

## DAFTAR PUSTAKA

- Abhilasha Narote, Abhijeet Pawar, Mansi Gaikwad, Tanuja Dalvi, & Purva Gondhalekar. (2022). Prediction of Diabetes Mellitus using Machine Learning. *International Journal of Advanced Research in Science, Communication and Technology*, 10(04), 17–20. <https://doi.org/10.48175/ijarsct-2988>
- Adem, K. (2020). Diagnosis of breast cancer with Stacked autoencoder and Subspace kNN. *Physica A: Statistical Mechanics and Its Applications*, 551, 124591. <https://doi.org/10.1016/j.physa.2020.124591>
- Aggarwal, C. C., Kong, X., Gu, Q., Han, J., & Yu, P. S. (2014). Active learning: A survey. *Data Classification: Algorithms and Applications*, 571–605. <https://doi.org/10.1201/b17320>
- Ali, H., Salleh, M. N. M., Saedudin, R., Hussain, K., & Mushtaq, M. F. (2019). Imbalance class problems in data mining: A review. *Indonesian Journal of Electrical Engineering and Computer Science*, 14(3), 1552–1563. <https://doi.org/10.11591/ijeecs.v14.i3.pp1552-1563>
- Alirezanejad, M., Enayatifar, R., Motameni, H., & Nematzadeh, H. (2020). Heuristic filter feature selection methods for medical datasets. *Genomics*, 112(2), 1173–1181. <https://doi.org/10.1016/j.ygeno.2019.07.002>
- Alkhasawneh, M. S. (2022). Software Defect Prediction through Neural Network and Feature Selections. *Applied Computational Intelligence and Soft Computing*, 2022, 1–16. <https://doi.org/10.1155/2022/2581832>
- Angel Viji, K. S., & Hevin Rajesh, D. (2019). An Efficient Technique to Segment the Tumor and Abnormality Detection in the Brain MRI Images Using KNN Classifier. *Materials Today: Proceedings*, 24, 1944–1954. <https://doi.org/10.1016/j.matpr.2020.03.622>
- Arslan, H., & Arslan, H. (2021). A new COVID-19 detection method from human genome sequences using CpG island features and KNN classifier. *Engineering Science and Technology, an International Journal*, 24(4), 839–847. <https://doi.org/10.1016/j.jestch.2020.12.026>
- Azuaje, F. (2006). Witten IH, Frank E: Data Mining: Practical Machine Learning Tools and Techniques 2nd edition. *BioMedical Engineering OnLine*, 5(1). <https://doi.org/10.1186/1475-925x-5-51>
- Bagui, S. C. (2005). Combining Pattern Classifiers: Methods and Algorithms. In *Technometrics* (Vol. 47, Issue 4). <https://doi.org/10.1198/tech.2005.s320>
- Bakri, R., Astuti, N. P., & Ahmar, A. S. (2022). Machine Learning Algorithms with Parameter Tuning to Predict Students' Graduation-on-time: A Case Study in Higher Education. *Journal of Applied Science, Engineering, Technology, and Education*, 4(2), 259–265. <https://doi.org/10.35877/454ri.asci1581>

- Barua, S., Islam, M. M., Yao, X., & Murase, K. (2014). MWMOTE - Majority weighted minority oversampling technique for imbalanced data set learning. *IEEE Transactions on Knowledge and Data Engineering*, 26(2), 405–425. <https://doi.org/10.1109/TKDE.2012.232>
- Bashir, S., Khattak, I. U., Khan, A., Khan, F. H., Gani, A., & Shiraz, M. (2022). A Novel Feature Selection Method for Classification of Medical Data Using Filters, Wrappers, and Embedded Approaches. *Complexity*, 2022. <https://doi.org/10.1155/2022/8190814>
- Basu, A., Roy, R., & Savitha, N. (2018). Performance Analysis of Regression and Classification Models in the Prediction of Breast Cancer. *Indian Journal of Science and Technology*, 11(3), 1–6. <https://doi.org/10.17485/ijst/2018/v11i3/119179>
- Beckmann, M., Ebecken, N. F. F., & Pires de Lima, B. S. L. (2015). A KNN Undersampling Approach for Data Balancing. *Journal of Intelligent Learning Systems and Applications*, 07(04), 104–116. <https://doi.org/10.4236/jilsa.2015.74010>
- Bekkar, M., Djemaa, H. K., & Alitouche, T. A. (2013). Evaluation Measures for Models Assessment over Imbalanced Data Sets. *Journal of Information Engineering and Applications*, 3(10), 27–38. <http://www.iiste.org/Journals/index.php/JIEA/article/view/7633>
- Bennett, R., Mulla, Z. D., Parikh, P., Hauspurg, A., & Razzaghi, T. (2022). An imbalance-aware deep neural network for early prediction of preeclampsia. In *PLoS ONE* (Vol. 17, Issue 4 April). <https://doi.org/10.1371/journal.pone.0266042>
- Bergstra, J., Bardenet, R., Bengio, Y., & Kégl, B. (2011). Algorithms for hyperparameter optimization. *Advances in Neural Information Processing Systems 24: 25th Annual Conference on Neural Information Processing Systems 2011, NIPS 2011*, 1–9.
- Bischl, B., Binder, M., Lang, M., Pielok, T., Richter, J., Coors, S., Thomas, J., Ullmann, T., Becker, M., Boulesteix, A. L., Deng, D., & Lindauer, M. (2023). Hyperparameter optimization: Foundations, algorithms, best practices, and open challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 13(2), 1–43. <https://doi.org/10.1002/widm.1484>
- Borowska, K., & Stepianiuk, J. (2016). Imbalanced data classification: A novel re-sampling approach combining versatile improved SMOTE and rough sets. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 9842 LNCS(1), 31–42. [https://doi.org/10.1007/978-3-319-45378-1\\_4](https://doi.org/10.1007/978-3-319-45378-1_4)
- Bunkhumpornpat, C., Sinapiromsaran, K., & Lursinsap, C. (2009). Safe-level-SMOTE: Safe-level-synthetic minority over-sampling technique for handling the class imbalanced problem. *Lecture Notes in Computer Science (Including*

*Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*), 5476 LNAI, 475–482. [https://doi.org/10.1007/978-3-642-01307-2\\_43](https://doi.org/10.1007/978-3-642-01307-2_43)

- Carreno, J. F., & Qiu, P. (2020). Feature selection algorithms for predicting preeclampsia: A comparative approach. *Proceedings - 2020 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2020*, 2626–2631. <https://doi.org/10.1109/BIBM49941.2020.9313108>
- Chawla, N. V., Japkowicz, N., & Kotcz, A. (2004). Editorial. *ACM SIGKDD Explorations Newsletter*, 6(1), 1–6. <https://doi.org/10.1145/1007730.1007733>
- Chen, H., Li, T., Fan, X., & Luo, C. (2019). Feature selection for imbalanced data based on neighborhood rough sets. *Information Sciences*, 483, 1–20. <https://doi.org/10.1016/j.ins.2019.01.041>
- Chen, Z., Duan, J., Kang, L., & Qiu, G. (2021). A hybrid data-level ensemble to enable learning from highly imbalanced dataset. *Information Sciences*, 554, 157–176. <https://doi.org/10.1016/j.ins.2020.12.023>
- Chopra, D., & Khurana, R. (2023). Introduction to Machine Learning with Python. In *Introduction to Machine Learning with Python*. <https://doi.org/10.2174/97898151244221230101>
- Datta, P., Das, P., & Kumar, A. (2022). Hyper parameter tuning based gradient boosting algorithm for detection of diabetic retinopathy: an analytical review. *Bulletin of Electrical Engineering and Informatics*, 11(2), 814–824. <https://doi.org/10.11591/eei.v11i2.3559>
- Dimitriadis, E., Rolnik, D. L., Zhou, W., Estrada-Gutierrez, G., Koga, K., Francisco, R. P. V., Whitehead, C., Hyett, J., da Silva Costa, F., Nicolaides, K., & Menkhorst, E. (2023). Pre-eclampsia. *Nature Reviews Disease Primers*, 9(1), 1–22. <https://doi.org/10.1038/s41572-023-00417-6>
- Ding, H., Chen, L., Dong, L., Fu, Z., & Cui, X. (2022). Imbalanced data classification: A KNN and generative adversarial networks-based hybrid approach for intrusion detection. *Future Generation Computer Systems*, 131, 240–254. <https://doi.org/10.1016/j.future.2022.01.026>
- Douzas, G., Bacao, F., & Last, F. (2018). Improving imbalanced learning through a heuristic oversampling method based on k-means and SMOTE. *Information Sciences*, 465, 1–20. <https://doi.org/10.1016/j.ins.2018.06.056>
- Drosou, K., & Koukouvinos, C. (2017). Proximal support vector machine techniques on medical prediction outcome. *Journal of Applied Statistics*, 44(3), 533–553. <https://doi.org/10.1080/02664763.2016.1177499>
- Farzaneh, F., Tavakolikia, Z., & Soleimanzadeh Mousavi, S. H. (2019). Assessment of occurrence of preeclampsia and some clinical and demographic risk factors in Zahedan city in 2017. *Clinical and Experimental Hypertension*, 41(6), 583–588. <https://doi.org/10.1080/10641963.2018.1523919>

