Article

Improving the performance of constructed neural networks with a pre-train phase

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Abstract

A multitude of problems in contemporary literature are addressed using machine learning models, the most widespread of which are artificial neural networks. Furthermore, in recent years, evolutionary techniques have emerged that identify both the architecture of artificial neural networks and their corresponding parameters. Among these techniques, one can also identify the artificial neural networks being constructed, in which the structure and parameters of the neural network are effectively identified using Grammatical Evolution. In this paper, we propose the use of an additional phase before the start of the construction of the artificial neural network, in which phase a genetic algorithm undertakes to identify initial values for the parameters of the neural network. After the end of this phase, the evolution process is carried out using as initial values those identified in the above process. The proposed work was applied on a series of classification and regression problems founded in the recent literature and it was compared against other methods used for neural network training as wll as against the original neural network construction method.

Keywords: Neural networks; Grammatical Evolution; Genetic algorithms.

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1. Introduction

2. Materials and Methods

3. Results

3.1. Experimental datasets

The validation of the proposed method was performed using a wide series of classification and regression datasets, available from various sources from the Internet. These datasets were downloaded from:

1. The UCI database, https://archive.ics.uci.edu/(accessed on 22 January 2025)[1]
2. The Keel website, https://sci2s.ugr.es/keel/datasets.php(accessed on 22 January 2025)[2].
3. The Statlib URL https://lib.stat.cmu.edu/datasets/index(accessed on 22 January 2025).

3.2. Experimental datasets

The following datasets were utilized in the conducted experiments:

1. **Appendictis** which is a medical dataset [3].
2. **Alcohol**, which is dataset regarding alcohol consumption [4].
3. **Australian**, which is a dataset produced from various bank transactions [5].
4. **Balance** dataset [6], produced from various psychological experiments.
5. **Cleveland**, a medical dataset which was discussed in a series of papers [7,8].
6. **Circular** dataset, which is an artificial dataset.
7. **Dermatology**, a medical dataset for dermatology problems [9].
8. **Ecoli**, which is related to protein problems [10].
9. **Glass** dataset, that contains measurements from glass component analysis.
10. **Haberman**, a medical dataset related to breast cancer.
11. **Hayes-roth** dataset [11].
12. **Heart**, which is a dataset related to heart diseases [12].
13. **HeartAttack**, which is a medical dataset for the detection of heart diseases
14. **Housevotes**, a dataset which is related to the Congressional voting in USA [13].
15. **Ionosphere**, a dataset that contains measurements from the ionosphere [14,15].
16. **Liverdisorder**, a medical dataset that was studied thoroughly in a series of papers[16,17].
17. **Lymography** [18].
18. **Mammographic**, which is a medical dataset used for the prediction of breast cancer [19].
19. **Parkinsons**, which is a medical dataset used for the detection of Parkinson's disease [20,21].
20. **Pima**, which is a medical dataset for the detection of diabetes[22].
21. **Phoneme**, a dataset that contains sound measurements.
22. **Popfailures**, a dataset related to experiments regarding climate [23].
23. **Regions2**, a medical dataset applied to liver problems [24].
24. **Saheart**, which is a medical dataset concerning heart diseases[25].
25. **Segment** dataset [26].
26. **Statheart**, a medical dataset related to heart diseases.
27. **Spiral**, an artificial dataset with two classes.
28. **Student**, which is a dataset regarding experiments in schools [27].
29. **Transfusion**, which is a medical dataset [28].
30. **Wdbc**, which is a medical dataset regarding breast cancer [29,30].
31. **Wine**, a dataset regarding measurements about the quality of wines [31,32].

32. **EEG**, which is dataset regardingEEG recordings [33,34]. From this dataset the following cases were used: Z_F_S, ZO_NF_S, ZONF_S and Z_O_N_F_S.
33. **Zoo**, which is a dataset regarding animal classification [35] .

