Appendix: Full data for the manuscript 'On Modularity of Neural Networks: Systematic Review and Open Challenges'

February 2024

Reviewed studies

[S1] T. Kimoto, K. Asakawa, M. Yoda, and M. Takeoka, "Stock market prediction system with modular neural networks," in *International Joint Conference on Neural Networks*, IEEE, 1990.

[S2] F. Sasagawa and K. Tajima, "Application of a neural network with a modular architecture to prediction of protein secondary structures-overlearning effects on predictions," in *International Conference on Neural Networks*, vol. 1, IEEE, 1993.

[S3] T. Hong, M. Fang, and D. Hilder, "Pd classification by a modular neural network based on task decomposition," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 3, no. 2, pp. 207–212, 1994.

[S4] J. Proriol, "Multi-modular neural networks for the classification of e+e- hadronic events," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 337, no. 2-3, pp. 566–572, 1994.

[S5] V. S. Desai, J. N. Crook, and G. A. Overstreet, "A comparison of neural networks and linear scoring models in the credit union environment," *European Journal of Operational Research*, vol. 95, no. 1, pp. 24–37, 1996.

[S6] R. Kumar, W.-C. Chen, and P. Rockett, "Bayesian labelling of image corner features using a grey-level corner model with a bootstrapped modular neural network," in *International Conference on Artificial Neural Networks*, IET, 1997.

[S7] G. Auda and M. Kamel, "CMNN: Cooperative modular neural networks for pattern recognition," *Pattern Recognition Letters*, vol. 18, no. 11-13, pp. 1391–1398, 1997.

[S8] S. Pillutla and A. Keyhani, "Power system stabilization based on modular neural network architecture," *International Journal of Electrical Power & Energy Systems*, vol. 19, no. 6, pp. 411–418, 1997.

[S9] G. Herries and T. Selige, "Application of supervised neural network approaches to remotely sensed optical imagery," in *International Geoscience and Remote Sensing. Symposium*, IEEE, 1998.

[S10] D. Park and L. R. Rilett, "Forecasting multiple-period freeway link travel times using modular neural networks," *Transportation research record*, vol. 1617, no. 1, pp. 163–170, 1998.

[S11] J. Shi, J. Ortigao, and J. Bai, "Modular neural networks for predicting settlements during tunneling," *Journal of geotechnical and geoenvironmental engineering*, vol. 124, no. 5, pp. 389–395, 1998.

[S12] M. Obaidat, H. Khalid, and B. Sadoun, "Ultrasonic transducer characterization by neural networks," *Information Sciences*, vol. 107, no. 1-4, pp. 195–215, 1998.

[S13] C. A. Perez, P. A. Galdames, and C. A. Holzmann, "Improvements on handwritten digit recognition by cooperation of modular neural networks," in *International Conference on Systems, Man, and Cybernetics*, vol. 5, IEEE, 1998.

[S14] M. Nasereddin and M. Mollaghasemi, "The development of a methodology for the use of neural networks and simulation modeling in system design," in *Conference on Winter simulation Simulation—a bridge to the future*, ACM Press, 1998.

[S15] X. Lamming and L. Cander, "Monthly median fof2 modelling cost 251 area by neural networks," *Physics and chemistry of the earth*, vol. 24, no. 4, pp. 349–354, 1998.

[S16] D. Park, L. R. Rilett, and G. Han, "Spectral basis neural networks for real-time travel time forecasting," *Journal of transportation engineering*, vol. 125, no. 6, pp. 515–523, 1998.

[S17] H. M. El-Bakry, M. A. Abo-Elsoud, and M. Kanel, "Modular neural networks for face detection," in *National Radio Science Conference*, IEEE, 2000.

[S18] H. M. El-Bakry, M. A. Abo-Elsoud, and M. S. Kamel, "Modular neural networks for solving high complexity tasks," in *International Symposium on Circuits and Systems*, vol. 3, IEEE, 2000.

[S19] B. Zhang and R. S. Govindaraju, "Prediction of watershed runoff using bayesian concepts and modular neural networks," *Water Resources Research*, vol. 36, no. 3, pp. 753–762, 2000.

