Supporting Information

Modeling the Higher Heating Value of Spanish Biomass via Neural Networks and Analytical Equations

Anbarasan Jayapal [1, †], Fernando Ordonez Morales[1, †], Muhammad Ishtiaq[1], Se Yun Kim [1,*], Nagireddy Gari Subba Reddy[2*]

[1]Department of Materials Engineering and Convergence Technology, Gyeongsang National University, Jinju, Gyeongsangnam-do, Republic of Korea 52828

[2]School of Materials Science and Engineering, Engineering Research Institute, Gyeongsang National University, Jinju 52828, Republic of Korea

*Corresponding authors Email Se Yun Kim: seyun@gnu.ac.kr, N. S. Reddy: nsreddy@gnu.ac.kr,

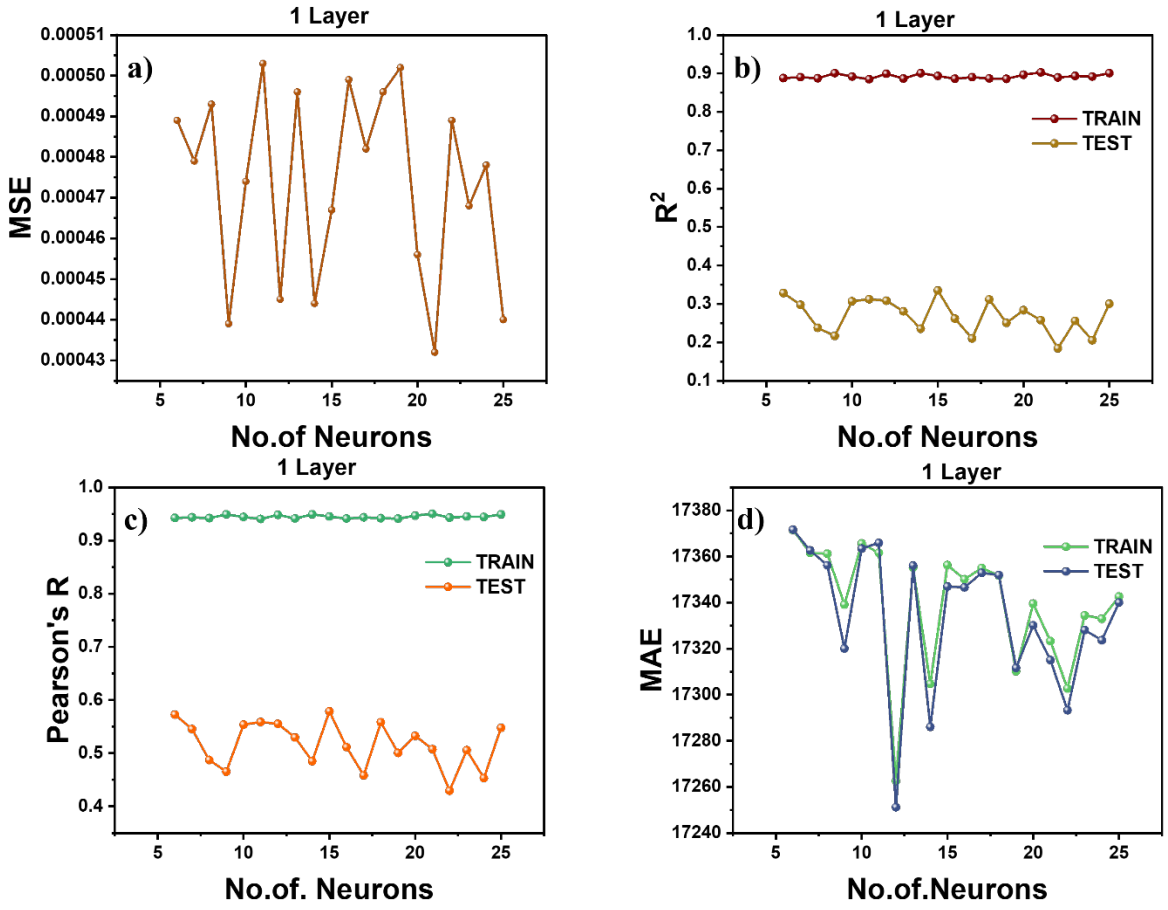


Figure S1. Training behavior graph of 1 layer: a) mean squared error; b) coefficient of determination (R^2); c) Pearson correlation coefficient; d) main average error.

