

DAFTAR PUSTAKA

- Alfeo, A. L., & Cimino, M. G. C. A. (2024). Counterfactual-Based Feature Importance for Explainable Regression of Manufacturing Production Quality Measure. *International Conference on Pattern Recognition Applications and Methods, 1*, 48–56. <https://doi.org/10.5220/0012369600003654>
- Alsagri, H., & Ykhlef, M. (2020). Quantifying feature importance for detecting depression using random forest. *International Journal of Advanced Computer Science and Applications, 11*(5), 628 – 635. <https://doi.org/10.14569/IJACSA.2020.0110577>
- Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Celar, L., & Byrne, R. M. J. (2023). How people reason with counterfactual and causal explanations for Artificial Intelligence decisions in familiar and unfamiliar domains. *Memory and Cognition, 51*(7), 1481–1496. <https://doi.org/10.3758/s13421-023-01407-5>
- Chandna, M. (2023). Ensemble Learning Based Electrical Load Prediction. *2023 International Conference on Power Energy, Environment and Intelligent Control, PEEIC SEMARANG 2023*, 74 – 77. <https://doi.org/10.1109/PEEIC59336.2023.10450323>
- Chandrasekaran, R., & Paramasivan, S. K. (2025). Advances in Deep Learning Techniques for Short-term Energy Load Forecasting Applications: A Review. *Archives of Computational Methods in Engineering, 32*(2), 663 – 692. <https://doi.org/10.1007/s11831-024-10155-x>
- Cheng, F., Ming, Y., & Qu, H. (2021). DECE: Decision Explorer with Counterfactual Explanations for Machine Learning Models. *IEEE Transactions on Visualization and Computer Graphics, 27*(2), 1438–1447. <https://doi.org/10.1109/TVCG.2020.3030342>

- Delaney, E. (2022). Case-based Explanation for Black-Box Time Series and Image Models with Applications in Smart Agriculture. *CEUR Workshop Proceedings*, 3418, 10–15.
- Ernesto, A. M. (2021). Short-term electricity load forecasting (Panama case study). *Mendeley Data*, (V1). <https://doi.org/10.17632/byx7sztj59.1>
- Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. Dalam *Cognitive Computation* (Vol. 16, Nomor 1, hlm. 45–74). Springer. <https://doi.org/10.1007/s12559-023-10179-8>
- Höllig, J., Markus, A. F., de Slegte, J., & Bagave, P. (2023). Semantic Meaningfulness: Evaluating Counterfactual Approaches for Real-World Plausibility and Feasibility. Dalam *Communications in Computer and Information Science: 1902 CCIS*. https://doi.org/10.1007/978-3-031-44067-0_32
- Höllig, J., Thoma, S., & Kulbach, C. (2022). Evolutionary Counterfactual Visual Explanation. *CEUR Workshop Proceedings*, 3457.
- Johannesen, N. J., Kolhe, M., & Goodwin, M. (2019). Relative evaluation of regression tools for urban area electrical energy demand forecasting. *Journal of Cleaner Production*, 218, 555 – 564. <https://doi.org/10.1016/j.jclepro.2019.01.108>
- Khan, A., & Rizwan, M. (2023). Load Forecasting Using Different Techniques. *Lecture Notes in Electrical Engineering*, 956, 131 – 151. https://doi.org/10.1007/978-981-19-6490-9_8
- Kommiya Mothilal, R., Mahajan, D., Tan, C., & Sharma, A. (2021). Towards Unifying Feature Attribution and Counterfactual Explanations: Different Means to the Same End. *AIES 2021 - Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, 652–663. <https://doi.org/10.1145/3461702.3462597>

- Lahouar, A., & Ben Hadj Slama, J. (2015). Day-ahead load forecast using random forest and expert input selection. *Energy Conversion and Management*, 103, 1040–1051. <https://doi.org/10.1016/j.enconman.2015.07.041>
- Liu, F. (2024). Financial Statement Analysis Based on RNN-RBM Model. *Journal of Electrical Systems*, 20(1). <https://doi.org/10.52783/jes.670>
- Magalhães, B., Bento, P., Pombo, J., Calado, M. do R., & Mariano, S. (2024). Short-Term Load Forecasting Based on Optimized Random Forest and Optimal Feature Selection. *Energies*, 17(8). <https://doi.org/10.3390/en17081926>
- Marzak, Z., Mouatassim, S., Benhra, J., & Benabbou, R. (2024). Contribution to Predicting Electricity Load using Random Forest. *2024 3rd International Conference on Embedded Systems and Artificial Intelligence, ESAI 2024*. <https://doi.org/10.1109/ESAI62891.2024.10913864>
- Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. Dalam *Artificial Intelligence* (Vol. 267, hlm. 1–38). Elsevier B.V. <https://doi.org/10.1016/j.artint.2018.07.007>
- Molnar, C. (2019). *Interpretable Machine Learning A Guide for Making Black Box Models Explainable*. <http://leanpub.com/interpretable-machine-learning>
- Mothilal, R. K., Sharma, A., & Tan, C. (2020). Explaining machine learning classifiers through diverse counterfactual explanations. *FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 607 – 617. <https://doi.org/10.1145/3351095.3372850>
- Piccialli, V., Romero Morales, D., & Salvatore, C. (2024). Supervised feature compression based on counterfactual analysis. *European Journal of Operational Research*, 317(2), 273 – 285. <https://doi.org/10.1016/j.ejor.2023.11.019>
- Prabhu, H., Sane, A., Dhadwal, R., Parlikkad, N. R., & Valadi, J. K. (2023). Interpretation of Drop Size Predictions from a Random Forest Model Using Local Interpretable Model-Agnostic Explanations (LIME) in a Rotating Disc Contactor. *Industrial and Engineering Chemistry Research*. <https://doi.org/10.1021/acs.iecr.3c00808>