[S20] N. Russell, H. Bakker, and R. Chaplin, "Modular neural network modelling for long-range prediction of an evaporator," *Control Engineering Practice*, vol. 8, no. 1, pp. 49–59, 2000.

[S21] J. Wenli, Z. Huoju, L. Qizhong, and Z. Yiyu, "Efficient radar target classification using modular neural networks," in *CIE International Conference on Radar*, pp. 1031–1034, IEEE, 2001.

[S22] T. Hong and M. Fang, "Detection and classification of partial discharge using a feature decomposition-based modular neural network," *Transactions on Instrumentation and Measurement*, vol. 50, no. 5, pp. 1349–1354, 2001.

[S23] W.-S. Soh and C.-K. Tham, "Modular neural networks for multi-service connection admission control," *Computer networks*, vol. 36, no. 2-3, pp. 181–202, 2001.

[S24] S. Mitra, P. Mitra, and S. K. Pal, "Evolutionary modular design of rough knowledge-based network using fuzzy attributes," *Neurocomputing*, vol. 36, no. 1-4, pp. 45–66, 2001.

[S25] B.-L. Lu, J. Shin, and M. Ichikawa, "Massively parallel classification of EEG signals using min-max modular neural networks," in *Artificial Neural Networks*, pp. 601–608, Springer Berlin Heidelberg, 2001.

[S26] P. Mitra, S. Mitra, and S. K. Pal, "Evolutionary modular MLP with rough sets and ID3 algorithm for staging of cervical cancer," *Neural Computing & Applications*, vol. 10, no. 1, pp. 67–76, 2001.

[S27] L. Y. Khuan, N. Hamzah, and R. Jailani, "Prediction of water quality index (wqi) based on artificial neural network (ann)," in *Student Conference on Research and Development*, pp. 157–161, IEEE, 2002.

[S28] D. Barraez, S. Garcia-Salicetti, B. Dorizzi, M. Padrón, and E. Ramos, "Modular neural networks for seismic tomography," in *International Conference on Pattern Recognition*, vol. 3, IEEE, 2002.

[S29] D. Doye and T. Sontakke, "Speech recognition using modular general fuzzy min-max neural network," *IETE Journal of Research*, vol. 48, no. 2, pp. 99–103, 2002.

[S30] T. Nagano, M. Hirahara, and H. Eguchi, "Submodular neural network is better than modular neural network and support vector machines for personal verification," in *International Joint Conference on Neural Networks*, vol. 3, pp. 2152–2156, IEEE, 2003.

[S31] R. Calvo and M. Figueiredo, "Reinforcement learning for hierarchical and modular neural network in autonomous robot navigation," in *Proceedings of the International Joint Conference on Neural Networks*, vol. 2, pp. 1340–1345, IEEE, 2003.

[S32] B.-L. Lu, Q. Ma, M. Ichikawa, and H. Isahara, "Efficient part-of-speech tagging with a min-max modular neural-network model," *Applied Intelligence*, vol. 19, no. 1-2, p. 65, 2003.

[S33] S. Sharma, G. Irwin, M. Tokhi, and S. McLoone, "Learning soft computing control strategies in a modular neural network architecture," *Engineering Applications of Artificial Intelligence*, vol. 16, no. 5-6, pp. 395–405, 2003.

[S34] A. Zeng, Q.-L. Zheng, D. Pan, and H. Peng, "Utilizing modular neural networks to predict mhc class ii-binding peptides," in *International Conference on Systems, Man and Cybernetics*, vol. 5, pp. 4588–4592, IEEE, 2004.

[S35] C.-K. Li and C.-T. Chiang, "Neural networks composed of single-variable cmacs," in *International Conference on Systems, Man and Cybernetics*, vol. 4, pp. 3482–3487, IEEE, 2004.

[S36] G. Daqi, W. Shuyan, and J. Yan, "An electronic nose and modular radial basis function network classifiers for recognizing multiple fragrant materials," *Sensors and Actuators B: Chemical*, vol. 97, no. 2-3, pp. 391–401, 2004.