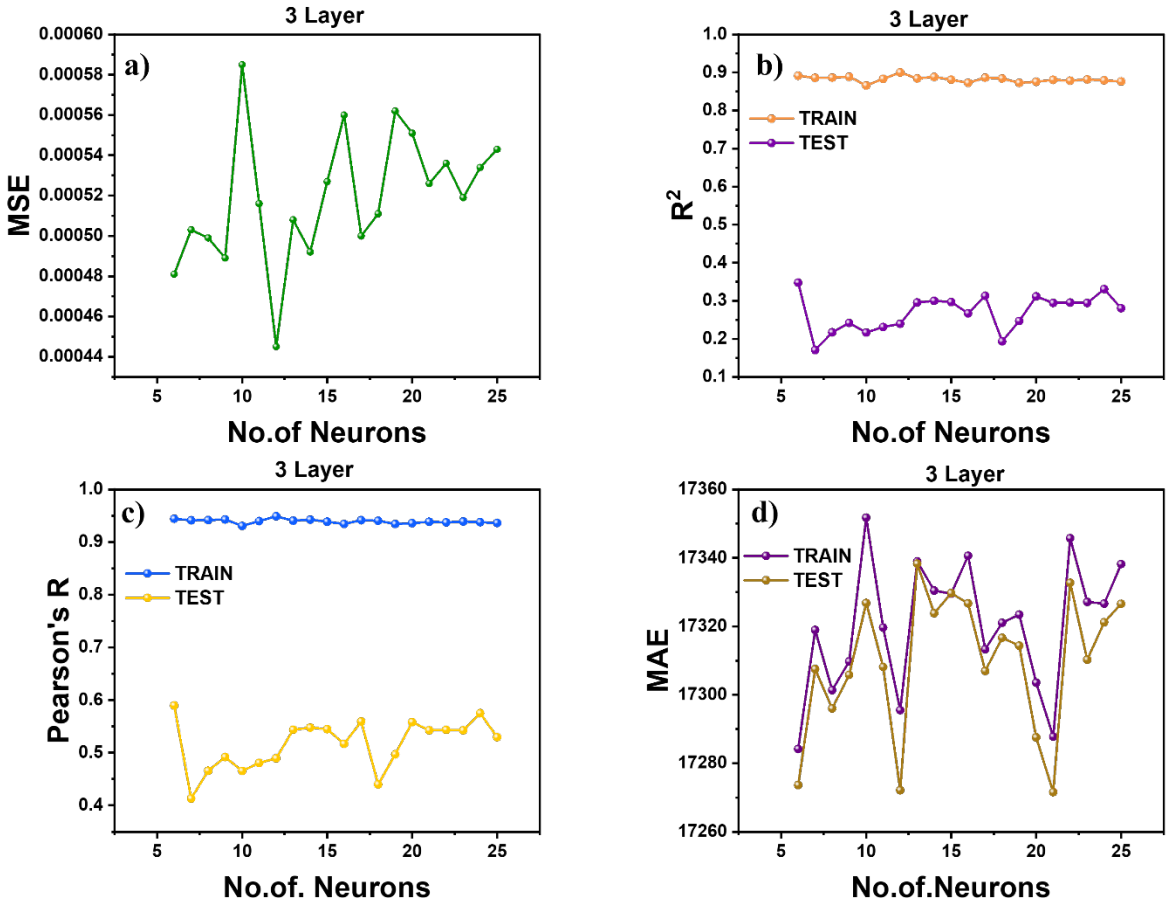


Figure S2 Training behavior graph of 3 layers: a) mean squared error; b) coefficient of determination (R^2); c) Pearson correlation coefficient; d) main average error.

Table S1. Raw data used to generate the ANN proposed empirical equations.

	Sample	M	A	VM	FC	N	C	S	H	O	HHV
1	Almond shell	8.68	2.2	82	15.8	0.3	46.35	0.22	5.67	47.46	18275
2	Beetroot pellets	12.5	9	76	15	1.19	38.94	0.51	5.23	54.13	15095
3	Briquette	5.84	0.8	85	14.2	1.24	46.74	0.1	6.39	45.52	18498
4	Holm oak branch chips	11.1	7.4	74.9	17.7	0.76	45.65	1.99	5.75	45.84	17181
5	Olive stone	11	1.4	78.3	20.4	1.81	46.55	0.11	6.33	45.2	17884

6	Pine and pine apple leaf pellets	8.2	3.2	75	21.8	0.4	42.26	0.27	4.81	52.27	18147
7	Pine chips	10.25	0.6	81.6	17.8	0.09	48.15	0.28	5.59	45.9	19427
8	Pine cone leaf	9.14	1.3	80	18.7	0.27	47.65	0.44	5.43	46.21	18633
9	Pine kernel shell	8.33	2.7	77.6	19.7	0.31	47.91	0.6	4.9	46.28	18893
10	Pine pellets	6.75	1.3	83.5	15.2	0.28	46.83	0.31	5.3	47.28	18840
11	Pine cone heart	23.1	3.5	66	30.5	0.29	42.22	0.84	5.06	51.59	16440
12	Sawdust	11.3	1.6	81	17.4	0.53	45.34	1.07	6.02	47.05	18016
13	Straw pellets (grass)	7.3	9.8	79	11.2	0.56	47.89	0.17	5.51	45.87	16584
14	Vine shoot chips	22	9.7	66	24.3	0.61	40.15	0.31	5.02	53.91	14631
15	Wood chips	25.6	1.5	68.6	29.9	0.13	42.2	0.27	5.51	51.88	15162
16	Wood pellets	7.7	1.3	82	17.1	0.6	46.79	0.32	6.13	46.15	18218
17	Barley straw	9.8	6.1	77.9	16	1.64	40.69	0.23	6.95	50.5	17369
18	Bean husk	9.99	8	74	18.2	0.66	39.66	0.31	5.38	53.98	15114
19	Building waste chips	7.9	0.8	86	13.2	0.08	47.26	0.17	6.45	46.04	18279
20	Cherry stone	7.57	0.87	85	14.1	0.43	48.57	0.19	6.21	44.6	19069
21	Chestnut shell	24.4	3.9	67	29.1	0.42	42.31	0.33	5.17	51.77	14310
22	Cocoa bean husk	8.8	9.96	69	21	2.64	43.25	0.29	5.89	47.93	17313
23	Coconut shell	8.6	1.4	79.2	19.4	0.15	47.93	0.24	6.05	45.63	18875
24	Coffee husk	9.6	5.8	76.2	18	2.53	45.06	0.48	6.42	45.51	18326
25	Corncob	7	2.4	83	14.6	0.22	44.78	0.21	6.02	48.77	17692
26	Date stone	9.4	1.4	82	16.6	1.03	43.37	0.32	6.23	49.05	18150
27	Grapevine waste	11.16	13.3	73	13.7	1.35	35.74	0.3	5.95	56.67	16467
28	Hazelnut shell	8.74	2.2	77	20.8	0.27	47.8	0.16	6.14	45.64	18872
29	Lemon rind	10.4	9.7	73.2	17.1	1.08	42.95	0.42	6.56	48.98	17184
30	Nectarine stone	8.2	1.1	76	22.9	0.5	48.57	0.23	6.22	44.48	19560
31	Pea husk	11.8	4.5	83	12.5	1.24	39.62	1.82	6.54	50.78	15464

32	Pea plant waste	8.7	5.8	78	15.9	0.9	44.06	0.39	4.73	49.91	17351
33	Peach stone	8.55	0.5	75.6	23.9	3.94	40.72	0.3	6.96	48.07	19590
34	Peanut shell	5.1	2.5	81	16.5	1.05	49.35	0.24	6.4	42.96	20088
35	Pepper plant waste	7.94	22.9	73.1	4	3.66	36.56	0.83	5.27	53.67	13656
36	Pistachio shell	8.75	1.3	82.5	16.2	0.11	44.69	0.18	5.16	49.87	17348
37	Plum stone	9.13	1.8	77	21.2	0.87	48.22	0.17	6.6	44.14	19136
38	Pomegranate peel	14	6.8	68	25.2	0.69	42.19	0.33	5.11	51.68	15173
39	Potato plant waste	9.9	15.8	69	14.7	1.13	38.33	0.44	5.07	55.03	15070
40	Rice husk	7.27	13.7	73	13.3	0.21	26.69	0.17	2.88	70.05	15899
41	Rye straw	8.7	3.2	79.9	16.9	1.16	40.18	0.32	6.85	51.48	17113
42	Sunflower seed husk	8.2	1.9	80	18.1	0.38	45.33	0.24	5.91	48.14	17998
43	Tomato plant waste	10.2	16.2	78	6	1.19	36.63	1.48	0.68	60.01	14154
44	Vine orujillo	9.5	12.7	79	8.3	1.91	44.15	0.58	5.31	48.04	17742
45	Vine shoot waste	31.4	4.1	64	31.9	0.63	34.6	0.24	5.61	58.91	13292
46	Walnut shell	8.7	2.3	79	18.7	0.22	46.97	0.1	6.27	46.44	18378
47	Wheat straw	7.7	5.3	76	18.2	1.18	45.58	0.59	6.04	46.6	17344
48	Wood sawdust	9.2	0.6	83	16.4	0.12	45.97	0.24	5.13	48.53	18207
49	American oak acorn	8.92	3.2	74	22.8	0.6	44.68	0.18	5.98	48.55	17372
50	Black poplar bark	9.8	8	71	20.8	0.42	43.25	0.34	6.33	49.66	17406
51	Black poplar wood	7.18	1.5	86	12.3	0.18	46.19	0.56	5.7	47.36	18392
52	Chestnut tree chips	9.83	1.3	78.2	20.5	0.23	45.3	0.17	6.1	48.2	17485
53	Chestnut tree shaving	8.35	0.4	79	20.6	0.12	45.88	0.27	5	48.73	17616
54	Cypress fruit	10.3	4.7	71.8	23.5	0.35	27.81	0.18	5.7	65.96	20172
55	Eucalyptus bark	8.6	6.2	77	16.8	1.69	46.53	0.3	5.87	45.61	16237
56	Eucalyptus chips	11	1.9	79	19.1	0.14	44.77	0.15	6.33	48.6	16494