Moreover a series of regression datasets was adopted in the conducted experiments. The list with the regression datasets has as follows:

1. **Abalone**, which is a dataset about the age of abalones [36].
2. **Airfoil**, a dataset founded in NASA [37].
3. **Auto**, a dataset related to the consumption of fuels from cars.
4. **BK**, which is used to predict the points scored in basketball games.
5. **BL**, a dataset that contains measurements from electricity experiments.
6. **Baseball**, which is a dataset used to predict the income of baseball players.
7. **Concrete**, which is a civil engineering dataset [38].
8. **DEE**, a dataset that is used to predict the price of electricity.
9. **Friedman**, which is an artificial dataset[39].
10. **FY,** which is a dataset regarding the longevity of fruit flies.
11. **HO**, a dataset located in the STATLIB repository.
12. **Housing**, regarding the price of houses [40].
13. **Laser**, which contains measurements from various physics experiments.
14. **LW**, a dataset regarding the weight of babes.
15. **Mortgage**, a dataset that contains measurements from the economy of USA.
16. **PL** dataset, located in the STALIB repository.
17. **Plastic**, a dataset regarding problems occurred with the pressure on plastics.
18. **Quake**, a dataset regarding the measurements of earthquakes.
19. **SN**, a dataset related to trellising and pruning.
20. **Stock**, which is a dataset regarding stocks.
21. **Treasury**, a dataset that contains measurements from the economy of USA.

Table 1. Experimental results using a variety of machine learning methods for the classification datasets.

DATASET	ADAM	BFGS	GENETIC	RBF	NEAT	PRUNE	NNC	PROPOSED
APPENDICITIS	16.50%	18.00%	24.40%	12.23%	17.20%	15.97%	14.40%	16.30%
ALCOHOL	57.78%	41.50%	39.57%	49.32%	66.80%	15.75%	37.72%	20.21%
AUSTRALIAN	35.65%	38.13%	32.21%	34.89%	31.98%	43.66%	14.46%	14.68%
BALANCE	12.27%	8.64%	8.97%	33.53%	23.14%	9.00%	23.65%	7.26%
CLEVELAND	67.55%	77.55%	51.60%	67.10%	53.44%	51.48%	50.93%	44.90%
CIRCULAR	19.95%	6.08%	5.99%	5.98%	35.18%	12.76%	12.66%	4.22%
DERMATOLOGY	26.14%	52.92%	30.58%	62.34%	32.43%	9.02%	21.54%	5.92%
ECOLI	64.43%	69.52%	54.67%	59.48%	43.44%	60.32%	49.88%	44.79%
GLASS	61.38%	54.67%	52.86%	50.46%	55.71%	66.19%	56.09%	49.43%
HABERMAN	29.00%	29.34%	28.66%	25.10%	24.04%	29.38%	27.53%	28.57%
HAYES-ROTH	59.70%	37.33%	56.18%	64.36%	50.15%	45.44%	33.69%	30.77%
HEART	38.53%	39.44%	28.34%	31.20%	39.27%	27.21%	15.67%	17.85%
HEARTATTACK	45.55%	46.67%	29.03%	29.00%	32.34%	29.26%	20.87%	20.67%
HOUSEVOTES	7.48%	7.13%	6.62%	6.13%	10.89%	5.81%	3.17%	7.39%
IONOSPHERE	16.64%	15.29%	15.14%	16.22%	19.67%	11.32%	11.29%	13.14%
LIVERDISORDER	41.53%	42.59%	31.11%	30.84%	30.67%	49.72%	32.35%	33.38%
LYMOGRAPHY	39.79%	35.43%	28.42%	25.50%	33.70%	22.02%	25.29%	25.14%
MAMMOGRAPHIC	46.25%	17.24%	19.88%	21.38%	22.85%	38.10%	17.62%	17.77%
PARKINSONS	24.06%	27.58%	18.05%	17.41%	18.56%	22.12%	12.74%	14.05%
PIMA	34.85%	35.59%	32.19%	25.78%	34.51%	35.08%	28.07%	24.34%
POPFAILURES	5.18%	5.24%	5.94%	7.04%	7.05%	4.79%	6.98%	7.19%
REGIONS2	29.85%	36.28%	29.39%	38.29%	33.23%	34.26%	26.18%	25.00%
SAHEART	34.04%	37.48%	34.86%	32.19%	34.51%	37.70%	29.80%	30.11%
SEGMENT	49.75%	68.97%	57.72%	59.68%	66.72%	60.40%	53.50%	9.59%
SPIRAL	47.67%	47.99%	48.66%	44.87%	48.66%	50.38%	48.01%	41.25%
STATHEART	44.04%	39.65%	27.25%	31.36%	44.36%	28.37%	18.08%	20.26%
STUDENT	5.13%	7.14%	5.61%	5.49%	10.20%	10.84%	6.70%	7.18%
TRANSFUSION	25.68%	25.84%	24.87%	26.41%	24.87%	29.35%	25.77%	23.59%
WDBC	35.35%	29.91%	8.56%	7.27%	12.88%	15.48%	7.36%	3.73%
WINE	29.40%	59.71%	19.20%	31.41%	25.43%	16.62%	13.59%	10.41%
Z_F_S	47.81%	39.37%	10.73%	13.16%	38.41%	17.91%	14.53%	6.60%
Z_O_N_F_S	78.79%	65.67%	64.81%	48.70%	77.08%	71.29%	48.62%	49.66%
ZO_NF_S	47.43%	43.04%	21.54%	9.02%	43.75%	15.57%	13.54%	3.94%
ZONF_S	11.99%	15.62%	4.36%	4.03%	5.44%	3.27%	2.64%	2.60%
ZOO	14.13%	10.70%	9.50%	21.93%	20.27%	8.53%	8.70%	5.10%
AVERAGE	**36.45%**	**35.71%**	**28.25%**	**30.73%**	**32.19%**	**27.94%**	**24.79%**	**19.63%**