[S37] K. V. Balakin, S. Ekins, A. Bugrim, Y. A. Ivanenkov, D. Korolev, Y. V. Nikolsky, A. A. Ivashchenko, N. P. Savchuk, and T. Nikolskaya, "Quantitative structure-metabolism relationship modeling of metabolic n-dealkylation reaction rates," *Drug metabolism and disposition*, vol. 32, no. 10, pp. 1111–1120, 2004.

[S38] M. O. Darter and V. S. Gordon, "Vehicle steering control using modular neural networks," in *IRI-2005 IEEE International Conference on Information Reuse and Integration, Conf, 2005.*, IEEE, 2005.

[S39] P. Melin, C. Felix, and O. Castillo, "Face recognition using modular neural networks and the fuzzy sugeno integral for response integration," *International journal of intelligent systems*, vol. 20, no. 2, pp. 275–291, 2005.

[S40] M. N. Almasri and J. J. Kaluarachchi, "Modular neural networks to predict the nitrate distribution in ground water using the on-ground nitrogen loading and recharge data," *Environmental Modelling & Software*, vol. 20, no. 7, pp. 851–871, 2005.

[S41] P. Melin, J. Urias, J. Quintero, M. Ramirez, and O. Blanchet, "Forecasting economic time series using modular neural networks and the fuzzy sugeno integral as response integration method," in *International Joint Conference on Neural Network*, IEEE, 2006.

[S42] R. Valdovinos and J. Sanchez, "Ensembles of multilayer perceptron and modular neural networks for fast and accurate learning," in *Mexican International Conference on Artificial Intelligence*, IEEE, 2006.

[S43] I. Turchenko, V. Kochan, and A. Sachenko, "Recognition of multi-sensor output signal using modular neural networks approach," in *International Conference - Modern Problems of Radio Engineering, Telecommunications, and Computer Science*, IEEE, 2006.

[S44] E. Schlessinger, P. J. Bentley, and R. B. Lotto, "Modular thinking," in *Annual conference on Genetic and evolutionary computation*, ACM, 2006.

[S45] K. Parasuraman, A. Elshorbagy, and S. K. Carey, "Spiking modular neural networks: A neural network modeling approach for hydrological processes," *Water Resources Research*, vol. 42, no. 5, 2006.

[S46] M.-Y. Kim and M.-K. Kim, "Dynamics of surface runoff and its influence on the water quality using competitive algorithms in artificial neural networks," *Journal of Environmental Science and Health, Part A*, vol. 42, no. 8, pp. 1057–1064, 2007.

[S47] Z.-Q. Zhao, D.-S. Huang, and W. Jia, "Palmprint recognition with 2dpca+PCA based on modular neural networks," *Neurocomputing*, vol. 71, no. 1-3, pp. 448–454, 2007.

[S48] R. M. Valdovinos and J. S. Sánchez, "Performance analysis of classifier ensembles: neural networks versus nearest neighbor rule," in *Iberian Conference on Pattern Recognition and Image Analysis*, pp. 105–112, Springer Berlin Heidelberg, 2007.

[S49] P. Melin, A. Mancilla, M. Lopez, and O. Mendoza, "A hybrid modular neural network architecture with fuzzy sugeno integration for time series forecasting," *Applied Soft Computing*, vol. 7, no. 4, pp. 1217–1226, 2007.

[S50] V. K. Valsalam and R. Miikkulainen, "Modular neuroevolution for multilegged locomotion," in *Annual conference on Genetic and evolutionary computation*, ACM, 2008.

[S51] A. Elshorbagy and K. Parasuraman, "Toward bridging the gap between data-driven and mechanistic models: cluster-based neural networks for hydrologic processes," *Practical Hydroinformatics: Computational Intelligence and Technological Developments in Water Applications*, pp. 389–403, 2008.

[S52] N. Gradojevic, R. Gencay, and D. Kukolj, "Option pricing with modular neural networks," *IEEE Transactions on Neural Networks*, vol. 20, no. 4, pp. 626–637, 2009.

[S53] T. Horiuchi and S. Kato, "A study on japanese historical character recognition using modular neural networks," in *International Conference on Innovative Computing, Information and Control*, IEEE, 2009.