- Fox, R., Kitt, J., Leeson, P., Aye, C. Y. L., & Lewandowski, A. J. (2019). *Preeclampsia: Risk Factors, Diagnosis, Management, and the Cardiovascular Impact on the Offspring*. 1–22.
- Fuadah, Y. N., Pramudito, M. A., & Lim, K. M. (2023). An Optimal Approach for Heart Sound Classification Using Grid Search in Hyperparameter Optimization of Machine Learning. *Bioengineering*, 10(1). <https://doi.org/10.3390/bioengineering10010045>
- Gan, D., Shen, J., An, B., Xu, M., & Liu, N. (2020). Integrating TANBN with cost sensitive classification algorithm for imbalanced data in medical diagnosis. *Computers and Industrial Engineering*, 140(December 2019), 106266. <https://doi.org/10.1016/j.cie.2019.106266>
- García-García, J. C., & García-Ródenas, R. (2021). A methodology for automatic parameter-tuning and center selection in density-peak clustering methods. *Soft Computing*, 25(2), 1543–1561. <https://doi.org/10.1007/s00500-020-05244-5>
- García, V., Sánchez, J. S., & Mollineda, R. A. (2012). On the effectiveness of preprocessing methods when dealing with different levels of class imbalance. *Knowledge-Based Systems*, 25(1), 13–21. <https://doi.org/10.1016/j.knosys.2011.06.013>
- Gbenga, D. E., Christopher, N., & Yetunde, D. C. (2017). Performance Comparison of Machine Learning Techniques for Breast Cancer Detection. *Nova Journal of Engineering and Applied Sciences*, 6(1), 1–8. <https://doi.org/10.20286/nova-jeas-060105>
- Géron, A. (2019). Hands-on Machine Learning with Scikit-Learning, Keras and Tensorflow. In *O'Reilly Media, Inc.*
- Gorunescu, F. (2011). *Data Mining - Intelligent Systems Reference Library*. 364. <https://link.springer.com/book/10.1007/978-3-642-19721-5>
- Guido, R., Groccia, M. C., & Conforti, D. (2022). A hyper-parameter tuning approach for cost-sensitive support vector machine classifiers. *Soft Computing*, 27(18), 12863–12881. <https://doi.org/10.1007/s00500-022-06768-8>
- Haixiang, G., Yijing, L., Shang, J., Mingyun, G., Yuanyue, H., & Bing, G. (2017). Learning from class-imbalanced data: Review of methods and applications. *Expert Systems with Applications*, 73, 220–239. <https://doi.org/10.1016/j.eswa.2016.12.035>
- Haixiang, G., Yijing, L., Yanan, L., Xiao, L., & Jinling, L. (2016). BPSO-Adaboost-KNN ensemble learning algorithm for multi-class imbalanced data classification. *Engineering Applications of Artificial Intelligence*, 49, 176–193. <https://doi.org/10.1016/j.engappai.2015.09.011>
- Han, H., Wang, W., & Mao, B. (2005). *Borderline-SMOTE: A New Over-Sampling Method in*. 878–887.
- Hartono, & Ongko, E. (2022). Avoiding Overfitting dan Overlapping in Handling

- Class Imbalanced Using Hybrid Approach with Smoothed Bootstrap Resampling and Feature Selection. *International Journal on Informatics Visualization*, 6(2), 343–348. <https://doi.org/10.30630/joiv.6.2.985>
- He, Haibo, & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9), 1263–1284. <https://doi.org/10.1109/TKDE.2008.239>
- He, Hongliang, Zhang, W., & Zhang, S. (2018). A novel ensemble method for credit scoring: Adaption of different imbalance ratios. *Expert Systems with Applications*, 98, 105–117. <https://doi.org/10.1016/j.eswa.2018.01.012>
- Hossain, R., & Timmer, D. D. (2021). Machine learning model optimization with hyper parameter tuning approach. *Global Journal of Computer Science and Technology*, 21(2), 7–13.
- Hussein, A. S., Li, T., Yohannese, C. W., & Bashir, K. (2019). A-SMOTE: A new preprocessing approach for highly imbalanced datasets by improving SMOTE. *International Journal of Computational Intelligence Systems*, 12(2), 1412–1422. <https://doi.org/10.2991/ijcis.d.191114.002>
- Islam, A., Belhaouari, S. B., Rehman, A. U., & Bensmail, H. (2022). KNNOR: An oversampling technique for imbalanced datasets[Formula presented]. *Applied Soft Computing*, 115, 108288. <https://doi.org/10.1016/j.asoc.2021.108288>
- Jain, D., & Singh, V. (2018a). Feature selection and classification systems for chronic disease prediction: A review. *Egyptian Informatics Journal*, 19(3), 179–189. <https://doi.org/10.1016/j.eij.2018.03.002>
- Jain, D., & Singh, V. (2018b). Feature selection and classification systems for chronic disease prediction: A review. *Egyptian Informatics Journal*, 19(3), 179–189. <https://doi.org/10.1016/j.eij.2018.03.002>
- Jhee, J. H., Lee, S., Park, Y., Lee, S. E., Kim, Y. A., Kang, W., Kwon, J., & Park, J. T. (2019). *Prediction model development of late-onset preeclampsia using machine learning-based methods*. 1–12.
- Jian, C., Gao, J., & Ao, Y. (2016). A new sampling method for classifying imbalanced data based on support vector machine ensemble. *Neurocomputing*, 193, 115–122. <https://doi.org/10.1016/j.neucom.2016.02.006>
- Jin, H. (2022). *Hyperparameter Importance for Machine Learning Algorithms*. 1–8. <http://arxiv.org/abs/2201.05132>
- Kaur, H., Pannu, H. S., & Malhi, A. K. (2019). A systematic review on imbalanced data challenges in machine learning: Applications and solutions. *ACM Computing Surveys*, 52(4). <https://doi.org/10.1145/3343440>
- Khaldy, M. Al, & Kambhampati, C. (2018). *Resampling imbalanced class and the effectiveness of feature selection methods for heart failure dataset*. 4(1), 37–45. <https://doi.org/10.15406/iratj.2018.04.00090>

