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References

Ahsan, M. M.; Ali, M. S.; and Siddique, Z. 2024. Enhancing and improving the performance of imbalanced class data using novel GBO and SSG: A comparative analysis. *Neural Networks: The Official Journal of the International Neural Network Society*, 173: 106157.

Badawy, M.; El-Fishawy, N.; Radad, M.; and H.Arafa, A. 2022. RN-SMOTE: Reduced Noise SMOTE based on DB-SCAN for enhancing imbalanced data classification. *Journal of King Saud University - Computer and Information Sciences*, 34.

Bae, S.-Y.; Lee, J.; Jeong, J.; Lim, C.; and Choi, J. 2021. Effective data-balancing methods for class-imbalanced genotoxicity datasets using machine learning algorithms and molecular fingerprints. *Computational Toxicology*, 20: 100178.

Batista, G. E. A. P. A.; Prati, R. C.; and Monard, M. C. 2004. A study of the behavior of several methods for balancing machine learning training data. *SIGKDD Explor. Newsl.*, 6(1): 20–29.

Bishop, C. M. 1996. *Neural Networks for Pattern Recognition*. Oxford, England: Clarendon Press.

Bria, A.; Marrocco, C.; and Tortorella, F. 2020. Addressing class imbalance in deep learning for small lesion detection on medical images. *Computers in biology and medicine*, 120

Brownlee, J. 2021. Tour of Evaluation Metrics for Imbalanced Classification. https://machinelearningmastery.com.

Cao, K.; Chen, Y.; Lu, J.; Arechiga, N.; Gaidon, A.; and Ma, T. 2021. Heteroskedastic and Imbalanced Deep Learning with Adaptive Regularization. ArXiv:2006.15766 [cs, stat]. Chabbouh, M.; Bechikh, S.; Mezura-Montes, E.; and Ben Said, L. 2023. Imbalanced multi-label data classification as a bi-level optimization problem: application to

miRNA-related diseases diagnosis. *Neural Computing and Applications*, 35: 1–19.

Chang, N.; Yu, Z.; Wang, Y.-X.; Anandkumar, A.; Fidler, S.; and Alvarez, J. M. 2021. Image-Level or Object-Level? A Tale of Two Resampling Strategies for Long-Tailed Detection. ArXiv:2104.05702 [cs].

Chawla, N. V.; Bowyer, K. W.; Hall, L. O.; and Kegelmeyer, W. P. 2002. SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 321–357.

Cheah, P. C. Y.; Yang, Y.; and Lee, B. G. 2023. Enhancing Financial Fraud Detection through Addressing Class Imbalance Using Hybrid SMOTE-GAN Techniques. *International Journal of Financial Studies*, 11(3): 110. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

Dang, W.; Yang, Z.; Dong, W.; Li, X.; and Shi, G. 2024. Inverse Weight-Balancing for Deep Long-Tailed Learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(10): 11713–11721. Number: 10.

Das, S.; Mullick, S. S.; and Zelinka, I. 2022. On Supervised Class-Imbalanced Learning: An Updated Perspective and Some Key Challenges. *IEEE Transactions on Artificial Intelligence*, 3(6): 973–993. Conference Name: IEEE Transactions on Artificial Intelligence.

Fan, J.; Han, F.; and Liu, H. 2014. Challenges of big data analysis. *National science review*, 1(2): 293–314.

Goodfellow, I. J.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; and Bengio, Y. 2014. Generative Adversarial Networks. ArXiv:1406.2661 [cs, stat].

Guo, L.-Z.; and Li, Y.-F. 2022. Class-Imbalanced Semi-Supervised Learning with Adaptive Thresholding. In *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, 8082–8094. PMLR.

Haixiang, G.; Yijing, L.; Shang, J.; Mingyun, G.; Yuanyue, H.; and Bing, G. 2017. Learning from class-imbalanced data: Review of methods and applications. *Expert Systems with Applications*, 73: 220–239.

Hammami, M.; Bechikh, S.; Louati, A.; Makhlouf, M.; and Said, L. B. 2020. Feature construction as a bi-level optimization problem. *Neural Computing and Applications*, 32(17): 13783–13804.

Han, H.; Wang, W.-Y.; and Mao, B.-H. 2005. Borderline-SMOTE: A New Over-Sampling Method in Imbalanced Data Sets Learning. In *Advances in Intelligent Computing*, volume 3644, 878–887. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN 978-3-540-28226-6 978-3-540-31902-3. Series Title: Lecture Notes in Computer Science.

Johnson, J. M.; and Khoshgoftaar, T. M. 2019. Survey on deep learning with class imbalance. *Journal of Big Data*, 6(1): 27.

Kanika; and Singla, J. 2020. A Survey of Deep Learning based Online Transactions Fraud Detection Systems. In 2020 International Conference on Intelligent Engineering and Management (ICIEM), 130–136.