[S54] V. K. Valsalam and R. Miikkulainen, "Evolving symmetric and modular neural networks for distributed control," in *Proceedings of the 11th Annual conference on Genetic and evolutionary computation*, ACM, 2009.

[S55] X. Chen, X. Liu, and Y. Jia, "Combining evolution strategy and gradient descent method for discriminative learning of bayesian classifiers," in *Annual conference on Genetic and evolutionary computation*, ACM, 2009.

[S56] S. Tapkın and Özdemir Akyılmaz, "A new approach to neural trip distribution models: NETDIM," *Transportation Planning and Technology*, vol. 32, no. 1, pp. 93–114, 2009.

[S57] H. M. El-Kaliouby and M. A. Al-Garni, "Inversion of self-potential anomalies caused by 2d inclined sheets using neural networks," *Journal of Geophysics and Engineering*, vol. 6, no. 1, pp. 29–34, 2009.

[S58] G. Chattopadhyay and S. Chattopadhyay, "Predicting daily total ozone over kolkata, india: skill assessment of different neural network models," *Meteorological Applications*, vol. 16, no. 2, pp. 179–190, 2009.

[S59] H. C. Tseng and B. Almogahed, "Modular neural networks with applications to pattern profiling problems," *Neurocomputing*, vol. 72, no. 10-12, pp. 2093–2100, 2009.

[S60] B. Gour, T. Bandopadhyaya, and R. Patel, "ART and modular neural network architecture for multilevel categorization and recognition of fingerprints," in *Conference on Knowledge Discovery and Data Mining*, IEEE, 2010.

[S61] R. R. Janghel, A. Shukla, R. Tiwari, and R. Kala, "Breast cancer diagnostic system using symbiotic adaptive neuro-evolution (SANE)," in *International Conference of Soft Computing and Pattern Recognition*, IEEE, 2010.

[S62] W. J. Jansen, S. Malki, L. Spaanenburg, and R. Kleihorst, "Smart collaboration in camera networks," in *International Conference on Advances in Mobile Computing and Multimedia*, ACM, 2010.

[S63] H.-C. Tsai and Y.-H. Lin, "Modular neural network programming with genetic optimization," *Expert Systems with Applications*, vol. 38, no. 9, pp. 11032–11039, 2011.

[S64] B. Ahmadi-Nedushan, "An optimized instance based learning algorithm for estimation of compressive strength of concrete," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 5, pp. 1073–1081, 2012.

[S65] P. Tahmasebi and A. Hezarkhani, "A fast and independent architecture of artificial neural network for permeability prediction," *Journal of Petroleum Science and Engineering*, vol. 86-87, pp. 118–126, 2012.

[S66] G. Baek, S.-P. Cheon, S. Kim, Y. Kim, H. Kim, C. Kim, and S. Kim, "Modular neural networks prediction model based a 2/o process control system," *International Journal of Precision Engineering and Manufacturing*, vol. 13, pp. 905–913, 2012.

[S67] V. R. Dhawale, J. A. Tidke, and S. V. Dudul, "Neural network based classification of pollen grains," in *International Conference on Advances in Computing, Communications and Informatics*, IEEE, 2013.

[S68] G. D. Suditu, S. Curteanu, and L. Bulgariu, "Neural networks-based modeling applied to a process of heavy metals removal from wastewaters," *Journal of Environmental Science and Health, Part A*, vol. 48, no. 11, pp. 1399–1412, 2013.

[S69] G. Kourakos and A. Mantoglou, "Development of a multi-objective optimization algorithm using surrogate models for coastal aquifer management," *Journal of Hydrology*, vol. 479, pp. 13–23, 2013.

[S70] M. Sheikhan and A. A. Sha'bani, "Pso-optimized modular neural network trained by owo-hwo algorithm for fault location in analog circuits," *Neural Computing and Applications*, vol. 23, pp. 519–530, 2013.

[S71] J. Schrum and R. Miikkulainen, "Evolving multimodal behavior with modular neural networks in ms. pac-man," in *Annual Conference on Genetic and Evolutionary Computation*, ACM, 2014.