Table 2. Experimental results using a variety of machine learning methods on the regression datasets.

DATASET	ADAM	BFGS	GENETIC	RBF	NEAT	PRUNE	NNC	PROPOSED
ABALONE	4.30	5.69	7.17	7.37	9.88	7.88	5.08	4.41
AIRFOIL	0.005	0.003	0.003	0.27	0.067	0.002	0.004	0.001
AUTO	70.84	60.97	12.18	17.87	56.06	75.59	17.13	11.73
BK	0.0252	0.28	0.027	0.02	0.15	0.027	0.10	0.058
BL	0.622	2.55	5.74	0.013	0.05	0.027	1.19	0.13
BASEBALL	77.90	119.63	103.60	93.02	100.39	94.50	61.57	60.42
CONCRETE	0.078	0.066	0.0099	0.011	0.081	0.0077	0.008	0.004
DEE	0.63	2.36	1.013	0.17	1.512	1.08	0.26	0.26
FRIEDMAN	22.90	1.263	1.249	7.23	19.35	8.69	6.29	1.25
FY	0.038	0.19	0.65	0.041	0.08	0.042	0.11	0.13
HO	0.035	0.62	2.78	0.03	0.169	0.03	0.015	0.073
HOUSING	80.99	97.38	43.26	57.68	56.49	52.25	25.47	15.96
LASER	0.03	0.015	0.59	0.03	0.084	0.007	0.025	0.004
LW	0.028	2.98	1.90	0.03	0.03	0.02	0.011	0.32
MORTGAGE	9.24	8.23	2.41	1.45	14.11	12.96	0.30	0.15
PL	0.117	0.29	0.29	2.118	0.09	0.032	0.047	0.021
PLASTIC	11.71	20.32	2.791	8.62	20.77	17.33	4.20	2.15
QUAKE	0.07	0.42	0.04	0.07	0.298	0.04	0.96	0.061
SN	0.026	0.40	2.95	0.027	0.174	0.032	0.026	0.10
STOCK	180.89	302.43	3.88	12.23	12.23	39.08	8.92	3.96
TREASURY	11.16	9.91	2.93	2.02	15.52	13.76	0.43	0.25
AVERAGE	**22.46**	**30.29**	**9.31**	**10.02**	**14.65**	**15.40**	**6.29**	**4.83**

3.3. Experiments with the weight factor I_w

Table 3. Experimental results using a variety of machine learning methods for the classification datasets.