57	Eucalyptus fruit	11.7	4.7	73.6	21.7	1.14	46.81	0.39	5.81	45.84	18522
58	Hazelnut and alder chips	9.5	5	77	18	0.4	45.47	0.2	5.94	47.99	17555
59	Horse chestnut burr	9.2	5.4	70	24.6	0.45	53.38	0.23	7.16	38.77	17165
60	Oak acorn	11.9	2.6	75.1	22.3	0.8	41.84	0.25	6.82	50.28	16165
61	Oak tree pruning	9.8	4.3	77	18.7	0.73	37.89	0.21	5.94	55.23	17592
62	Olive tree pruning	8.7	13	78	9	1.47	45.36	0.28	5.47	47.42	17342
63	Pine and eucalyptus chips	13.4	3.6	71.6	24.8	1.59	45.9	0.19	6.3	46.03	16987
64	Pine shaving	9.2	0.8	85	14.2	0.07	48.67	0.26	5.08	45.92	19793
65	Almond tree leaves	7.5	9.3	87.19	3.5	2.85	43.25	0.34	5.5	48.06	17560
66	Apple tree leaves	9.3	12	71.9	16.1	1.61	44.45	0.23	6.15	47.56	17510
67	Black poplar leaves	9.4	7.8	71.2	21	1.03	58.3	0.35	8.41	31.92	18165
68	Cherry tree leaves	10.4	7.4	71	21.6	1.49	45.52	0.19	6.25	46.55	17734
69	Chestnut tree leaves	8.2	4.9	72.41	22.7	2.21	47.82	0.27	6.24	43.46	18757
70	Feijoa leaves	6.9	6.7	71.2	22.1	1.23	45.28	0.2	6.03	47.25	17805
71	Hazelnut tree leaves	9.1	8	79	13.4	2.05	45.14	0.31	6.79	45.71	17870
72	Oak tree leaves	9.1	3.8	72	24.2	3.04	46.9	0.38	5.47	44.2	18312
73	Orange tree leaves	9.2	15.4	73.2	11.4	2.59	41.11	0.4	5.28	50.62	16170
74	Peach tree leaves	7.44	10.2	75	14.7	2.03	59.59	0.77	9.76	27.86	18336
75	Almond tree branches	7.1	5.4	75.6	19	0.65	47.35	0.16	6.36	45.47	18351
76	Apple tree branches	7.7	5	74	21	0.81	46.24	0.39	11.55	41.01	17821
77	Black poplar branches	8.4	4	89	18.4	0.33	45.62	0.59	0.03	53.43	18411
78	Cherry tree branches	7.7	4.4	74	21.5	0.52	46.42	0.17	6.21	46.68	19361
79	Grapevine branches	10.4	7.6	71.5	20.9	0.76	45	0.46	6.95	46.83	16818

80	Horse chestnut tree branches	8.8	6.9	73.5	19.6	1.05	43.71	0.43	6.27	48.54	17469
81	Kiwi branches	8.2	4.5	74	21.5	1.06	46.41	2.44	6.09	43.99	17812
82	Lemon tree branches	8.4	4.7	76.7	18.6	0.54	54.74	0.33	5.72	38.68	17564
83	Medlar tree branches	9.9	8.4	74	17.6	0.52	44.36	0.18	6.17	48.77	17645
84	Mimosa branches	8.28	4	75	21	0.75	45.81	0.17	6.19	47.08	17752
85	Oak tree branches	8.2	4.2	78.4	17.4	2.87	48.26	0.33	6.28	42.26	17717
86	Orange tree branches	8	4.5	79	16.9	0.56	45.76	0.21	6.12	47.34	16305
87	Gorse	43	5	45.2	50.2	1.49	43.49	0.33	5.53	49.16	18599
88	Miscanthus	7.53	9.6	79	11.4	0.1	47.09	0.1	6.3	46.42	18072
89	Oats and vetch	7.8	7.33	72	20.7	0.92	41.69	0.29	5.82	51.27	16661
90	Sorghum	6.1	17	62	21	0.73	40.79	0.23	4.38	53.87	11872
91	Triticale	9.8	6.2	75	18.8	1.23	42.14	0.76	5.8	50.07	16645
92	Barley grain	9.9	3	76.9	20.1	1.79	41.59	0.35	6.08	50.18	16519
93	Maize grain	11.1	2.1	78.9	19.1	1.17	40.96	0.23	6.92	50.71	16429
94	Oats bran	9.9	4.15	77	18.9	2.17	44.01	0.29	7.17	46.36	18058
95	Rye grain	10.76	1.8	78.9	19.3	1.2	41.11	0.21	6.76	50.72	16141
96	Sainfoin	9.6	9.2	73	17.8	1.8	41.68	0.57	5.9	50.05	16412
97	Soya grain	10.9	4.8	77	18.2	1.16	44.42	0.24	6.33	47.86	16711
98	Wheat grain	10.3	2.8	80	17.2	0.24	49.22	0.26	6.52	43.76	16325
99	Wheat bran	9	3.5	78	18.5	2.34	42.74	0.31	6.62	47.98	17370

Table S2. Analytical equations based on proximate analysis data selected from the literature.

