Supplementary Materials

Discovering polyimides and their composites with targeted mechanical properties through explainable machine learning

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modulus (Et)										
		PI-H					PI-F			
	Ε	3	σ	Et	Ε	3	σ	Et		
Number of availabl e data points	15	106	128	125	66	671	731	540		
Propert y range	2.08-2500	0.11-156	4.5-367. 6	0.0106-8. 7	0.1-6500	0.58-80 8	. 11-1197	0.27-28.1		
unit	MPa	%	MPa	GPa	MPa	%	MPa	GPa		

Supplementary Table 1. The mechanical properties collected for various PI structures, including elastic modulus (E), elongation at break (ϵ), tensile strength (σ) and tensile modulus (E_t)

Supplementary Table 2. The DOI of our data source literature

D0	I
10.1016/j.compscitech.2013.07.005	10.1002/app.35292
10.1039/c4ra07716d	10.1155/2010/354364
10.1021/cm200909x	10.1177/096739111402200205
10.1002/adv.21886	10.1002/polb.23515
10.1002/pat.1565	10.1002/pola.29172
10.1021/am4005094	10.1016/j.polymdegradstab.2018.01.006
10.1002/pc.22637	10.1016/j.apsusc.2020.147654
10.1021/am300999g	10.1002/app.50869
10.1007/s10965-011-9564-z	10.1016/j.compstruct.2020.113305
10.1007/s10854-018-0045-6	10.1007/s12221-021-9142-x
10.1021/am302494c	10.1021/acsami.1c01992
10.1002/app.43677	10.1016/j.matchemphys.2020.123972
10.1021/am504342j	10.1016/j.cjche.2020.09.066
10.1002/pc.22895	10.1016/j.compstruct.2021.114340
10.1021/am2002229	10.1016/j.polymer.2021.124113
10.1039/c8ra01965g	10.1007/s10443-021-09878-y
10.1002/pi.5555	10.3390/polym13234057
10.1016/j.polymer.2018.02.017	10.1007/s10934-020-01028-2
10.1007/s10904-017-0641-6	10.1021/acsami.1c10055
10.1016/j.polymer.2011.09.033	10.3390/nano11030562
10.1002/app.41544	10.2478/msp-2021-0043
10.1016/j.compositesb.2011.11.071	10.1016/j.apsusc.2020.148833
10.1016/j.apsusc.2014.06.130	10.1002/pc.26165
10.1002/app.39881	10.1016/j.polymer.2021.123957
10.1007/s10965-014-0463-y	10.1039/d1na00415h
10.1016/j.compscitech.2011.06.013	10.7503/cjcu20200689
10.1007/s10118-016-1813-5	10.3390/polym13183175
10.1002/app.31523	10.1002/pc.26099
10.1016/j.memsci.2015.12.057	10.1002/macp.202000376
10.1016/j.compositesa.2015.09.009	10.1016/j.cej.2021.129341
10.1080/14658011.2018.1493274	10.1039/d1ra07500d
10.1002/pc.22854	10.1016/j.polymer.2021.123963
10.1002/pi.2889	10.3390/polym13234174
10.1002/pc.23249	10.3390/coatings11010025
10.1007/s11595-016-1502-9	10.1108/ILT-08-2021-0309
10.1002/pc.23815	10.1021/acsami.0c21842
10.1002/app.46826	10.3390/cryst11111383
10.1016/j.matlet.2014.11.003	10.1007/s12221-021-0148-1
10.1007/s13233-009-0048-5	10.7503/cjcu20200482
10.1021/am400635x	10.1002/pc.26174
10.1002/app.45168	10.1016/j.polymer.2021.124098

