Table 2: Performance comparison of the various incremental learning methods on different shuffles of data of six multi-class classification applications, the first number denotes the mean accuracies over the different shuffles, the second number the standard deviation over the shuffles; first part includes results on the new methods, second on state-of-the-art methods for evolving/incremental (fuzzy) classifiers

Method	Plates	CD-Imp.	Iris	Steel	Vehicle	Ecoli
EFC AP-SC w/o reliability	61.7 ± 2.0	70.5 ± 1.4	95.2 ± 2.1	68.6 ± 1.9	61.7 ± 3.0	82.7 ± 4.0
EFC AP-SC with ign. in conf.	73.4 ± 0.9	74.9 ± 1.3	96.6 ± 2.0	67.9 ± 1.4	66.6 ± 2.4	84.7 ± 2.0
EFC AP-SC no resp. on ign.	73.9 ± 0.5	76.0 ± 1.2	96.6 ± 1.7	71.4 ± 2.8	67.2 ± 2.8	83.3 ± 2.9
EFC AP-SC no resp. on conf.	74.7±0.9	**82.6±1.5**	97.0 ± 1.6	70.7±2.3	73.3±2.3	86.3±3.5
EFC AP-TS w/o reliability	66.4 ± 1.6	71.9 ± 1.2	97.3±1.6	62.8 ± 2.0	82.0 ± 2.5	86.1 ± 1.4
EFC AP-TS with ign. in conf.	71.5 ± 1.4	74.7 ± 0.7	95.8 ± 1.2	65.8 ± 1.3	82.0 ± 1.9	85.5 ± 1.2
EFC AP-TS no resp. on ign.	74.4±1.2	76.1±1.2	96.6 ± 1.2	**76.3±2.4**	**83.1±2.0**	86.2±2.9
EFC AP-TS no resp. on conf.	**74.9±0.9**	79.7±1.2	**97.6±1.8**	68.2±2.1	82.3±2.5	**87.2±2.9**
EFC SM (direct map.)	36.4 ± 4.0	62.0 ± 2.5	94.8 ± 2.7	64.1 ± 2.3	53.2 ± 2.5	80.4 ± 3.6
EFC MM (one-vs-rest)	62.7 ± 1.8	73.1 ± 1.1	96.3 ± 1.3	65.5 ± 1.6	79.3 ± 1.5	86.0 ± 2.3
eVQ-Class var. A	57.9 ± 0.8	64.1 ± 2.4	93.7 ± 5.5	67.2 ± 1.8	54.3 ± 5.0	84.2 ± 3.6
eVQ-Class var. B	60.3 ± 1.1	74.9 ± 1.6	95.6 ± 1.1	39.3 ± 1.5	62.0 ± 1.9	84.6 ± 3.3

[7] J. Fürnkranz. Round robin classification. *Journal of Machine Learning Research*, 2:721–747, 2002.

[8] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning: Data Mining, Inference and Prediction - Second Edition*. Springer, New York Berlin Heidelberg, 2009.

[9] H. He and E.A. Garcia. Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9):1263–1284, 2009.

[10] E. Huellermeier. Uncertainty in clustering and classification. In A. Deshpande and A. Hunter, editors, *Springer Lecture Notes in Computer Science*, volume 6379 of *LNAI*, pages 16–19. Springer, 2010.

[11] J. Hühn and E. Hüllermeier. FR3: A fuzzy rule learner for inducing reliable classifiers. *IEEE Transactions on Fuzzy Systems*, 17(1):138–149, 2009.

[12] E. Hüllermeier and Klaus Brinker. Learning valued preference structures for solving classification problems. *Fuzzy Sets and Systems*, 159(18):2337–2352, 2008.

[13] N. Kasabov. *Evolving Connectionist Systems: The Knowledge Engineering Approach - Second Edition*. Springer Verlag, London, 2007.

[14] E.P. Klement, R. Mesiar, and E. Pap. *Triangular Norms*. Kluwer Academic Publishers, Dordrecht Norwell New York London, 2000.

[15] L. Kuncheva. *Fuzzy Classifier Design*. Physica-Verlag, Heidelberg, 2000.

[16] A. Lemos, W. Caminhas, and F. Gomide. Fuzzy multivariate gaussian evolving approach for fault detection and diagnosis. In E. Hüllermeier, R. Kruse, and F. Hoffmann, editors, *Proc. of the 13th International Conference on Information Processing and Management of Uncertainty, Part II (Applications)*, volume 81 of *CCIS*, pages 360–369. Springer, Dortmund, Germany, 2010.

[17] E. Lima, M. Hell, R. Ballini, and F. Gomide. Evolving fuzzy modeling using participatory learning. In P. Angelov, D. Filev, and N. Kasabov, editors, *Evolving Intelligent Systems: Methodology and Applications*, pages 67–86. John Wiley & Sons, New York, 2010.

[18] E. Lughofer. Evolving vector quantization for classification of on-line data streams. In *Proc. of the Conference on Computational Intelligence for Modelling, Control and Automation (CIMCA 2008)*, pages 780–786, Vienna, Austria, 2008.

[19] E. Lughofer. Extensions of vector quantization for incremental clustering. *Pattern Recognition*, 41(3):995–1011, 2008.

[20] E. Lughofer. FLEXFIS: A robust incremental learning approach for evolving TS fuzzy models. *IEEE Transactions on Fuzzy Systems*, 16(6):1393–1410, 2008.

[21] E. Lughofer. On-line evolving image classifiers and their application to surface inspection. *Image and Vision Computing*, 28(7):1065–1079, 2010.

[22] E. Lughofer. *Evolving Fuzzy Systems — Methodologies, Advanced Concepts and Applications*. Springer, Berlin Heidelberg, 2011. ISBN: 978-3-642-18086-6.

[23] E. Lughofer. On-line incremental feature weighing in evolving fuzzy classifiers. *Fuzzy Sets and Systems*, 163(1):1–23, 2011.

[24] V. Malathi, N. S. Marimuthu, and S. Baskar. A comprehensive evaluation of multicategory classification methods for fault classification in series compensated transmission line. *Neural Computing & Applications*, 19:595–600, 2010.

[25] S.J. Qin, W. Li, and H.H. Yue. Recursive PCA for adaptive process monitoring. *Journal of Process Control*, 10(5):471–486, 2000.

[26] B. Quost, T. Denoeux, and M.-H. Masson. Pairwise classifier combination using belief functions. *Pattern Recognition Letters*, 28(5):644–653, 2007.

[27] S. Raiser, E. Lughofer, C. Eitzinger, and J.E. Smith. Impact of object extraction methods on classification performance in surface inspection systems. *Machine Vision and Applications*, 21(5):627–641, 2010.

[28] R. R. Yager. A model of participatory learning. *IEEE Transactions on Systems, Man and Cybernetics*, 20(5):1229–1234, 1990.