- Khan, S., Khan, A., Maqsood, M., Aadil, F., & Ghazanfar, M. A. (2019). Optimized Gabor Feature Extraction for Mass Classification Using Cuckoo Search for Big Data E-Healthcare. *Journal of Grid Computing*, 17(2), 239–254. <https://doi.org/10.1007/s10723-018-9459-x>
- Kong, J., Kowalczyk, W., Nguyen, D. A., Back, T., & Menzel, S. (2019). Hyperparameter Optimisation for Improving Classification under Class Imbalance. *2019 IEEE Symposium Series on Computational Intelligence, SSCI 2019*, 3072–3078. <https://doi.org/10.1109/SSCI44817.2019.9002679>
- Kraiem, M. S., Sánchez-Hernández, F., & Moreno-García, M. N. (2021). Selecting the suitable resampling strategy for imbalanced data classification regarding dataset properties. An approach based on association models. *Applied Sciences (Switzerland)*, 11(18). <https://doi.org/10.3390/app11188546>
- Landset, S., Khoshgoftaar, T. M., Richter, A. N., & Hasanin, T. (2015). A survey of open source tools for machine learning with big data in the Hadoop ecosystem. *Journal of Big Data*, 1–36. <https://doi.org/10.1186/s40537-015-0032-1>
- Li, J., Zhu, Q., & Wu, Q. (2020). A parameter-free hybrid instance selection algorithm based on local sets with natural neighbors. *Applied Intelligence*, 50(5), 1527–1541. <https://doi.org/10.1007/s10489-019-01598-y>
- Li, J., Zhu, Q., Wu, Q., & Fan, Z. (2021). A novel oversampling technique for class-imbalanced learning based on SMOTE and natural neighbors. *Information Sciences*, 565, 438–455. <https://doi.org/10.1016/j.ins.2021.03.041>
- Li, Y. xin, Shen, X. ping, Yang, C., Cao, Z. zeng, Du, R., Yu, M. da, Wang, J. ping, & Wang, M. (2021). Novel electronic health records applied for prediction of pre-eclampsia: Machine-learning algorithms. *Pregnancy Hypertension*, 26(August), 102–109. <https://doi.org/10.1016/j.preghy.2021.10.006>
- Lin, Y. C., Mallia, D., Clark-Sevilla, A. O., Catto, A., Leshchenko, A., Haas, D. M., Wapner, R., Pe'er, I., Raja, A., & Salleb-Aouissi, A. (2022). Preeclampsia Predictor with Machine Learning: A Comprehensive and Bias-Free Machine Learning Pipeline. *MedRxiv*, 2022.06.08.22276107.
- Liu, J., & Zio, E. (2019). Integration of feature vector selection and support vector machine for classification of imbalanced data. *Applied Soft Computing Journal*, 75, 702–711. <https://doi.org/10.1016/j.asoc.2018.11.045>
- Liu, M., Yang, X., Chen, G., Ding, Y., Shi, M., Sun, L., Huang, Z., Liu, J., Liu, T., Yan, R., & Li, R. (2022). Development of a prediction model on preeclampsia using machine learning-based method: a retrospective cohort study in China. *Frontiers in Physiology*, 13(August), 1–9. <https://doi.org/10.3389/fphys.2022.896969>
- Liu, N., Li, X., Qi, E., Xu, M., Li, L., & Gao, B. (2020). A novel ensemble learning paradigm for medical diagnosis with imbalanced data. *IEEE Access*, 8, 171263–171280. <https://doi.org/10.1109/ACCESS.2020.3014362>