10.1016/j.coco.2016.11.002 10.1016/j.clay.2016.12.012 10.1021/acs.iecr.7b02183 10.1016/j.matdes.2016.12.082 10.1002/app.31255 10.1016/j.compscitech.2017.10.014 10.1002/pat.3444 10.1039/c8ra02479k 10.1016/j.mtcomm.2017.10.010 10.1016/j.compositesb.2013.08.042 10.3390/ijms14058698 10.1080/00914037.2013.812089 10.1016/j.polymdegradstab.2013.03.003 10.1002/app.35412 10.1007/s10965-015-0806-3 10.1007/s13233-009-0120-1 10.1002/pi.2939 10.1002/app.42358 10.1016/j.polymer.2015.04.015 10.7503/cjcu20170011 10.1007/s40242-014-4242-4 10.1016/j.apsusc.2017.06.087 10.2494/photopolymer.27.131 10.1016/j.eurpolymj.2012.05.015 10.1016/j.apsusc.2015.11.201 10.1007/s11814-011-0053-1 10.1142/S1793292018500984 10.1002/pc.23402 10.1177/0967391111019002-321 10.1179/1743289811Y.000000053 10.1016/j.compositesb.2016.12.057 10.1016/j.polymer.2016.02.056 10.1002/pola.27242 10.1002/app.35054 10.1016/j.compositesb.2013.08.065 10.1080/10601325.2018.1476823 10.1007/s11595-015-1098-5 10.1002/app.44000 10.1002/mame.201600113 10.1016/j.matdes.2017.11.041 10.1177/09540083211044054

10.3390/molecules26082143 10.1016/j.micromeso.2021.111074 10.1016/j.apsusc.2021.150051 10.1021/acsnano.0c09391 10.1016/j.jpcs.2021.110180 10.1080/10601325.2021.1934011 10.3390/nano11030812 10.1016/j.coco.2021.100773 10.1002/mame.202000705 10.1088/2053-1591/ac161f 10.3390/ma14061402 10.1021/acsami.1c15018 10.1007/s10853-021-06201-9 10.3390/ma15134656 10.1007/s11771-022-5047-0 10.1016/j.compositesb.2021.109405 10.1016/j.carbon.2022.07.020 10.1039/d2na00078d 10.3390/polym14214565 10.3390/polym14153154 10.1515/rams-2022-0044 10.1007/s10965-022-03071-w 10.3390/polym14061269 10.3390/polym14183803 10.1016/j.apsusc.2022.152558 10.3390/membranes12100961 10.1016/j.polymer.2022.124792 10.1177/09673911221087806 10.1002/pat.5564 10.3390/polym14050965 10.1016/j.seppur.2021.119993 10.3390/polym14030389 10.1016/j.triboint.2021.107427 10.3390/polym14122453 10.1007/s42765-021-00093-9 10.1016/j.eurpolymj.2022.111260 10.1016/j.petsci.2021.10.027 10.1016/j.polymer.2022.125358 10.1016/j.matchemphys.2022.125716 10.1021/acssuschemeng.1c07621



Supplementary Figure 1. Structure distribution of mechanical properties in different datasets. (a) ε in PI-H dataset. (b) σ in PI-H dataset. (c) E_t in PI-H dataset. (d) ε in PI-F dataset. (e) σ in PI-F dataset. (f) E_t in PI-F dataset.



Supplementary Figure 2. Original data distribution of mechanical properties in different datasets. (a) ε in PI-H dataset. (b) σ in PI-H dataset. (c) E_t in PI-H dataset. (d) ε in PI-F dataset. (e) σ in PI-F dataset. (f) E_t in PI-F dataset.



Supplementary Figure 3. Normalized data distribution of mechanical properties in different datasets. (a) ε in PI-H dataset. (b) σ in PI-H dataset. (c) E_t in PI-H dataset. (d) ε in PI-F dataset. (e) σ in PI-F dataset. (f) E_t in PI-F dataset.



Supplementary Figure 4. Pairwise relationships (a) between ε , σ and E_t in the PI-H dataset, and (b) between ε , σ and E_t in the PI-F dataset.

	8	PI_H datasa	t	PI_F datasat			
	C C	1 1-11 Uatasι	F.				
	3	0	Ŀt	3	0	Lt	
RFR	-0.2	0.51	0.28	0.36	0.56	0.33	
LR	-10248.66	-5983.75	-4039.05	0.33	0.36	-0.52	
SVR	-0.32	-0.03	-0.18	-0.11	-0.1	-0.12	
RR	-15.27	-350.23	-101.64	0.28	0.43	-0.36	
GPR	-6.52	-3.06	-2.57	0.49	0.65	0.43	
AR	-0.26	0.37	0.13	0.15	0.37	-0.65	
GBR	-0.22	0.49	0.2	0.53	0.71	0.53	
BR	0.43	0.35	0.18	0.5	0.74	0.45	
ETR	-0.39	0.45	0.34	0.36	0.32	0.26	
DTR	-0.96	-0.14	0.13	0.29	0.36	0.04	
MLP	-320.28	-32.4	-60920.5	0.29	0.27	0.27	

Supplementary Table 3. Values of R² in the test set for 7 mechanical properties by using 11 common models without tuning parameters of each model.

