

## DAFTAR PUSTAKA

- Al-Barazanchi, H., Verma, A., and Wang, S. X. (2018). Intelligent plankton image classification with deep learning. *International Journal of Computational Vision and Robotics*, 8(6):561–571.
- Anderson, D. M., Cembella, A. D., and Hallegraeff, G. M. (2012). Progress in understanding harmful algal blooms: Paradigm shifts and new technologies for research, monitoring, and management. *Annual Review of Marine Science*, 4(1):143–176.
- Ardhi, O. D. W., Soeprobowati, T. R., Adi, K., Prakasa, E., and Rachman, A. (2022). Deep learning methods for plankton identification: A bibliometric analysis and general review. In *2022 1st International Conference on Smart Technology, Applied Informatics, and Engineering (APICS)*, pages 96–101.
- Ardhi, O. D. W., Soeprobowati, T. R., Adi, K., Prakasa, E., and Rachman, A. (2024a). Enhanced U-Net models with encoder and augmentation for phytoplankton segmentation. *International Journal of Advances in Applied Sciences*, 13(4):1009–1018.
- Ardhi, O. D. W., Soeprobowati, T. R., Adi, K., Prakasa, E., and Rachman, A. (2024b). Enhanced you only look once approach for automatic phytoplankton identification. *IAES International Journal of Artificial Intelligence*, 13(3):3426–3436.
- Bachimanchi, H. (2024). Deep-learning-powered data analysis in plankton ecology. *Limnology and Oceanography Letters*.
- Bai, Y., Lin, Z., Dai, J., et al. (2023). Qwen-VL: A versatile vision-language model for understanding, localization, text reading, and beyond. *arXiv*.
- Basu, S. and Mackey, K. (2018). Phytoplankton as key mediators of the biological carbon pump: Their responses to a changing climate. *Sustainability*, 10(3).
- Benfield, M., Grosjean, P., Culverhouse, P., Irigoien, X., Sieracki, M., Lopez-Urrutia, A., Dam, H., Hu, Q., Davis, C., Hanson, A., Pilskaln, C., Riseman, E., Schulz, H., Utgoff, P., and Gorsky, G. (2007). RAPID: Research on automated plankton identification. *Oceanography*, 20(2):172–187.
- Bengio, Y. (2012). Practical recommendations for gradient-based training of deep architectures. *arXiv*.
- Bochkovskiy, A., Wang, C.-Y., and Liao, H.-Y. M. (2020). Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934*.
- Brierley, A. S. (2017). Plankton. *Current Biology*, 27(11):R478–R483.

- Bu, X., Liu, K., Liu, J., and Ding, Y. (2023). A harmful algal bloom detection model combining moderate resolution imaging spectroradiometer multi-factor and meteorological heterogeneous data. *Sustainability*, 15(21):15386.
- Buda, M., Maki, A., and Mazurowski, M. A. (2018). A systematic study of the class imbalance problem in convolutional neural networks. *Neural Networks*, 106:249–259.
- Caballero, I., Fernández, R. G., Moreno, Ó., Mamán, L., and Navarro, G. (2020). New capabilities of Sentinel-2A/B satellites combined with in situ data for monitoring small harmful algal blooms in complex coastal waters. *Scientific Reports*, 10(1).
- Capinha, C., Ceia-Hasse, A., Kramer, A. M., and Meijer, C. (2021). Deep learning for supervised classification of temporal data in ecology. *Ecological Informatics*, 61:101252.
- Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., and Zagoruyko, S. (2020a). End-to-end object detection with transformers. In *Computer Vision – ECCV 2020*, volume 12346, pages 213–229. Springer International Publishing.
- Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., and Zagoruyko, S. (2020b). End-to-end object detection with transformers. In Vedaldi, A., Bischof, H., Brox, T., and Frahm, J.-M., editors, *Computer Vision – ECCV 2020*, volume 12346, pages 213–229. Springer International Publishing.
- Chen, W., Yang, K., Yu, Z., Shi, Y., and Chen, C. L. P. (2024). A survey on imbalanced learning: latest research, applications and future directions. *Artificial Intelligence Review*, 57:137.
- Cheng, K., Wang, Y., Bi, H., and Benfield, M. C. (2019). Enhanced convolutional neural network for plankton identification and enumeration. *PLOS ONE*.
- Cheng, X., Ren, Y., Cheng, K., Cao, J., and Hao, Q. (2020). Method for training convolutional neural networks for in situ plankton image recognition and classification based on the mechanisms of the human eye. *Sensors*, 20(9):2592.
- Cowen, R. K. and Guigand, C. M. (2008). In situ ichthyoplankton imaging system (ISIIS): System design and preliminary results. *Limnology and Oceanography: Methods*, 6(2):126–132.
- Culverhouse, P. F., Williams, R., Benfield, M. C., Flood, P. R., Sell, A. F., Mazzocchi, M. G., Buttino, I., and Sieracki, M. E. (2006). Automatic image analysis of plankton: Future perspectives. *Marine Ecology Progress Series*, 312:297–309.
- DeepSeek-VL Team (2023). Deepseek-VL: Vision-language model with strong generalization. *arXiv*.