- Macarena Espinilla, 1 Javier Medina, 1 Ángel-Luis García-Fernández, 1 Sixto Campaña, 2 and Jorge Londoño<sup>3</sup>. (2017). Fuzzy Intelligent System for Patients with Preeclampsia in Wearable Devices. *Mobile Information Systems*, 2017. <https://doi.org/10.1155/2017/7838464>
- Mahfouz, M. A., Shoukry, A., & Ismail, M. A. (2021). EKNN: Ensemble classifier incorporating connectivity and density into kNN with application to cancer diagnosis. *Artificial Intelligence in Medicine*, 111(December 2019), 101985. <https://doi.org/10.1016/j.artmed.2020.101985>
- Manoochehri, Z., Manoochehri, S., Soltani, F., Tapak, L., & Sadeghifar, M. (2021). Predicting preeclampsia and related risk factors using data mining approaches: A cross-sectional study. *International Journal of Reproductive BioMedicine*, 19(11), 959–968. <https://doi.org/10.18502/ijrm.v19i11.9911>
- Mantovani, R. G., Horvath, T., Cerri, R., Vanschoren, J., & De Carvalho, A. C. P. L. F. (2017). Hyper-Parameter Tuning of a Decision Tree Induction Algorithm. *Proceedings - 2016 5th Brazilian Conference on Intelligent Systems, BRACIS 2016*, 37–42. <https://doi.org/10.1109/BRACIS.2016.018>
- Marić, I., Tsur, A., Aghaeepour, N., Montanari, A., Stevenson, D. K., Shaw, G. M., & Winn, V. D. (2020). Early prediction of preeclampsia via machine learning. *American Journal of Obstetrics and Gynecology MFM*, 2(2), 100100. <https://doi.org/10.1016/j.ajogmf.2020.100100>
- Marin, I., Pavaloiu, B. I., Marian, C. V., Racovita, V., & Goga, N. (2019). Early detection of preeclampsia based on a machine learning approach. *2019 7th E-Health and Bioengineering Conference, EHB 2019*, 23–26. <https://doi.org/10.1109/EHB47216.2019.8970025>
- Maroco, J., Silva, D., Rodrigues, A., Guerreiro, M., Santana, I., & De Mendonça, A. (2011). Data mining methods in the prediction of Dementia: A real-data comparison of the accuracy, sensitivity and specificity of linear discriminant analysis, logistic regression, neural networks, support vector machines, classification trees and random forests. *BMC Research Notes*, 4(1), 299. <https://doi.org/10.1186/1756-0500-4-299>
- Martel, A. (2023). *Distance rank score: unsupervised filter method for feature selection on imbalanced dataset*. 1–14.
- Mayrink, J., Costa, M. L., & Cecatti, J. G. (2018). Preeclampsia in 2018: Revisiting Concepts, Physiopathology, and Prediction. *Scientific World Journal*, 2018. <https://doi.org/10.1155/2018/6268276>
- Mera-Gaona, M., López, D. M., Vargas-Canas, R., & Neumann, U. (2021). Framework for the ensemble of feature selection methods. *Applied Sciences (Switzerland)*, 11(17), 1–16. <https://doi.org/10.3390/app11178122>
- Mienye, I. D., & Sun, Y. (2021). Performance analysis of cost-sensitive learning methods with application to imbalanced medical data. *Informatics in Medicine Unlocked*, 25, 100690. <https://doi.org/10.1016/j.imu.2021.100690>

- Mikat, B., Gellhaus, A., Wagner, N., Birdir, C., & Kimmig, R. (2012). *Early Detection of Maternal Risk for Preeclampsia*. 2012. <https://doi.org/10.5402/2012/172808>
- Modak, R., Pal, A., Pal, A., & Ghosh, M. K. (2020). Prediction of preeclampsia by a combination of maternal spot urinary protein-creatinine ratio and uterine artery doppler. *International Journal of Reproduction, Contraception, Obstetrics and Gynecology*, 9(2), 635. <https://doi.org/10.18203/2320-1770.ijrcog20200350>
- Moeloek, A., Lampung, P., Januari, P., Aulia, D., Graharti, R., Kedokteran, F., Lampung, U., Obstetrik, B., Kedokteran, F., Lampung, U., Klinik, B. P., Kedokteran, F., & Lampung, U. (2019). *Hubungan Diabetes Melitus dengan Kejadian Preeklampsia di RSUD DR . H . Relationship between Diabetes Mellitus with The Incidence of Preeclampsia in RSUD DR . H . Abdul Moeloek Lampung on The Period*. 8, 180–186.
- Moghadas, E., Rezazadeh, J., & Farahbakhsh, R. (2020). An IoT patient monitoring based on fog computing and data mining: Cardiac arrhythmia usecase. *Internet of Things (Netherlands)*, 11. <https://doi.org/10.1016/j.iot.2020.100251>
- Morais, R. F. A. B. De, & Vasconcelos, G. C. (2017). *Under-Sampling the Minority Class to Improve the Performance of Over-Sampling Algorithms in Imbalanced Data Sets Under-Sampling the Minority Class to Improve the Performance of Over-Sampling Algorithms in Imbalanced Data Sets*. September.
- Moreira, M. W. L., Rodrigues, J. J. P. C., Oliveira, A. M. B., Ramos, R. F., & Saleem, K. (2016). A preeclampsia diagnosis approach using Bayesian networks. *2016 IEEE International Conference on Communications, ICC 2016*. <https://doi.org/10.1109/ICC.2016.7510893>
- Moreno-Ibarra, M. A., Villuendas-Rey, Y., Lytras, M. D., Yáñez-Márquez, C., & Salgado-Ramírez, J. C. (2021). Classification of diseases using machine learning algorithms: A comparative study. *Mathematics*, 9(15), 1–21. <https://doi.org/10.3390/math9151817>
- Mueni, F., & Mwangi, M. (2019). *Informatics in Medicine Unlocked A 24-hour ambulatory blood pressure monitoring system for preeclampsia management in antenatal care*. 16(May). <https://doi.org/10.1016/j.imu.2019.100199>
- Musyoka, F. M., Thiga, M. M., & Muketha, G. M. (2019). A 24-hour ambulatory blood pressure monitoring system for preeclampsia management in antenatal care. *Informatics in Medicine Unlocked*, 16(June). <https://doi.org/10.1016/j.imu.2019.100199>
- Nagarajan, S. M., Muthukumar, V., Murugesan, R., Joseph, R. B., & Munirathanam, M. (2021). Feature selection model for healthcare analysis and classification using classifier ensemble technique. *International Journal of Systems Assurance Engineering and Management*.