- Rakesh, P., Shruti, J. R., Thippeswamy, I., Nithya, B. L., & Dheeraj, V. (2024). A Surrogate Approach to Explainable AI for Predictive Maintenance: Techniques and Applications. *5th International Conference on Circuits, Control, Communication and Computing, I4C 2024*, 160 – 165. <https://doi.org/10.1109/I4C62240.2024.10748524>
- Slack, D., Hilgard, S., Lakkaraju, H., & Singh, S. (2021). Counterfactual Explanations Can Be Manipulated. *Advances in Neural Information Processing Systems*, 1, 62 – 75. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85131724636&partnerID=40&md5=9d53e059a6617fc1bd4ca1ea18e5337f>
- Suffian, M., Alonso-Moral, J. M., & Bogliolo, A. (2024). Introducing User Feedback-Based Counterfactual Explanations (UFCE). *International Journal of Computational Intelligence Systems*, 17(1). <https://doi.org/10.1007/s44196-024-00508-6>
- Vannostrand, P. M., Hofmann, D. M., Ma, L., Genin, B., Huang, R., & Rundensteiner, E. A. (2024). Counterfactual Explanation Analytics: Empowering Lay Users to Take Action Against Consequential Automated Decisions. *Proceedings of the VLDB Endowment*, 17(12), 4349–4352. <https://doi.org/10.14778/3685800.3685872>
- Vasenin, D., Pasetti, M., Astolfi, D., Rinaldi, S., & Savvin, N. (2024). Enhancing Short-Term Load Forecasting Through Machine Learning Ensemble Models and by Incorporating Weather Data. *7th Edition Global Conference on Wireless and Optical Technologies, GCWOT 2024*. <https://doi.org/10.1109/GCWOT63882.2024.10805705>
- Wallace, M. L., Mentch, L., Wheeler, B. J., Tapia, A. L., Richards, M., Zhou, S., Yi, L., Redline, S., & Buysse, D. J. (2023). Use and misuse of random forest variable importance metrics in medicine: demonstrations through incident stroke prediction. *BMC Medical Research Methodology*, 23(1). <https://doi.org/10.1186/s12874-023-01965-x>

- Wang, H., Zhang, N., Du, E., Yan, J., Han, S., & Liu, Y. (2022). A comprehensive review for wind, solar, and electrical load forecasting methods. *Global Energy Interconnection*, 5(1), 9–30. <https://doi.org/10.1016/j.gloi.2022.04.002>
- Wang, Z., Miliou, I., Samsten, I., & Papapetrou, P. (2023). Counterfactual Explanations for Time Series Forecasting. *Proceedings - IEEE International Conference on Data Mining, ICDM*, 1391–1396. <https://doi.org/10.1109/ICDM58522.2023.00180>
- You, D., Niu, S., Dong, S., Yan, H., Chen, Z., Wu, D., Shen, L., & Wu, X. (2023). Counterfactual explanation generation with minimal feature boundary. *Information Sciences*, 625, 342 – 366. <https://doi.org/10.1016/j.ins.2023.01.012>
- Zhu, F., & Wu, G. (2021). Load forecasting of the power system: An investigation based on the method of random forest regression. *Energy Engineering: Journal of the Association of Energy Engineering*, 118(6), 1703 – 1712. <https://doi.org/10.32604/EE.2021.015602>
- Zuin, G., & Veloso, A. (2024). Navigating Time's Possibilities: Plausible Counterfactual Explanations for Multivariate Time-Series Forecast through Genetic Algorithms. *2024 IEEE 23rd International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, 2575–2582. <https://doi.org/10.1109/TrustCom63139.2024.00359>

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