- Ding, X., Guo, Y., Ding, G., and Han, J. (2019). ACNet: Strengthening the kernel skeletons for powerful CNN via asymmetric convolution blocks. In *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1911–1920.
- Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., and Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv*.
- Eerola, T., Batrakhonov, D., Barazandeh, N. V., Kraft, K., Haraguchi, L., Lensu, L., Suikkanen, S., Seppälä, J., Tamminen, T., and Kälviäinen, H. (2024). Survey of automatic plankton image recognition: Challenges, existing solutions and future perspectives. *Artificial Intelligence Review*, 57(5):114.
- Ellen, J. S., Graff, C. A., and Ohman, M. D. (2019). Improving plankton image classification using context metadata. *Limnology and Oceanography: Methods*, 17(8):439–461.
- Freedman, D. and Lane, D. (1983). A nonstochastic interpretation of reported significance levels. *Journal of Business & Economic Statistics*, 1(4):292–298.
- Gobler, C. J. (2020). Climate change and harmful algal blooms: Insights and perspective. *Harmful Algae*.
- Good, P. (2013). *Permutation Tests: A Practical Guide to Resampling Methods for Testing Hypotheses*. Springer, New York, 3 edition.
- Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*, volume 1. MIT Press, Cambridge.
- Google DeepMind (2023). Gemini: A family of highly capable multimodal models. *arXiv*.
- Goyal, P., Dollár, P., Girshick, R., Noordhuis, P., Wesolowski, L., Kyrola, A., Tulloch, A., Jia, Y., and He, K. (2017). Accurate, large minibatch sgd: Training imagenet in 1 hour. *arXiv preprint arXiv:1706.02677*.
- Grant, S. D., Richford, K., Burdett, H. L., McKee, D., and Patton, B. R. (2020). Low-cost, open-access quantitative phase imaging of algal cells using the transport of intensity equation. *Royal Society Open Science*, 7(1):191921.
- Griffith, A. W. and Gobler, C. J. (2020). Harmful algal blooms: A climate change co-stressor in marine and freshwater ecosystems. *Harmful Algae*.
- Guemas, E., Routier, B., Ghelfenstein-Ferreira, T., Cordier, C., Hartuis, S., Marion, B., Bertout, S., Varlet-Marie, E., Costa, D., and Pasquier, G. (2024). Automatic patient-level recognition of four *Plasmodium* species on thin blood smear by