<https://doi.org/10.1007/s13198-021-01126-7>

- Nair, P., & Kashyap, I. (2019). Optimization of kNN classifier using hybrid preprocessing model for handling imbalanced data. *International Journal of Engineering Research and Technology*, *12*(5), 697–704.
- Navaratnam, K., Alfirevic, Z., Baker, P. N., Glud, C., Grüttner, B., Kublickiene, K., Zeeman, G., & Kenny, L. C. (2013). A multi-centre phase IIa clinical study of predictive testing for preeclampsia: Improved pregnancy outcomes via early detection (IMPROvED). *BMC Pregnancy and Childbirth*, *13*, 1–7. <https://doi.org/10.1186/1471-2393-13-226>
- Nwe, M. M., & Lynn, K. T. (2020). KNN-Based Overlapping Samples Filter Approach for Classification of Imbalanced Data. In *Studies in Computational Intelligence* (Vol. 845). Springer International Publishing. [https://doi.org/10.1007/978-3-030-24344-9\\_4](https://doi.org/10.1007/978-3-030-24344-9_4)
- Obstetri, P. (2016). *PRE-EKLAMSIA*.
- Pan, Z., Wang, Y., & Ku, W. (2017). A new k-harmonic nearest neighbor classifier based on the multi-local means. *Expert Systems with Applications*, *67*, 115–125. <https://doi.org/10.1016/j.eswa.2016.09.031>
- Panda, B. (2020). *A survey on application of Population Based Algorithm on Hyperparameter Selection*. April. <https://doi.org/10.13140/RG.2.2.11820.21128>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.
- Piri, S., Delen, D., & Liu, T. (2018). A synthetic informative minority over-sampling (SIMO) algorithm leveraging support vector machine to enhance learning from imbalanced datasets. *Decision Support Systems*, *106*(April 2023), 15–29. <https://doi.org/10.1016/j.dss.2017.11.006>
- Rajesh, K. N. V. P. S., & Dhuli, R. (2018). Classification of imbalanced ECG beats using re-sampling techniques and AdaBoost ensemble classifier. *Biomedical Signal Processing and Control*, *41*, 242–254. <https://doi.org/10.1016/j.bspc.2017.12.004>
- Ramos-pérez, I., Arnaiz-gonzález, Á., Rodríguez, J. J., & García-osorio, C. (2022). *When is resampling beneficial for feature selection with imbalanced wide data ? 188*.
- Rana, S., Lemoine, E., Granger, J., & Karumanchi, S. A. (2019). Preeclampsia: Pathophysiology, Challenges, and Perspectives. *Circulation Research*, *124*(7), 1094–1112. <https://doi.org/10.1161/CIRCRESAHA.118.313276>
- Rekha, G., Tyagi, A. K., & Reddy, V. K. (2019). A wide scale classification of class

- imbalance problem and its solutions: A systematic literature review. *Journal of Computer Science*, 15(7), 886–929. <https://doi.org/10.3844/jcssp.2019.886.929>
- Rezende, K. B. de C., Cunha, A. J. L. A. da, Pritsivelis, C., Faleiro, E. C., Amim Junior, J., & Bornia, R. G. (2019). How do maternal factors impact preeclampsia prediction in Brazilian population? *Journal of Maternal-Fetal and Neonatal Medicine*, 32(7), 1051–1056. <https://doi.org/10.1080/14767058.2017.1399115>
- Rokotyanskaya, E. A., Panova, I. A., Malyshkina, A. I., Fetisova, I. N., Fetisov, N. S., Kharlamova, N. V., & Kuligina, M. V. (2020). Technologies for prediction of preeclampsia. *Sovremennye Tehnologii v Medicine*, 12(5), 78–86. <https://doi.org/10.17691/stm2020.12.5.09>
- Sáez, J. A., Luengo, J., Stefanowski, J., & Herrera, F. (2015). SMOTE-IPF: Addressing the noisy and borderline examples problem in imbalanced classification by a re-sampling method with filtering. *Information Sciences*, 291(C), 184–203. <https://doi.org/10.1016/j.ins.2014.08.051>
- Saranya, G., & Pravin, A. (2024). Grid Search based Optimum Feature Selection by Tuning hyperparameters for Heart Disease Diagnosis in Machine learning. *The Open Biomedical Engineering Journal*, 17(1), 1–13. <https://doi.org/10.2174/18741207-v17-e230510-2022-ht28-4371-8>
- Serra, B., Mendoza, M., Scazzocchio, E., Meler, E., Nolla, M., Sabrià, E., Rodríguez, I., & Carreras, E. (2020). A new model for screening for early-onset preeclampsia. *American Journal of Obstetrics and Gynecology*, 222(6), 608.e1-608.e18. <https://doi.org/10.1016/j.ajog.2020.01.020>
- Shaban, W. M., Rabie, A. H., Saleh, A. I., & Abo-Elsoud, M. A. (2020). A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier. *Knowledge-Based Systems*, 205, 106270. <https://doi.org/10.1016/j.knosys.2020.106270>
- Shardlow, M. (2016). An Analysis of Feature Selection Techniques. *The University of Manchester*, 14(1), 1–7.
- Shi, Z. (2020). Improving k-Nearest Neighbors Algorithm for Imbalanced Data Classification. *IOP Conference Series: Materials Science and Engineering*, 719(1). <https://doi.org/10.1088/1757-899X/719/1/012072>
- Simbolon, O., Widyawati, M. N., Kurnianingsih, K., Kubota, N., & Ng, N. (2020). Predicting the Risk of Preeclampsia using Soft Voting-based Ensemble and Its Recommendation. *2020 International Symposium on Community-Centric Systems, CcS 2020*. <https://doi.org/10.1109/CcS49175.2020.9231400>
- Singh, N. D., & Dhall, A. (2018). *Clustering and Learning from Imbalanced Data*. 1–9. <http://arxiv.org/abs/1811.00972>
- Soongsatitanon, A., & Phupong, V. (2022). Prediction of preeclampsia using first