[S72] T. Praczyk, "Using augmenting modular neural networks to evolve neuro-controllers for a team of underwater vehicles," *Soft Computing*, vol. 18, no. 12, pp. 2445–2460, 2014.

[S73] V. Srivastava, B. K. Tripathi, and V. K. Pathak, "Biometric recognition by hybridization of evolutionary fuzzy clustering with functional neural networks," *Journal of Ambient intelligence and humanized computing*, vol. 5, pp. 525–537, 2014.

[S74] Doreswamy and M. U. Salma, "Fast modular artificial neural network for the classification of breast cancer data," in *International Symposium on Women in Computing and Informatics*, ACM, 2015.

[S75] D. Sánchez, P. Melin, and O. Castillo, "Optimization of modular granular neural networks using a hierarchical genetic algorithm based on the database complexity applied to human recognition," *Information Sciences*, vol. 309, pp. 73–101, 2015.

[S76] M. Carcenac and S. Redif, "A highly scalable modular bottleneck neural network for image dimensionality reduction and image transformation," *Applied Intelligence*, vol. 44, no. 3, pp. 557–610, 2015.

[S77] M. A. Al-Garni, "Interpretation of magnetic anomalies due to dipping dikes using neural network inversion," *Arabian Journal of Geosciences*, vol. 8, no. 10, pp. 8721–8729, 2015.

[S78] N. R. Devi, D. V. S. S. S. Sarma, and P. V. R. Rao, "Diagnosis and classification of stator winding insulation faults on a three-phase induction motor using wavelet and MNN," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 23, no. 5, pp. 2543–2555, 2016.

[S79] T. Šarić, G. Šimunović, D. Vukelić, K. Šimunović, and R. Lujić, "Estimation of cnc grinding process parameters using different neural networks," *Tehnički vjesnik*, vol. 25, no. 6, pp. 1770–1775, 2018.

[S80] G. Li, X. Wang, and W. Djordje, "Perceptual visual reasoning with knowledge propagation," in *International Conference on Multimedia*, ACM, 2019.

[S81] M. Ali, A. Sarwar, V. Sharma, and J. Suri, "Artificial neural network based screening of cervical cancer using a hierarchical modular neural network architecture (hmnna) and novel benchmark uterine cervix cancer database," *Neural Computing and Applications*, vol. 31, pp. 2979–2993, 2019.

[S82] K. Chaturvedi and D. K. Vishwakarma, "Face recognition in an unconstrained environment using ConvNet," in *International Conference on Big Data Engineering and Technology*, ACM, 2020.

[S83] R. Pan and H. Rajan, "On decomposing a deep neural network into modules," in *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ACM, 2020.

[S84] A. Goel, S. Aghajanzadeh, C. Tung, S.-H. Chen, G. K. Thiruvathukal, and Y.-H. Lu, "Modular neural networks for low-power image classification on embedded devices," *ACM Transactions on Design Automation of Electronic Systems (TODAES)*, vol. 26, no. 1, pp. 1–35, 2020.

[S85] C. F. S. Leite and Y. Xiao, "Optimal sensor channel selection for resource-efficient deep activity recognition," in *International Conference on Information Processing in Sensor Networks*, ACM, 2021.

[S86] S. Li, S. Yang, Y. Wang, W. Yue, and J. Qiao, "A modular neural network-based population prediction strategy for evolutionary dynamic multi-objective optimization," *Swarm and Evolutionary Computation*, vol. 62, p. 100829, 2021.

Table 1: Electronic sources searched in order, and the number of papers found and finally included.

Electronic sources	Papers	Selected papers (+ earlier duplicates)
IEEE Xplore	80	25
ACM Digital Library	87	12 (+ 1)
Scopus	121	22 (+ 8)
Web of Science	196	27 (+ 38)
Total	484	86

Table 2: Accuracy range of Modular solutions described in studies when compared to Monolithic

