Supplementary File For the Manuscript "XG-RVFL: A Robust and Scalable Randomized Neural Network with FleXi Guardian Loss"

References

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TABLE S.I: Details of binary and multiclass datasets, including the number of samples, features, and target classes.

Dataset Name	**# of Samples**	**# of Features**	**# of Classes**
	Binary Datasets		
acute_inflammation	120	6	2
acute_nephritis	120	6	2
blood	748	4	2
breast_cancer	286	9	2
breast_cancer_wisc_prog	198	33	2
chess_krvkp	3196	36	2
congressional_voting	435	16	2
conn_bench_sonar_mines_rocks	208	60	2
connect_4	67557	42	2
credit_approval	690	15	2
cylinder_bands	512	35	2
echocardiogram	131	10	2
fertility	100	9	2
haberman_survival	306	3	2
heart_hungarian	294	12	2
hepatitis	155	19	2
ilpd_indian_liver	583	9	2
magic	19020	10	2
miniboone	130064	50	2
molec_biol_promoter	106	57	2
musk_1	476	166	2
musk_2	6598	166	2
ozone	2536	72	2
parkinsons	195	22	2
pima	768	8	2
pittsburg_bridges_T_OR_D	102	7	2
planning	182	12	2
ringnorm	7400	20	2
spambase	4601	57	2
spect	265	22	2
spectf	267	44	2
statlog_german_credit	1000	24	2
statlog_heart	270	13	2
tic_tac_toe	958	9	2
titanic	2201	3	2
twonorm	7400	20	2
vertebral_column_2clases	310	6	2
	Multiclass Datasets		
audiology_std	196	59	18
car	1728	6	4
contrac	1473	9	3
dermatology	366	34	6
ecoli	336	7	8
glass	214	9	6
hayes_roth	160	3	3
heart_cleveland	303	13	5
heart_switzerland	123	12	5
heart_va	200	12	5
image_segmentation	2310	18	7
iris	150	4	3
led_display	1000	7	10
low_res_spect	531	100	9
lymphography	148	18	4
molec_biol_splice	3190	60	3
nursery	12960	8	5
pittsburg_bridges_MATERIAL	106	7	3
pittsburg_bridges_REL_L	103	7	3
pittsburg_bridges_TYPE	105	7	6
seeds	210	7	3
synthetic_control	600	60	6
vertebral_column_3clases	310	6	3
wine_quality_red	1599	11	6
wine_quality_white	4898	11	7

TABLE S.II: Accuracy of the proposed XG-RVFL model against the baseline models on each of the 37 binary datasets.

Dataset ↓ | **Model** →	**RVFL** [1]	**RVFLwoDL** [2]	**Total-var-RVFL** [3]	**IF-RVFL** [4]	**NF-RVFL-K** [5]	**NF-RVFL-R** [5]	**NF-RVFL-C** [5]	**HE-RVFL** [6]	**XG-RVFL**†
acute_inflammation	100	100	100	100	100	100	100	100	100
acute_nephritis	100	100	100	100	100	100	100	92.5	100
blood	76.5065	76.9056	76.9065	77.4398	77.8398	77.838	77.4398	77.6738	77.9732
breast_cancer_wisc_prog	81.359	80.3846	82.359	78.359	81.8846	83.359	80.9103	76.3163	80.3846
breast_cancer	70.1754	70.1754	70.1754	71.9298	72.6921	72.3351	70.8953	95.4861	90.1754
chess_krvkp	72.0313	71.936	73.7833	72.6262	81.7908	82.6045	85.2322	95.6508	82.5039
congressional_voting	63.6782	63.2184	63.908	58.8506	63.908	63.908	64.1379	61.3766	64.1379
conn_bench_sonar_mines_rocks	62.079	60.5226	64.4251	54.8316	66.2602	65.8885	63.4611	96.6346	93.6585
connect_4	75.4518	75.4059	75.4992	75.3407	75.5022	75.4844	76.2156	89.858	75.4859
credit_approval	85.2174	85.3623	85.5072	86.5217	85.942	85.942	85.7971	96.9292	86.9565
cylinder_bands	66.4154	65.8081	67.7727	63.4875	69.724	68.9606	70.1294	66.7969	68.3229
echocardiogram	84.6724	83.9031	85.4701	80.7692	85.4416	85.4416	85.4416	72.6089	86.9801
fertility	91	91	92	92	92	91	91	90	91
haberman_survival	73.4902	73.8181	74.4738	75.1348	75.1296	75.1296	75.4574	74.4959	74.8017
heart_hungarian	73.8223	74.4886	75.8738	76.8849	76.5576	76.9024	78.2466	91.8919	96.2712
hepatitis	85.1613	82.5806	85.8065	85.8065	87.0968	85.8065	85.8065	82.4561	86.4516
ilpd_indian_liver	71.5311	72.2149	72.5626	72.7277	72.3917	72.3932	72.2178	71.5305	72.7336
magic	78.7487	78.5279	78.7171	77.5289	76.3302	76.3407	78.4017	89.858	95.163
miniboone	81.4984	79.2741	81.8659	83.3469	84.0217	84.3969	89.8363	96.9292	93.2441
molec_biol_promoter	72.7706	74.632	78.2684	78.3983	82.0779	82.0346	82.0346	100	96.1905
musk_1	72.0614	69.7675	72.4846	71.864	76.0482	75.2149	74.1645	93.4874	96.6316
musk_2	84.5909	84.5909	85.1818	84.5909	83.4091	83.9394	85.9545	90.4091	95.4091
ozone	97.1217	97.1217	97.1611	97.1612	97.1612	97.2005	97.1612	96.806	97.1612
parkinsons	80.5128	80.5128	82.0513	78.4615	83.0769	83.0769	84.1026	79.4537	85.1282
pima	72.0075	72.2698	72.92	73.8282	72.9174	73.6983	72.6594	65.3646	70.3115
pittsburg_bridges_T_OR_D	87.1905	87.1905	89.1429	89.1905	88.2381	90.1905	90.1905	90.1538	90.2857
planning	71.3814	71.3814	72.4925	69.8048	71.9369	73.018	71.9369	73.5749	71.9369
ringnorm	51.5541	51.5405	52.0405	51.473	51.6486	51.6081	51.6892	51.9865	51.8378
spambase	88.546	87.0472	88.6116	85.0883	88.9583	88.9582	89.3931	92.7609	99.3913
spect	68.3019	66.7925	69.0566	68.3019	69.434	69.0566	68.6792	64.5353	66.7925
spectf	79.3431	79.7205	79.7135	79.3431	79.7205	79.7205	79.7205	81.6316	81.2369
statlog_german_credit	76.9	75.7	77	76.7	77.7	77.1	77.7	70.5	73.3
statlog_heart	80.3704	80	81.4815	81.8519	82.2222	81.4815	81.8519	74.4403	81.1111
tic_tac_toe	88.8264	88.9278	91.8521	81.4316	68.5684	65.3125	79.3216	90.3125	95
titanic	77.9168	77.9168	78.6901	79.0532	79.0532	78.4623	79.0532	82.5971	79.0532
twonorm	51.5	51.5676	51.6892	51.2027	51.3649	51.7973	51.6622	51.7027	51.8378
vertebral_column_2clases	71.2903	70.6452	72.5806	85.4839	81.6129	79.0323	80.3226	93.2692	96.7742
Average Accuracy	77.43	77.1	78.37	77.48	78.64	78.5	79.14	82.75	83.67