- trimester placental protein 13 and uterine artery Doppler. *Journal of Maternal-Fetal and Neonatal Medicine*, 35(22), 4412–4417. <https://doi.org/10.1080/14767058.2020.1849127>
- Sufriyana, H., Wu, Y. W., & Su, E. C. Y. (2020). Artificial intelligence-assisted prediction of preeclampsia: Development and external validation of a nationwide health insurance dataset of the BPJS Kesehatan in Indonesia. *EBioMedicine*, 54. <https://doi.org/10.1016/j.ebiom.2020.102710>
- Sun, Y., Wong, A. K. C., & Kamel, M. S. (2009). Classification of imbalanced data: A review. *International Journal of Pattern Recognition and Artificial Intelligence*, 23(4), 687–719. <https://doi.org/10.1142/S0218001409007326>
- Suprihatin, E., & Wuryaningsih, S. H. (2019). *Prediksi Preeklampsia Secara Dini Melalui Pengukuran Body Mass Index , Mean Arterial Pressure , Dan Roll Over Test Di Puskesmas Pacar Keling Surabaya*. 11–14.
- Tahir, M., Badriyah, T., & Syarif, I. (2018). Classification Algorithms of Maternal Risk Detection For Preeclampsia With Hypertension During Pregnancy Using Particle Swarm Optimization. *EMITTER International Journal of Engineering Technology*, 6(2), 236–253. <https://doi.org/10.24003/emitter.v6i2.287>
- Tarimo, C. S., Bhuyan, S. S., Li, Q., Ren, W., Mahande, M. J., & Wu, J. (2021). Combining resampling strategies and ensemble machine learning methods to enhance prediction of neonates with a low apgar score after induction of labor in Northern Tanzania. *Risk Management and Healthcare Policy*, 14(September), 3711–3720. <https://doi.org/10.2147/RMHP.S331077>
- Taunk, K. (2019). 2019 International Conference on Intelligent Computing and Control Systems, ICCS 2019. *2019 International Conference on Intelligent Computing and Control Systems, ICCS 2019, Iccics*, 1255–1260.
- Thakur, S., Dharavath, R., & Edla, D. R. (2020). Spark and Rule-KNN based scalable machine learning framework for EEG deceit identification. *Biomedical Signal Processing and Control*, 58, 101886. <https://doi.org/10.1016/j.bspc.2020.101886>
- Thammasiri, D., Delen, D., Meesad, P., & Kasap, N. (2014). A critical assessment of imbalanced class distribution problem: The case of predicting freshmen student attrition. *Expert Systems with Applications*, 41(2), 321–330. <https://doi.org/10.1016/j.eswa.2013.07.046>
- Uddin, S., Haque, I., Lu, H., Moni, M. A., & Gide, E. (2022). Comparative performance analysis of K-nearest neighbour (KNN) algorithm and its different variants for disease prediction. *Scientific Reports*, 12(1), 1–11. <https://doi.org/10.1038/s41598-022-10358-x>
- Upadhyay, K., & Kaur, P. (2021). A Review on Data level Approaches to address the Class Imbalance Problem. *International Conference on Challenges in Engineering Science and Technology*, April.