ID	Task	Monolithic performance	Modular performance	Accuracy	Training
S1	Time series	54.3%	99.1%	better	shorter
S2	Pattern detection	59.8%	60.89%	better	NA
S3	Pattern detection	88.31%	93.6%	better	shorter
S4	Multi sensor classification	73.5%	73.7%	better	NA
S5	Time series	80.75%	80.46%	mixed	shorter
S7	Pattern detection	80.00%	95.00%	better	shorter
S9	Image classification	82.00%	85.00%	better	NA
S10	Time series	85.20%	88.00%	better	NA
S12	Function generation	100.00%	78.35%	worse	NA
S13	Image classification	91.0%	93.5%	better	NA
S14	Model creation	92.00%	94.00%	better	shorter
S16	Function generation	11.8%	11.9%	mixed	NA
S17	Face detection	83.00%	97.00%	better	NA
S19	Time series	80.00%	81.00%	better	shorter
S20	Time series	96.5%	98.00%	better	shorter
S21	Pattern detection	90.00%	100.00%	better	NA
S22	Pattern detection	83.21%	89.61%	better	shorter
S24	Data classification	71.1%	74.8%	better	shorter
S25	Input classification	80.5%	81.8%	better	shorter
S26	Input classification	79.23%	80.02%	better	NA
S27	Pattern detection	92.6%	93.3%	better	shorter
S28	Pattern detection	78.00%	99.00%	better	shorter
S29	Input classification	59.1%	67.8%	better	NA
S30	Image detection	99.8%	99.9%	better	longer
S32	Text detection	89.1%	94.2%	better	shorter
S34	Pattern detection	78.80%	93.51%	better	longer
S36	Input classification	90.90%	96.67%	better	longer
S37	Input classification	78.3%	82.0%	better	NA
S38	Image Detection	18.99%	74.68%	mixed[**]	longer
S39	Face detection	50.00%	100.00%	better	shorter
S40	Input modeling/classification	77.8%	85.4%	better	shorter
S42	Image classification	95.00%	80.00%	worse	longer
S46	Time series	70.40%	75.40%	better	shorter
S47	Image Detection	97.67%	97.47%	mixed	longer
S48	Input classification	97.1%	88.4%	worse	longer
S52	Time series	97.98%	99.95%	better	longer
S53	Image classification	85.00%	95.00%	better	NA
S55	Image classification & detection	99.25%	97.85%	worse	NA
S58	Input modeling/classification	97.18%	95.2%	worse	NA
S60	Image classification	98%	100%	better	longer
S61	Image classification	97.54% 97.88%[*]	96.49% 95.08%	worse	NA
S62	Video classification	84.00%	98.00%	mixed	shorter
S67	Image classification	55.00%	85.00%	better	shorter
S68	Function generation	93.48%	97.28%	better	longer
S72	Sensor detection	67.00%	70.00%	better	NA
S73	Human recognition	99.00%	97.13%	worse	NA
S74	Image classification	97.98%	98.22%	better	shorter
S75	Human recognition	97.00%	99.00%	better	NA
S78	Pattern detection	95.8%	96.9%	better	shorter
S79	Function generation	87.48%	86.65%	worse	NA
S80	Image classification & detection	54.06%	57.33%	better	NA
S81	Image classification	76.40%	95.32%	better	shorter
S82	Face detection	97.52% 99.99%[*]	93.4% 97.49%	worse	NA
S83	Image classification	85% - 95%[*]	85% - 95%	mixed	NA
S84	Image classification	82% - 54.8%[*]	91.21% - 68.7%	better	shorter
S85	Sensor detection	100% - 88.9%[*]	99% - 86.4%	mixed	shorter

[*] Studies report the results of multiple experiments. [**]Unusable due to too long execution time

Table 3: Performance range of Modular solutions in Studies with alternate measurement methods or presentation of results