S. No	Model	Fuel Type	HHV Prediction Equation	R^2	Reference
1	Akkaya (AKK)	Coal	$HHV = 33.078 – 0.72(M/100) + 0.012(M/100)^2 – 1.163(M/100)^3 – 0.342(Ash/100)^2$	0.004	[1,5]
2	Bento (BEN)	Wastes	$HHV = 44.75 \cdot VM – 5.85 \cdot M + 21.2$	0.012	[1,5]
3	CAL_1	Biomass	$HHV = 20.086 – 0.261 \cdot Ash$	0.066	[6]
4	CAL_2	Biomass	$HHV = –13.173 + 0.416 \cdot VM$	0.012	[1,6,7]
5	CAL_3	Biomass	$HHV = –2.057 – 0.092 \cdot Ash + 0.279 \cdot VM$	0.024	[1,6,7]
6	CHA_1	MSW > 100 mm	$HHV = 6295.7 – 64.05 \cdot M$	0.002	[1,8]
7	CHA_2	MSW 25–100 mm	$HHV = 5112.0 – 52.08 \cdot M$	0.002	[1,8,11]
8	CHU	Biomass	$HHV = 0.1905 \cdot VM + 0.2521 \cdot FC$	0.12	[1,2,13]
9	COR_1	Biomass/Coal	$HHV = 0.3543 \cdot FC + 0.1708 \cdot VM$	0.02	[1,6,7,14]
10	COR_2	Biomass/Coal	$HHV = 35.430 – 183.5 \cdot VM – 354.3 \cdot Ash$	0.05	[28,33,34]
11	DEM_1	Biomass	$HHV = 0.196 \cdot FC + 14.119$		[2]
12	DEM_2	Biomass	$HHV = 0.312 \cdot FC + 0.1534 \cdot VM$	0.029	[2]
13	GOU	Coal	$HHV = 82 \cdot FC + a \cdot VM$	0.06	[9]
14	J&G	Biomass	$HHV = –10.81408 + 0.3133 \cdot (VM + FC)$	0.05	[6,8,9]
15	KUC	Coal	$HHV = 75.56 – 1.3 \cdot (VM + Ash) + 7.03 \times 10^{-3} \cdot (VM + Ash)^2$	0.001	[9]
16	KAT_1	MSW	$HHV = 356.248 \cdot VM – 6998.497$	0.012	[10]
17	KAT_2	MSW	$HHV = 356.047 \cdot VM – 118.035 \cdot FC – 5600.613$	0.006	[10]
18	MAJ	Coal	$HHV = –0.03 \cdot Ash – 0.11 \cdot M + 0.33 \cdot VM + 0.35 \cdot FC$	0.04	[1]
19	PAR	Solid Fuels	$HHV = 0.3536 \cdot FC + 0.1559 \cdot VM – 0.0078 \cdot Ash$	0.02	[1]
20	SCH	Coal	$HHV = 4.183 \times 10^{-3} (8000 + VM \cdot (70 – 1.65 \cdot VM))$	0.016	[1]
21	$S\&A_1$	Biomass	$HHV = –3.0368 + 0.2218 \cdot VM + 0.2601 \cdot FC$	0.005	[1]
22	$S\&A_2$	Biomass	$HHV = 19.914 – 0.2324 \cdot Ash$	0.06	[1]
23	THI_1	Sewage sludge	$HHV = 259.83 \cdot (VM + FC) – 2454.76$	0.012	[2,3]
24	THI_2	Sewage sludge	$HHV = 255.75 \cdot VM + 283.88 \cdot FC – 2386.38$	0.012	[15]
25	THI_3	Sewage sludge	$HHV = 278.07 \cdot (VM + FC) – 50.44 \cdot M – 2875.52$	0.019	[4]
26	THI_4	Sewage sludge	$HHV = 219.98 \cdot VM + 327.44 \cdot FC – 68.39 \cdot M$	0.017	[4]
27	THI_5	Sewage sludge	$HHV = 276.04 \cdot VM + 289.70 \cdot FC – 51.45 \cdot M – 2847.53$	0.015	[4]
28	TRA	Wastes	$HHV = 45 \cdot VM – 6 \cdot M$	0.009	[4]
29	BOI	Hydrocarbon	$HHV = (1 – M/100)(–0.3517 \cdot C – 1.1625 \cdot H + 0.1109 \cdot O – 0.0628 \cdot N – 0.1109 \cdot S)$	0.18	[4]

30	CAL_7	Biomass	$HHV = -1.642 - 0.024 \cdot Ash + 0.475 \cdot (C + N) - 0.376 \cdot (H + N)$	0.18	[17]
31	IGT	Coal (O > 15%)	$HHV = 0.341 \cdot C + 1.322 \cdot H - 0.12 \cdot O - 0.12 \cdot N + 0.0686 \cdot S - 0.0153 \cdot Ash$	0.16	[18]
32	CAL_9	Biomass	$HHV = 9.756 - 309.454 \cdot VM^{-1} + 6.164 \cdot H^{-1} + 0.006 \cdot C^2$	0.14	[18]
33	C&P	General	$HHV = 0.3491 \cdot C + 1.1783 \cdot H + 0.1005 \cdot S - 0.1034 \cdot O - 0.0151 \cdot N - 0.0211 \cdot Ash$	0.15	[15]
34	DUL	Coal	$HHV = 81 \cdot C + 342.5 \cdot (H - O/8) + 22.5 \cdot S - 6 \cdot (9 \cdot H + M)$	0.12	[18]
35	L&D	Liquid fuels	$HHV = (1 - M/100)(-0.3578 \cdot C - 1.1357 \cdot H + 0.0845 \cdot O - 0.0594 \cdot N - 0.1119 \cdot S)$	0.18	[17]
36	$M\&G_1$	Coal/Char	$HHV = 146.58 \cdot C + 568.78 \cdot H + 29.4 \cdot S - 6.58 \cdot Ash - 51.53 \cdot (O + N)$	0.12	[10]
37	$M\&G_2$	Coal/Char	$HHV = 198.11 \cdot C + 620.31 \cdot H + 80.93 \cdot S + 44.95 \cdot Ash - 5153$	0.02	[17]
38	M&S	Coal/Waste	$HHV = 144.54 \cdot C + 610.2 \cdot H + 40.5 \cdot S - [65.8 - 30.96 \cdot O/100 - Ash] \cdot O$	0.16	[16]
39	S&K	Coal	$HHV = 81 \cdot (C - 3 \cdot O / 4) + 342.5 \cdot H + 22.5 \cdot S - 57.3 \cdot O / 4 - 6 \cdot (9 \cdot H + M)$	0.10	[18]