- Urbanowicz, R. J., Meeker, M., La Cava, W., Olson, R. S., & Moore, J. H. (2018). Relief-based feature selection: Introduction and review. *Journal of Biomedical Informatics*, 85(June), 189–203. <https://doi.org/10.1016/j.jbi.2018.07.014>
- Valarmathi, R., & Sheela, T. (2021). Heart disease prediction using hyper parameter optimization (HPO) tuning. *Biomedical Signal Processing and Control*, 70(July), 103033. <https://doi.org/10.1016/j.bspc.2021.103033>
- Vijayashree, J., & Sultana, H. P. (2018). A Machine Learning Framework for Feature Selection in Heart Disease Classification Using Improved Particle Swarm Optimization with Support Vector Machine Classifier. *Programming and Computer Software*, 44(6), 388–397. <https://doi.org/10.1134/S0361768818060129>
- Wah, Y. B., Rahman, H. A. A., He, H., & Bulgiba, A. (2016). Handling imbalanced dataset using SVM and k-NN approach. *AIP Conference Proceedings*, 1750(June 2016). <https://doi.org/10.1063/1.4954536>
- Wang, J., & Wang, A. (2023). *Python Tutorial*. 11–41. [https://doi.org/10.1007/978-3-031-17646-3\\_2](https://doi.org/10.1007/978-3-031-17646-3_2)
- Wang, M., Wei, Z., Jia, M., Chen, L., & Ji, H. (2022). Deep learning model for multi-classification of infectious diseases from unstructured electronic medical records. *BMC Medical Informatics and Decision Making*, 22(1), 1–13. <https://doi.org/10.1186/s12911-022-01776-y>
- Wang, W., & Sun, D. (2021). The improved AdaBoost algorithms for imbalanced data classification. *Information Sciences*, 563, 358–374. <https://doi.org/10.1016/j.ins.2021.03.042>
- Wang, Y., Wei, Y., Yang, H., Li, J., Zhou, Y., & Wu, Q. (2020). Utilizing imbalanced electronic health records to predict acute kidney injury by ensemble learning and time series model. *BMC Medical Informatics and Decision Making*, 20(1), 1–13. <https://doi.org/10.1186/s12911-020-01245-4>
- Wang, Z., Jia, P., Xu, X., Wang, B., Zhu, Y., & Li, D. (2021). Sample and feature selecting based ensemble learning for imbalanced problems. *Applied Soft Computing*, 113, 107884. <https://doi.org/10.1016/j.asoc.2021.107884>
- Weissgerber, T. L., & Mudd, L. M. (2015). Preeclampsia and Diabetes. *Current Diabetes Reports*, 15(3). <https://doi.org/10.1007/s11892-015-0579-4>
- Wirth, R., & Hipp, J. (2000). CRISP-DM: towards a standard process model for data mining. Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining, 29-39. *Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining*, 24959, 29–39. [https://www.researchgate.net/publication/239585378\\_CRISP-DM\\_Towards\\_a\\_standard\\_process\\_model\\_for\\_data\\_mining](https://www.researchgate.net/publication/239585378_CRISP-DM_Towards_a_standard_process_model_for_data_mining)
- Xu, Z., Shen, D., Nie, T., & Kou, Y. (2020a). A hybrid sampling algorithm

- combining M-SMOTE and ENN based on Random forest for medical imbalanced data. *Journal of Biomedical Informatics*, 107(May 2019), 103465. <https://doi.org/10.1016/j.jbi.2020.103465>
- Xu, Z., Shen, D., Nie, T., & Kou, Y. (2020b). A hybrid sampling algorithm combining M-SMOTE and ENN based on Random forest for medical imbalanced data. *Journal of Biomedical Informatics*, 107(May), 103465. <https://doi.org/10.1016/j.jbi.2020.103465>
- Xu, Z., Shen, D., Nie, T., Kou, Y., Yin, N., & Han, X. (2021). A cluster-based oversampling algorithm combining SMOTE and k-means for imbalanced medical data. *Information Sciences*, 572, 574–589. <https://doi.org/10.1016/j.ins.2021.02.056>
- Yildirim, M., & Cinar, A. (2020). Classification of Alzheimer's disease MRI images with CNN based hybrid method. *Ingenierie Des Systemes d'Information*, 25(4), 413–418. <https://doi.org/10.18280/isi.250402>
- Yu, T., & Zhu, H. (2020). *Hyper-Parameter Optimization: A Review of Algorithms and Applications*. 1–56. <http://arxiv.org/abs/2003.05689>
- Zhang, F., Petersen, M., Johnson, L., Hall, J., & O'bryant, S. E. (2022). Hyperparameter Tuning with High Performance Computing Machine Learning for Imbalanced Alzheimer's Disease Data. *Applied Sciences (Switzerland)*, 12(13). <https://doi.org/10.3390/app12136670>
- Zhang, J., Han, L., Li, W., Chen, Q., Lei, J., Long, M., Yang, W., Li, W., Zeng, L., & Zeng, S. (2019). Early prediction of preeclampsia and small-for-gestational-age via multi-marker model in Chinese pregnancies: A prospective screening study. *BMC Pregnancy and Childbirth*, 19(1), 1–10. <https://doi.org/10.1186/s12884-019-2455-8>
- Zhang, X., Chen, Y., Salerno, S., Li, Y., Zhou, L., Zeng, X., & Li, H. (2022). Prediction of severe preeclampsia in machine learning. *Medicine in Novel Technology and Devices*, 15(July). <https://doi.org/10.1016/j.medntd.2022.100158>
- Zhang, Y., Cao, G., Wang, B., & Li, X. (2019). A novel ensemble method for k-nearest neighbor. *Pattern Recognition*, 85, 13–25. <https://doi.org/10.1016/j.patcog.2018.08.003>
- Zhang, Z. (2016). Introduction to machine learning: K-nearest neighbors. *Annals of Translational Medicine*, 4(11). <https://doi.org/10.21037/atm.2016.03.37>
- Zhu, C., & Wang, Z. (2017). Entropy-based matrix learning machine for imbalanced data sets. *Pattern Recognition Letters*, 88, 72–80. <https://doi.org/10.1016/j.patrec.2017.01.014>