ID	Task	Monolithic performance	Modular performance	Accuracy	Training
S6	Image detection	Figure image had a weaker result	Figure image had a better result	better	NA
S8	Time series	9% deviation on change	7% deviation on change	better	shorter
S11	Function generation/Input detection	70mm error	33.4mm error	better	NA
S15	Time series	0.458 Mhz RMSE	0.396 Mhz RMSE	better	NA
S18	Complexity compression	9 neurons, O(121) 65 weights A comparison between MNN and non MNNs used to implement 16 logic functions.	5 neurons, 51 weights 10 switches, 1 inverter O(54)	better	NA
S23	Multi sensor classification (traffic control)	27.18% (link utilization)	83.59% (link utilization)	better	shorter
S31	Sensor detection	3800 iterations 5 targets/8 collisions	3800 iterations 14 targets / 14 collisions At the end the robot is able to reach targets without collision	better	NA
S33	Input classification	0.002 MSE	0.0005 MSE	better	NA
S35	Input classification	More memory used	Less memory used	better	shorter
S41	Time series	0.3 pounds Fitness avg price distance from graph	0.01 pounds	better	NA
S43	Multi sensor classification Pattern detection	~2%	~2%	better	NA
S44	Multi sensor classification	4279.77 Average Survival Age Iterations	5537.19 Average Survival Age Iterations	better	NA
S45	Input modeling/classification	56.6 W/m2	53.5 W/m2	better	NA
S49	Time series	Larger deviation on table results	Very small deviation	better	NA
S50	Multi sensor classification	32 fitness (mean Chebyshev distance from optimal path)	65 fitness	better	NA
S51	Input classification	67.2W/m2 RMSE	64.4W/m2 RMSE	better	NA
S54	Multi sensor classification	32 fitness (mean Chebyshev distance from optimal path)	68 fitness	better	NA
S56	Input modeling/classification	2206 RMSE	1004 RMSE	better	NA
S57	Input modeling/classification	Worse fit to field data in figures	Better fit to field data in figures	better	NA
S59	Pattern classification	Fig shows similar or slightly weaker flight trajectory prediction when compared to the modular approach	Fig shows comparable or slightly better flight trajectory prediction as compared with the monolithic approaches	better	shorter
S63	Function generation/Input detection	2 MPa, 0.2 $/m3, and 20.7 cm training root mean square error (RMSE)	0.98MPa 0.27 $/m3 0.35 cm training root mean square error (RMSE)	better	longer (if parallel)
S64	Function generation/Input detection	1.3087Mpa RMSE	1.646Mpa RMSE	worse	longer (if parallel)
S65	Input modeling/classification	0.0143 MSE	0.0077 MSE	better	shorter
S66	Input modeling/classification	0.0154 RMSE	0.0176 RMSE	better	NA
S69	Input modeling/classification	Smaller economic and environmental cost in figure	Higher economic and environmental cost in figure	better	shorter
S70	Input modeling/classification	99.3% at 50% value tolerance (lower tolerance better)	99.6% at 40% value tolerance	better	shorter
S71	Multi sensor classification	16.014 (pacman score)	32.647 (pacman score)	better	NA
S76	Image transformation	Unstable waveforms at bottleneck	Robust waveforms at bottleneck	better	NA
S77	Input modeling/classification	Inversion illustrates good agreement with the ones published in the literatures.	Inversion illustrates good agreement with the ones published in the literatures.	mixed	NA
S86	Function generation/Input detection	Performs slightly better on never repeating environments	Performs better on repeating environments	mixed	NA

Table 4: Comparison of MNN efficiency values vs. monolithic. The first value in brackets is MNN, second Monolithic in results with values. Studies missing these measurements were excluded from the list.

ID	Avg. execution time	Avg. memory	Avg. energy consumption
S20	Faster (general mention)	-	-
S24	Faster (general mention)	-	-
S25	Faster (11.919s vs 727.33s)	-	-
S32	Faster (437s vs 6298s)	-	-
S35	-	Smaller (general mention)	-
S38	Slower (0.18s vs 3.68s)	-	-
S40	Faster (180 times faster)	Smaller (general mention)	-
S46	Faster (general mention)	-	-
S48	Slower (127.2s vs 4.2s)	-	-
S59	Faster (300s vs 8500s)	-	-
S69	Faster (28h vs 333h)	-	-
S70	Faster (693s vs 1760s)	-	-
S74	Faster (420s vs 3033s)	-	-
S84	Faster (0.358s vs 0.796s)	Smaller (3.512MB vs >50MB)	Smaller (1.533J vs 3.168J)
S85	Faster (0.4ms vs 28.7ms)	Smaller (2.0MB vs 17.1MB)	Smaller (1.8 mJ vs 79.2 mJ)