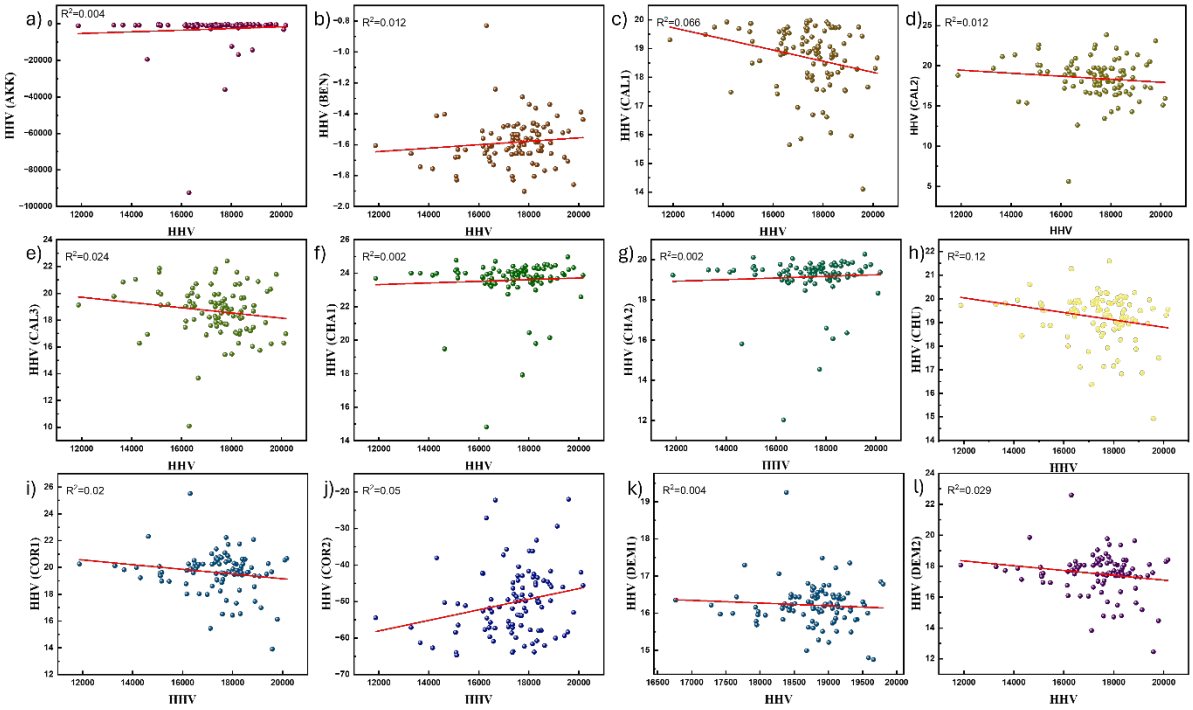


Figure S3. Comparison between the developed ANN with traditional empirical equations: a) AKK, b) BEN, c) CAL1, d) CAL2, e) CAL3, f) CHA1, g) CHA2, h) CHU, i) COR1, j) COR2, k) DEM1, l) DEM2**.**

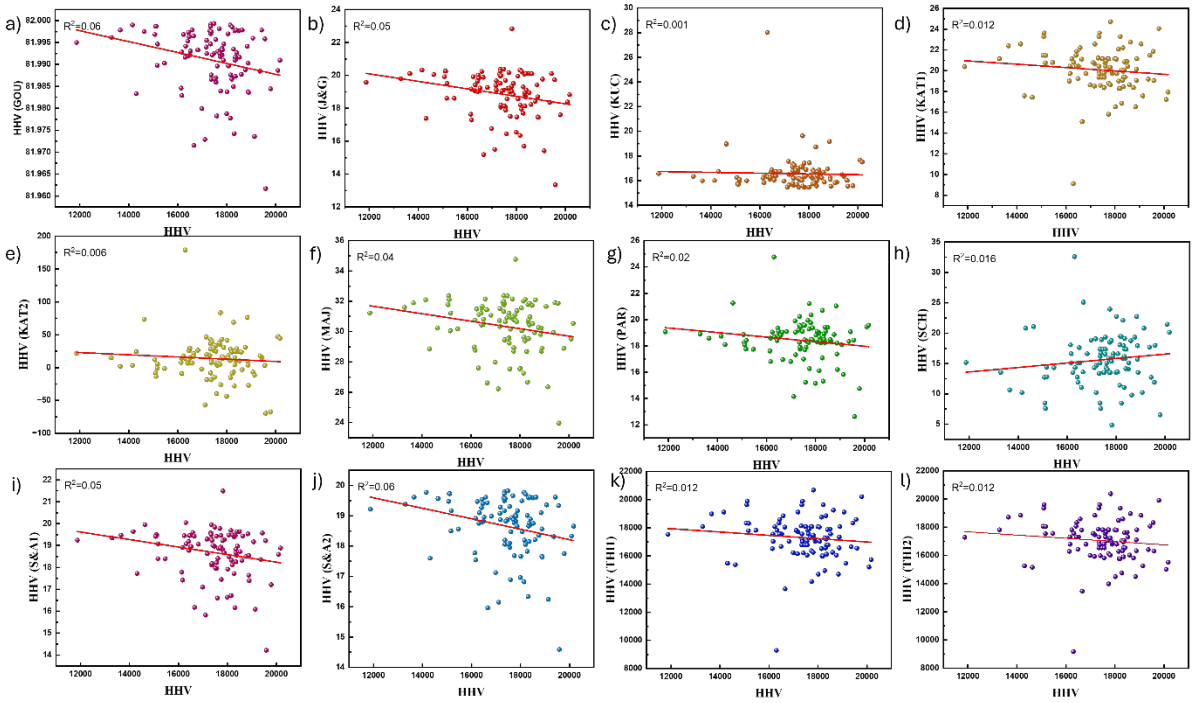


Figure S4. Comparison between the developed ANN with traditional empirical equations: a) GOU, b) J&G, c) KUC, d) KAT1, e) KAT2, f) MAJ, g) PAR, h) SCH, i) S&A1, j) S&A2, k) THI1, l) THI2**.**