- Khan, S. H.; Hayat, M.; Bennamoun, M.; Sohel, F. A.; and Togneri, R. 2018. Cost-Sensitive Learning of Deep Feature Representations From Imbalanced Data. *IEEE Transactions on Neural Networks and Learning Systems*, 29(8): 3573–3587. Conference Name: IEEE Transactions on Neural Networks and Learning Systems.
- Korkmaz, S. 2020. Deep Learning-Based Imbalanced Data Classification for Drug Discovery. *Journal of Chemical Information and Modeling*, 4180–4190.
- Kovács, G. 2019. An empirical comparison and evaluation of minority oversampling techniques on a large number of imbalanced datasets. *Applied Soft Computing*, 83: 105662.
- Kumar, P.; Bhatnagar, R.; Gaur, K.; and Bhatnagar, A. 2021. Classification of Imbalanced Data:Review of Methods and Applications. *IOP Conference Series: Materials Science and Engineering*, 1099(1): 012077.
- Li, M.; Zhang, X.; Thrampoulidis, C.; Chen, J.; and Oymak, S. 2022. AutoBalance: Optimized Loss Functions for Imbalanced Data. ArXiv:2201.01212 [cs].
- Liu, H.; Simonyan, K.; and Yang, Y. 2019. DARTS: Differentiable Architecture Search. ArXiv:1806.09055 [cs, stat].
- Luketina, J.; Berglund, M.; Greff, K.; and Raiko, T. 2016. Scalable Gradient-Based Tuning of Continuous Regularization Hyperparameters. ArXiv:1511.06727 [cs].
- Majeed, A.; and Hwang, S. O. 2023. CTGAN-MOS: Conditional Generative Adversarial Network Based Minority-Class-Augmented Oversampling Scheme for Imbalanced Problems. *IEEE Access*, 11: 85878–85899.
- Makki, S.; Assaghir, Z.; Taher, Y.; Haque, R.; Hacid, M.-S.; and Zeineddine, H. 2019. An Experimental Study With Imbalanced Classification Approaches for Credit Card Fraud Detection. *IEEE Access*, 7: 93010–93022.
- Nguyen, H. M.; Cooper, E. W.; and Kamei, K. 2011. Borderline over-sampling for imbalanced data classification. *Int. J. Knowl. Eng. Soft Data Paradigm.*, 3(1): 4–21.
- Pradipta, G. A.; Wardoyo, R.; Musdholifah, A.; and Sanjaya, I. N. H. 2021. Radius-SMOTE: A New Oversampling Technique of Minority Samples Based on Radius Distance for Learning From Imbalanced Data. *IEEE Access*, 9: 74763–74777.
- Rosales-Pérez, A.; García, S.; and Herrera, F. 2023. Handling Imbalanced Classification Problems With Support Vector Machines via Evolutionary Bilevel Optimization. *IEEE Transactions on Cybernetics*, 53(8): 4735–4747. ArXiv:2204.10231 [cs].
- Sharma, A.; Singh, P. K.; and Chandra, R. 2022. SMOTified-GAN for Class Imbalanced Pattern Classification Problems. *IEEE Access*, 10: 30655–30665. Conference Name: IEEE Access.
- Singh, A.; Ranjan, R. K.; and Tiwari, A. 2022. Credit Card Fraud Detection under Extreme Imbalanced Data: A Comparative Study of Data-level Algorithms. *Journal of Experimental & Theoretical Artificial Intelligence*, 34(4): 571–598.
- Song, H.; Kim, M.; and Lee, J.-G. 2023. Toward Robustness in Multi-label Classification: A Data Augmentation Strategy against Imbalance and Noise. ArXiv:2312.07087 [cs].

- Strelcenia, E.; and Prakoonwit, S. 2023. A Survey on GAN Techniques for Data Augmentation to Address the Imbalanced Data Issues in Credit Card Fraud Detection. *Machine Learning and Knowledge Extraction*, 5(1): 304–329.
- Yang, Y.; Akbarzadeh Khorshidi, H.; and Aickelin, U. 2023. A Diversity-Based Synthetic Oversampling Using Clustering for Handling Extreme Imbalance. *SN Computer Science*, 4(6): 848.
- Zhang, H.; Cisse, M.; Dauphin, Y. N.; and Lopez-Paz, D. 2018. mixup: Beyond Empirical Risk Minimization. ArXiv:1710.09412 [cs, stat].
- Zhou, P.; Xiong, C.; Socher, R.; and Hoi, S. C. H. 2020. Theory-Inspired Path-Regularized Differential Network Architecture Search. In *Advances in Neural Information Processing Systems*, volume 33, 8296–8307. Curran Associates, Inc.