 1837, 1810	2364, 2371, 2366, 2373, 2400, 2353, 1442, 1437, 1816, 2350, 1836, 1842, 1460, 1887, 2013, 1385, 2324, 2088, 1416, 1789, 1658, 1781
400-2400	26	3	548, 570, 560, 581, 531, 701, 544, 540, 743, 1023, 952, 527, 1059, 741, 1539, 1754, 700, 942, 1009, 998, 1065, 562, 559, 1000, 574, 597	548, 549, 550, 547, 551, 546, 560, 553, 572, 583, 2378, 2373, 2367, 2382, 2326, 600, 2045, 2071, 1435, 1425, 1993, 1446, 1840, 1940, 1539, 435

Table S3. Description of artificial intelligence algorithms (AIAs).

Algorithms	Abbreviation	Description	References
------------	--------------	-------------	------------

AdaBoost	AdB	Boosting algorithm that combines weak learners to create a strong classifier.	[41]
CN2 rule inducer	CN2	Decision tree algorithm that creates a set of if-then rules to classify data.	[41]
Constant	Const	Algorithm that always predicts the same class, regardless of input.	[41]
Gradient Boosting	G-Boo	Boosting algorithm that combines multiple decision trees to create a strong classifier.	[41]
Kernel k Nearest Neighbours	KNN	Non-parametric algorithm that classifies data based on the k closest training examples in a feature space.	[41]
Logistic Regression	Log-Reg	Parametric algorithm that models the probability of a binary outcome based on input features.	[41]
Naive Bayes	Nai-Bay	Probabilistic algorithm that models the likelihood of each class given the input features.	[41]
Neural Network	NN	Algorithm that models complex non-linear relationships between inputs and outputs using layers of interconnected nodes.	[41]
Stochastic Gradient Descent	SGD	Optimization algorithm that minimizes the error of a model by adjusting the weights of the inputs.	[41]
Random Forest	RF	Ensemble learning algorithm that combines multiple decision trees to create a strong classifier.	[41]
Support Vector Machines	SVM	Algorithm that finds the hyperplane that best separates two classes in a feature space.	[41]
Tree	Tree	Decision tree algorithm that recursively partitions data based on input features.	[41]

*** references were based explication of models.

41. [Https://orangedatamining.com/widget-catalog/](https://orangedatamining.com/widget-catalog/) Orange Models.