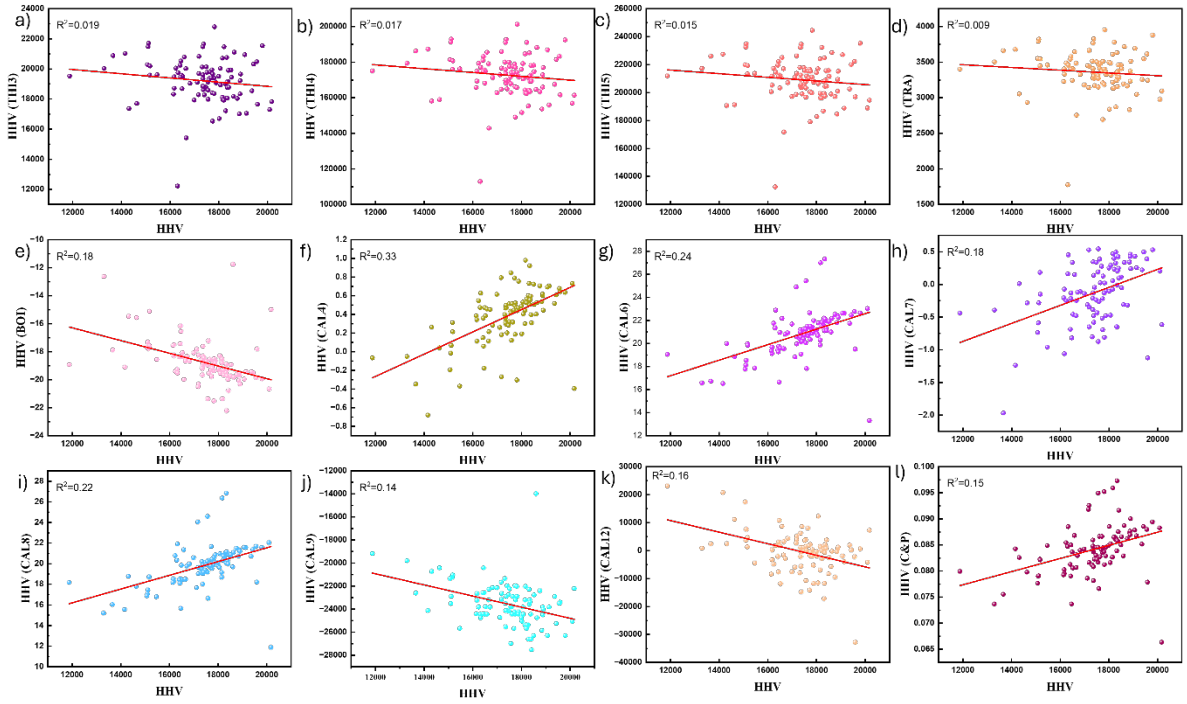


Figure S5. Comparison between the developed ANN with traditional empirical equations: a) THI3, b) THI4, c) THI5, d) TRA, e) BOI, f) CAL4, g) CAL6, h) CAL7, i) CAL8, j) CAL9, k) CAL12, l) C&P**.**

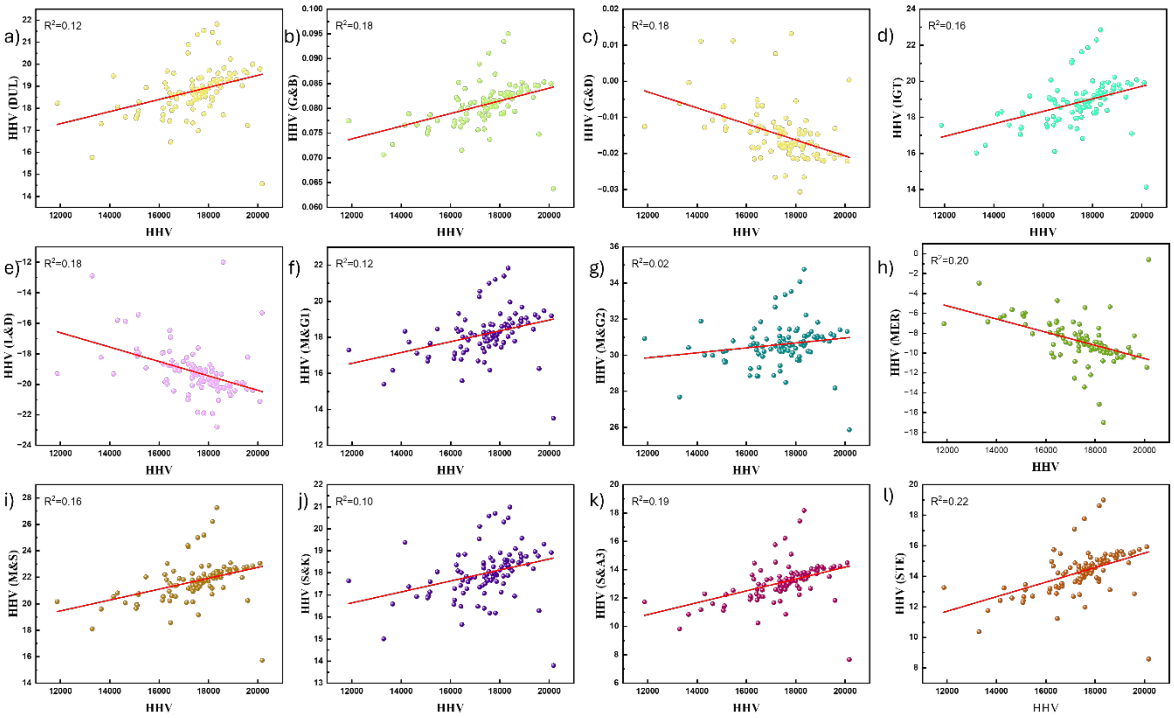


Figure S6. Comparison between the developed ANN with traditional empirical equations: a) DUL, b) G&B, c) G&D, d) IGT, e) L&D, f) M&G1, g) M&G2, h) MER, i) M&S, j) S&K, k) S&A3, l) STE**.**

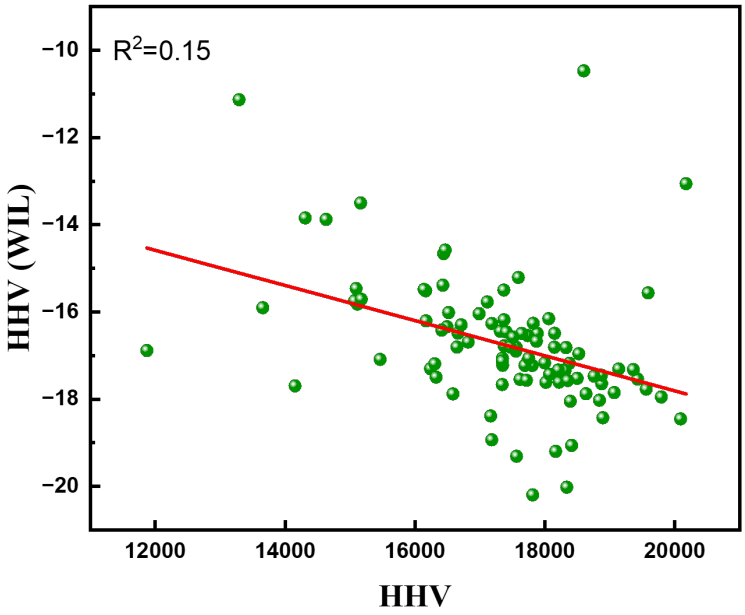


Figure S7. Comparison between the developed ANN with traditional empirical equation for WIL**.**

Table S3. Actual vs. Predicted HHV for non-Spanish Biomass Samples.