DATASET	$I_w = 2$	$I_w = 3$	$I_w = 5$	$I_w = 10$
APPENDICITIS	15.03%	15.67%	17.93%	16.30%
ALCOHOL	21.11%	25.63%	22.20%	20.21%
AUSTRALIAN	13.93%	14.01%	14.06%	14.68%
BALANCE	8.71%	8.91%	8.61%	7.26%
CLEVELAND	42.09%	42.24%	43.60%	44.90%
CIRCULAR	14.71%	6.93%	4.11%	4.22%
DERMATOLOGY	9.09%	6.78%	6.78%	5.92%
ECOLI	48.21%	56.21%	50.12%	44.79%
GLASS	54.76%	54.51%	52.40%	49.43%
HABERMAN	30.31%	29.11%	28.82%	28.57%
HAYES-ROTH	27.74%	31.31%	28.90%	30.77%
HEART	15.00%	15.32%	15.69%	17.85%
HEARTATTACK	18.61%	18.72%	19.17%	20.67%
HOUSEVOTES	5.80%	6.83%	6.88%	7.39%
IONOSPHERE	11.58%	15.16%	15.88%	13.14%
LIVERDISORDER	31.12%	31.70%	31.89%	33.38%
LYMOGRAPHY	21.76%	23.83%	26.84%	25.14%
MAMMOGRAPHIC	16.33%	16.49%	16.72%	17.77%
PARKINSONS	13.33%	13.47%	13.97%	14.05%
PIMA	23.57%	23.82%	23.76%	24.34%
POPFAILURES	4.98%	5.51%	7.11%	7.19%
REGIONS2	24.63%	25.10%	25.58%	25.00%
SAHEART	29.41%	29.27%	30.48%	30.11%
SEGMENT	39.10%	24.74%	15.17%	9.59%
SPIRAL	47.10%	43.25%	42.66%	41.25%
STATHEART	18.06%	19.12%	19.01%	20.26%
STUDENT	3.73%	4.00%	4.54%	7.18%
TRANSFUSION	24.81%	24.38%	24.28%	23.59%
WDBC	3.25%	3.40%	3.60%	3.73%
WINE	9.08%	8.94%	9.37%	10.41%
Z_F_S	5.43%	5.53%	5.89%	6.60%
Z_O_N_F_S	48.60%	49.67%	48.79%	49.66%
ZO_NF_S	3.30%	3.11%	3.52%	3.94%
ZONF_S	1.97%	2.06%	2.24%	2.60%
ZOO	5.13%	6.57%	5.63%	5.10%
AVERAGE	**20.32%**	**20.33%**	**19.89%**	**19.63%**

Table 4. Experimental results using a variety of machine learning methods on the regression datasets.

DATASET	$I_w = 2$	$I_w = 3$	$I_w = 5$	$I_w = 10$
ABALONE	4.49	4.40	4.33	4.41
AIRFOIL	0.002	0.002	0.002	0.001
AUTO	17.16	16.14	14.55	11.73
BK	0.13	0.18	0.12	0.058
BL	0.005	0.19	0.14	0.13
BASEBALL	59.05	52.43	54.83	60.42
CONCRETE	0.005	0.004	0.003	0.004
DEE	0.27	0.26	0.26	0.26
FRIEDMAN	6.49	4.56	1.96	1.25
FY	0.07	0.12	0.26	0.13
HO	0.03	0.02	0.08	0.073
HOUSING	27.19	25.53	21.47	15.96
LASER	0.003	0.003	0.003	0.004
LW	0.11	0.09	0.14	0.32
MORTGAGE	0.25	0.25	0.19	0.15
PL	0.022	0.021	0.021	0.021
PLASTIC	3.17	2.33	2.18	2.15
QUAKE	0.043	0.045	0.049	0.061
SN	0.03	0.04	0.06	0.10
STOCK	8.79	8.15	8.91	3.96
TREASURY	0.39	0.40	0.38	0.25
AVERAGE	**6.08**	**5.48**	**5.24**	**4.83**

4. Conclusions

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