Supplementary Table 4. Values of R² in the test set after Grid Search for different models that we selected

]	PI-H datase	t		PI-F dataset		
	3	σ	$\mathbf{E}_{\mathbf{t}}$	3	σ	Et	
RFR	0.22	0.53	0.4	0.64	0.75	0.64	
ETR	0.47	0.53	0.48	0.56	0.8	0.56	
GBR	0.35	0.57	0.39	0.59	0.74	0.59	
BR	0.14	0.22	0.25	0.59	0.78	0.59	

by using Optuna								
		PI-H datas	et]	PI-F dataset			
	3	σ	Et	3	σ	Et		
RFR	0.68	0.69	0.63	0.74	0.79	0.75		
ETR	0.53	0.52	0.6	0.74	0.82	0.64		
GBR	0.39	0.83	0.78	0.79	0.85	0.83		
BR	/	/	/	0.73	0.8	0.78		

Supplementary Table 5. Values of R² in the test set after hyperparameter optimization by using Optuna

Supplementary Table 6. Values of R^2 in the test set after repeated training

Rando		PI-H datase	et	PI-F dataset		
m seed	3	σ	$\mathbf{E}_{\mathbf{t}}$	3	σ	$\mathbf{E}_{\mathbf{t}}$
0	0.68	0.83	0.78	0.79	0.85	0.83
1	0.66	0.78	0.72	0.81	0.87	0.79
10	0.69	0.81	0.75	0.83	0.83	0.78
25	0.63	0.86	0.76	0.77	0.81	0.82
50	0.72	0.81	0.74	0.75	0.85	0.83
Average	0.68±0.05	0.82±0.04	0.75±0.03	0.79±0.05	0.84±0.03	0.81±0.03

Supplementary Table 7. Values of R², MAE, MSE, RMSE and MAPE in the test set

		PI-H datase	t		PI-F dataset		
	3	σ	$\mathbf{E}_{\mathbf{t}}$	3	σ	$\mathbf{E}_{\mathbf{t}}$	
R ²	0.68	0.83	0.78	0.79	0.85	0.83	
MAE	1.5	18.7	1.2	5.3	41.1	0.9	
MSE	7.3	650.8	2.1	60.2	5878.7	1.6	
RMSE	1.9	25.5	1.6	7.8	76.7	1.3	
MAPE	19.3	11.9	14.7	17.1	12.1	14.8	

		Trainin	Predictio				
		g Time	n Speed	Hyperparameters			
		(ms)	(ms)				
				n_estimators=231,			
	ç	600	0.18	criterion='friedman_mse', max_depth=98,			
	U	000		min_samples_split=3, max_features=39,			
				max_leaf_nodes=132			
				Loss='squared_error',			
				learning_rate=0.6648117460909637,			
PI_H	æ	300	0.17	n_estimators=242,			
datase	U	500	0.17	criterion='friedman_mse',			
t t				min_samples_split=77, max_depth=83,			
e				max_features=11, max_leaf_nodes=231			
				Loss='squared_error',			
				learning_rate=0.8683573694740211,			
	E٠	100	0.17	n_estimators=257,			
	Ξι	100	0.17	criterion='friedman_mse',			
				min_samples_split=4, max_depth=48,			
				max_features=30, max_leaf_nodes=31			
				Loss='huber',			
				learning_rate=0.20863039129499694,			
	3	5700	0.24	n_estimators=115,			
		2700	0.21	criterion='friedman_mse',			
				min_samples_split=18, max_depth=64,			
				max_features=84, max_leaf_nodes=54			
				Loss='huber',			
PI-F				learning_rate=0.16382086787423966,			
datase	σ	2200	0.15	n_estimators=269,			
t	Ũ	2200	0.10	criterion='friedman_mse',			
·				min_samples_split=9, max_depth=36,			
				max_features=80, max_leaf_nodes=25			
				Loss='squared_error',			
				learning_rate=0.2999766914200086,			
	Et	1600	0.21	n_estimators=280,			
		1000	0.21	criterion='friedman_mse',			
				min_samples_split=16, max_depth=85,			
				max_features=94, max_leaf_nodes=43			

Supplementary Table 8. Some related information of our 7 models