† denotes the proposed model.

TABLE S.III: Accuracy of the proposed XG-RVFL model against the baseline models on each of the 25 multiclass datasets.

Dataset ↓ | **Model** →	**RVFL** [1]	**RVFLwoDL** [2]	**Total-var-RVFL** [3]	**NF-RVFL-K** [5]	**NF-RVFL-R** [5]	**NF-RVFL-C** [5]	**XG-RVFL**†
audiology_std	69.3205	65.7564	50.3718	70.3718	71.3846	67.8077	66.2436
car	72.6265	72.1057	72.6234	70.8337	70.0139	71.0626	72.8506
contrac	40.458	40.1183	41.3386	42.3673	41.4934	41.5416	70.8707
dermatology	97.5379	97.0011	97.2714	97.8193	97.5454	97.5379	97.235
ecoli	60.9175	61.2116	51.0667	60.6277	60.619	61.5145	62.0817
glass	37.6855	39.0808	34.4297	42.8239	42.3477	40.4873	55.3699
hayes_roth	61.875	60.625	62.5	61.875	61.875	65	63.125
heart_cleveland	59.7268	59.377	61.0328	61.3388	61.0383	60.0437	60.0546
heart_switzerland	45.6667	46.4667	48.9	46.5333	47.9	49.7	46.5667
heart_va	40	40	40.5	42.5	41	41.5	40.5
image_segmentation	87.6623	87.0996	88.3117	83.5931	83.2035	83.6797	73.4199
iris	74.6667	74	74.6667	74.6667	73.3333	74.6667	82.6667
led_display	72.6	72.5	73.5	72.2	72.7	73.4	67.3
low_res_spect	87.7605	86.6285	73.9852	87.5666	87.3849	87.7605	82.3012
lymphography	86.4138	85.0345	86.4138	87.1034	85.7701	88.5057	84.3448
molec_biol_splice	52.6959	51.8809	54.2633	68.652	69.2163	68.3072	78.9969
nursery	70.3935	70.1775	63.0093	66.3889	66.7824	71.9444	66.6667
pittsburg_bridges_MATERIAL	75.1948	77.013	80.6494	75.9307	77.6623	76.9697	82.9221
pittsburg_bridges_REL_L	62.1429	63.1429	64.1429	69.0476	67.2381	62.1905	67.9524
pittsburg_bridges_TYPE	42.8571	42.8571	43.8095	44.7619	45.7143	44.7619	51.9048
seeds	89.0476	87.1429	90	90	90.4762	90.4762	91.9048
synthetic_control	42.1667	42.5	57.8333	54.8333	51.1667	55.5	70.3333
vertebral_column_3clases	65.1613	65.1613	84.1935	69.0323	67.4194	65.4839	85.9355
wine_quality_red	59.4769	59.4755	59.9134	60.8533	60.4156	60.5388	78.3333
wine_quality_white	52.3699	52.5332	52.472	52.6349	52.4106	53.4925	57.9767
Average Accuracy	64.26	63.96	64.29	66.17	65.84	66.15	70.17

† denotes the proposed model.