S. No	Biomass	Input Variables	Actual HHV	Predicted HHV	Error %	Ref
1	Akhrot Shell (UA)	C,H,O,N,S	20.008	19.95	0.28	19
2	Alabama Oak Wood Waste (UA)	C,H,O,N,S	19.22	20.10	4.57	20
3	Alfalfa Seed Straw (UA)	C,H,O,N,S	18.45	18.53	0.43	21
4	Corn Stalks (UA)	C,H,O,N,S	18.25	17.43	-4.49	22
5	English Walnut Prunings (UA)	C,H,O,N,S	19.63	19.94	1.57	23
6	Eucalyptus Camaldulensis Crop (UA)	C,H,O,N,S	19.42	19.52	0.51	23
7	Fibreboard Waste Wood (UA)	C,H,O,N,S	19.64	19.16	-2.44	24
8	Flax Straw (UA)	C,H,O,N,S	19.08	19.62	2.83	24
9	Hemp(Cannabis Sativa L.)Whole Plant (UA)	C,H,O,N,S	18.06	17.35	-3.93	21
10	Horse Chestnut Tree Branch (UA)	C,H,O,N,S	19.02	20.02	5.25	25
11	Ailanthus wood (PA)	FC, VM, Ash	19	18.35	-3.42	26
12	Grewia optiva (Bhimal)* (PA)	FC, VM, Ash	18	18.26	1.44	21
13	Hazelnut tree leaves* (PA)	FC, VM, Ash	17.87	17.92	0.27	27
14	Sour cheery stone (PA)	FC, VM, Ash	17.59	16.10	-8.47	28
15	Mulberry stick (PA)	FC, VM, Ash	18.35	17.78	-3.10	29
16	Sunflower seed shell (PA)	FC, VM, Ash	17.6	16.6	-5.6	30
17	Tobacco stalk (PA)	FC, VM, Ash	17.7	17.20	-2.8	26
18	Slash Pine bark (PA)	FC, VM, Ash	21.77	20.94	-3.8	31
19	Corncob waste (PA)	FC, VM, Ash	17.69	17.08	-3.4	27
20	Spruce wood (PA)	FC, VM, Ash	20.1	19.26	-4.1	26

N.B.: HHV: Higher Heating Value; M: Moisture; A: Ash; VM: Volatile Matter; FC: Fixed Carbon; N: Nitrogen; C: Carbon; S: Sulphur; H: Hydrogen; Oxygen; UA: Ultimate Analysis; PA: Proximate Analysis.

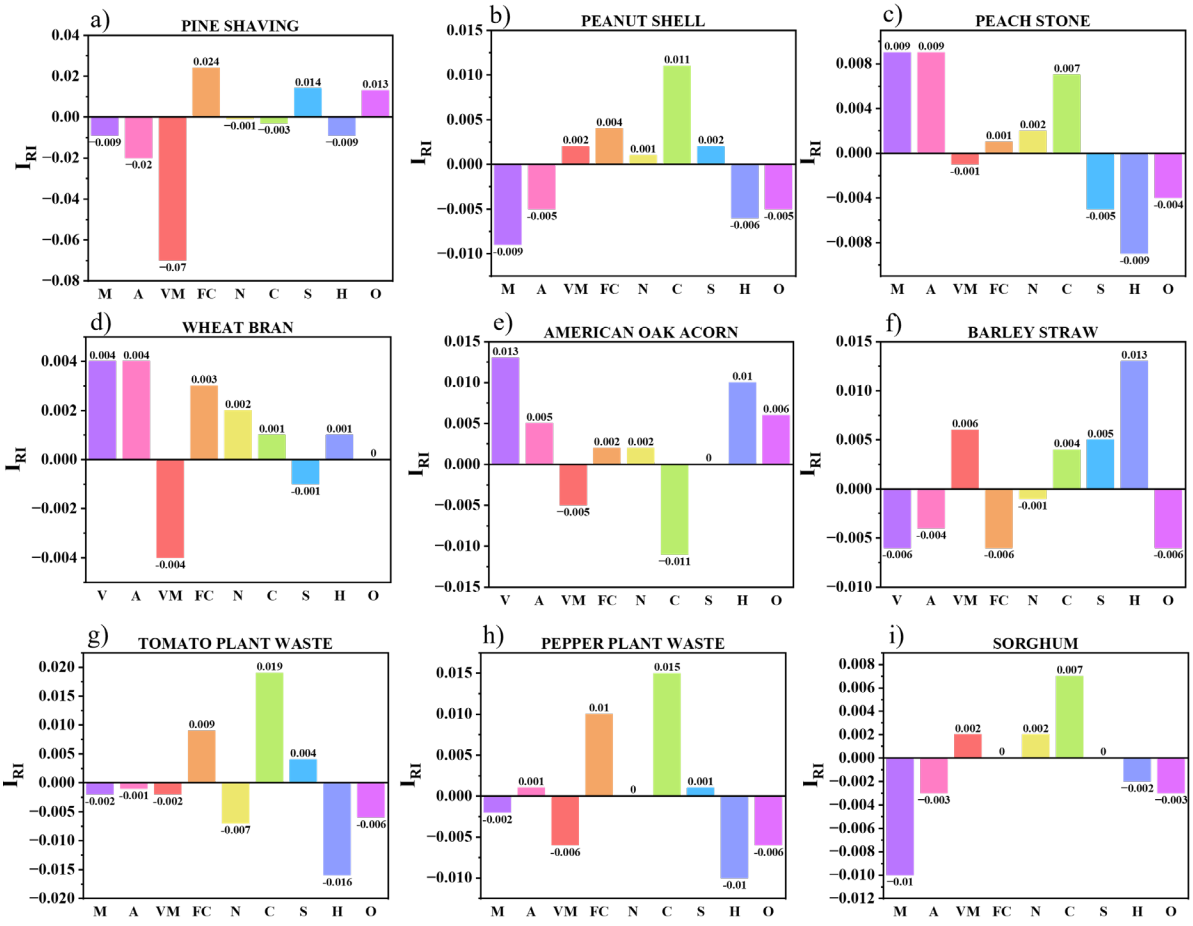


Figure S8. Relative Importance Index of Physicochemical Variables on (a-c) high values of higher heating value, (d-f) average values of higher heating value, and (g-i) low values of higher heating value**.**

References:

1. Thipkhunthod P, Pharino C, Kitchaicharoen J, Phungrassami H. *Predicting the heating value of sewage sludges in Thailand from proximate and ultimate analyses.* Fuel, 2005; 84:849–857.
2. Kathiravale S, Yunus MNM, Sopian K, Samsuddin AH, Rahman RA. *Modeling the heating value of municipal solid waste.* Fuel, 2003; 82:1119–1125.
3. Abu-Qudais M, Abu-Qudais HA, Abu-Qudais J. *Energy content of municipal solid waste in Jordan and its potential utilization.* Energy Convers Manag, 2000; 41:983–991.
4. Callejón-Ferré AJ, López-Martínez JA, Manzano-Agugliaro F, Díaz-Pérez M. *Energy potential of greenhouse crop residues in southeastern Spain and evaluation of their heating value predictors.* Renew Sustain Energy Rev, 2011; 15:948–955.
5. Chang YF, Chang CN, Chen YW. *Multiple regression models for lower heating value of municipal solid waste in Taiwan.* J Environ Manag, 2007; 85:891–899.
6. Yin CY. *Prediction of higher heating value of biomass from proximate and ultimate analyses.* Fuel, 2011; 90:1128–1132.
7. Cordero T, Marquez F, Rodriguez-Mirasol J, Rodriguez JJ. *Predicting heating values of lignocellulosics from proximate analysis.* Fuel, 2001; 80:1567–1571.
8. Parikh J, Channiwala SA, Ghosal GK. *A correlation for calculating HHV from proximate analysis of solid fuels.* Fuel, 2005; 84:487–494.
9. Majumder AK, Jain R, Banerjee S, Barnwal JP. *An approach for developing an analytical relation of the HHV from proximate analysis of coal.* Fuel, 2008; 87:3077–3081.
10. Sheng C, Azevedo JLT. *Estimating the higher heating value of biomass fuels from basic analysis data.* Biomass Bioenergy, 2005; 28:499–507.
11. Ahmaruzzaman M. *A review on the utilization of fly ash.* Prog Energy Combust Sci, 2010; 36:327–363.
12. Jiménez L, González F. *Thermal behaviour of lignocellulosic residues treated with phosphoric acid.* Fuel, 1991; 70(8):947–950.
13. Goutal M. *Sur le pouvoir calorifique de la houille.* Comptes Rendus de l'Académie des Sciences, 1902; 134:477–479.
14. Kucukbayrak S, Goksel M, Gok S. *Estimation of calorific values of Turkish lignites using neural networks and regression analysis.* Fuel, 1991; 70:979–981.
15. Meraz L, Dominguez A, Kornhauser I, Rojas F. *Thermochemical concept-based equation to estimate waste combustion enthalpy from elemental analysis.* Fuel, 2003; 82:1499–1507.
16. Channiwala SA, Parikh PP. *A unified correlation for estimating HHV of solid, liquid and gaseous fuels.* Fuel, 2002; 81(8):1051–1063.
17. Dulong E. *Formule pour le pouvoir calorifique des combustibles.* Annales de Chimie et de Physique, 1830.
18. Mason DM, Gandhi K. *Formulas for heating value of coal and coal char.* Fuel Process Technol, 1983; 7:11–22.
19. Abdollahi, S.A.; Ranjbar, S.F.; Jahromi, D.R. Applying feature selection and machine learning techniques to estimate the biomass higher heating value. *Sci. Rep.* **2023**, *13*, 16093
20. Arvidsson, M.; Morandin, M.; Harvey, S. Biomass gasification-based syngas production for a conventional oxo synthesis plant-greenhouse gas emission balances and economic evaluation. *J. Clean. Prod.* **2015**, *99*, 192–205.
21. Skodras, G.; GrammelisO, P.; Basinas, P.; Kakaras, E.; Sakellaropoulos, G. Pyrolysis and combustion characteristics of biomass and waste-derived feedstock. *Ind. Eng. Chem. Res.* **2006**, *45*, 3791–3799.
22. Brandic, I.; Pezo, L.; Bilandzija, N.; Peter, A.; Suric, J.; Voca, N. Comparison of Different Machine Learning Models for Modelling the Higher Heating Value of Biomass. *Mathematics* **2023**, *11*, 2098.
23. Lehtonen, E.; Anttila, P.; Hakala, K.; Luostarinen, S.; Lehtoranta, S.; Merilehto, K.; Lehtinen, H.; Maharjan, A.; Mäntylä, V.; Niemeläinen, O.; et al. An open web-based GIS service for biomass data in Finland. *Environ. Model. Softw.* **2024**, *176*, 105972.
24. Noushabadi, A.S.; Dashti, A.; Ahmadijokani, F.; Hu, J.; Mohammadi, A.H. Estimation of higher heating values (HHVs) of biomass fuels based on ultimate analysis using machine learning techniques and improved equation. *Renew. Energy* **2021**, *179*, 550–562.
25. Capareda, S.C. 1—Comprehensive biomass characterization in preparation for conversion. In *Sustainable Biochar for Water and Wastewater Treatment*; Mohan, D., Pittman, C.U., Mlsna, T.E., Eds.; Elsevier: Amsterdam, The Netherlands, 2022; pp. 1–37.

26. Daskin, M.; Erdogan, A.; Güleç, F.; Okolie, J.A. Generalizability of empirical correlations for predicting higher heating values of biomass. *Energy Source Part A* **2024**, *46*, 5434–5450.
27. Yahya, A.M.; Adeleke, A.A.; Nzerem, P.; Ikubanni, P.P.; Ayuba, S.; Rasheed, H.A.; Gimba, A.; Okafor, I.; Okolie, J.A.; Paramasivam, P. Comprehensive Characterization of Some Selected Biomass for Bioenergy Production. *ACS Omega* **2023**, *8*, 43771–43791.
28. Dashti, A.; Noushabadi, A.S.; Raji, M.; Razmi, A.; Ceylan, S.; Mohammadi, A.H. Estimation of biomass higher heating value (HHV) based on the proximate analysis: Smart modeling and correlation. *Fuel* **2019**, *257*, 115931.
29. Technologies Energy Research Centre of The Netherlands. Database for the Physico-Chemical Composition of (Treated) Lignocellulosic Biomass, Micro- and Macroalgae, Various Feedstocks for Biogas Production and Biochar.
30. Simon, F.; Girard, A.; Krotki, M.; Ordoñez, J. Modelling and simulation of the wood biomass supply from the sustainable management of natural forests. *J. Clean. Prod.* **2021**, *282*, 124487.
31. Malhi, A.; Knapic, S.; Främling, K. Explainable Agents for Less Bias in Human-Agent Decision Making. In Proceedings of the Explainable, Transparent Autonomous Agents and Multi-Agent Systems: Second International Workshop, EXTRAAMAS 2020, Auckland, New Zealand, 9–13 May 2020; Revised Selected Papers, Auckland, New Zealand, 2020. pp. 129–146.