- a real-time detection transformer (RT-DETR) object detection algorithm: A proof-of-concept and evaluation. *Microbiology Spectrum*, 12(2):e01440–23.
- Guiry, M. D. and Guiry, G. M. (2026). AlgaeBase: World-wide electronic publication. <https://www.algaebase.org>. National University of Ireland, Galway. Accessed January 11, 2026.
- Guo, B., Nyman, L., Nayak, A. R., Milmore, D., McFarland, M., Twardowski, M. S., Sullivan, J. M., Yu, J., and Hong, J. (2021). Automated plankton classification from holographic imagery with deep convolutional neural networks. *Limnology and Oceanography: Methods*, 19(1):21–36.
- Gupta, A., Harrison, P. J., Wieslander, H., Pielawski, N., Kartasalo, K., Partel, G., Solorzano, L., Suveer, A., Klemm, A. H., Spjuth, O., Sintorn, I., and Wählby, C. (2019). Deep learning in image cytometry: A review. *Cytometry Part A*, 95(4):366–380.
- Hidayatullah, P., Syakrani, N., Sholahuddin, M. R., Gelar, T., and Tubagus, R. (2025). YOLOv8 to YOLO11: A comprehensive architecture in-depth comparative review. *arXiv preprint arXiv:2501.13400*.
- Hill, P., Kumar, A., Temimi, M., and Bull, D. (2020). HABNet: Machine learning, remote sensing-based detection of harmful algal blooms. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13:3229–3239.
- Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2):65–70.
- Irison, J.-O., Ayata, S.-D., Lindsay, D. J., Karp-Boss, L., Stemmann, L., and Katz, L. A. (2022). Machine learning for the study of plankton and marine snow from images. *Annual Review of Marine Science*, 14(1):277–301.
- Takechi, S., Sekiuchi, T., Ito, H., Ueno, S., Takeuchi, Y., Suzuki, K., and Togawa, M. (2021). Identification and counting of pacific oyster *Crassostrea gigas* larvae by object detection using deep learning. *Aquacultural Engineering*, 95:102197.
- Kerr, T., Clark, J. R., Fileman, E. S., Widdicombe, C. E., and Pugeault, N. (2020). Collaborative deep learning models to handle class imbalance in flowcam plankton imagery. *IEEE Access*, 8:170013–170032.
- Khanam, R. and Hussain, M. (2024). YOLOv11: An overview of the key architectural enhancements. *arXiv*.
- Kitchenham, B. and Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering. Technical Report EBSE-2007-01, EBSE Technical Report, School of Computer Science and Mathematics, Keele University.

- Kitchenham, B., Pretorius, R., Budgen, D., Brereton, O. P., Turner, M., Niazi, M., and Linkman, S. (2010). Systematic literature reviews in software engineering – a tertiary study. *Information and Software Technology*, 52(8):792–805.
- Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6):84–90.
- Kyathanahally, S. P., Hardeman, T., Merz, E., Bulas, T., Reyes, M., Isles, P., Pomati, F., and Baity-Jesi, M. (2021). Deep learning classification of lake zooplankton. *Frontiers in Microbiology*, 12:746297.
- Kyathanahally, S. P., Hardeman, T., Reyes, M., Merz, E., Bulas, T., Brun, P., Pomati, F., and Baity-Jesi, M. (2022). Ensembles of data-efficient vision transformers as a new paradigm for automated classification in ecology. *Scientific Reports*, 12(1):18590.
- Lang, K., Cai, H., and Wang, X. (2022). A plankton detection method based on neural networks and digital holographic imaging. *Chemosensors*, 10(6):217.
- LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553):436–444.
- Li, Y., Guo, J., Guo, X., Hu, Z., and Tian, Y. (2021). Plankton detection with adversarial learning and a densely connected deep learning model for class imbalanced distribution. *Journal of Marine Science and Engineering*, 9(6):636.
- Litjens, G., Kooi, T., Bejnordi, B. E., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42:60–80.
- Loshchilov, I. and Hutter, F. (2019). Decoupled weight decay regularization. *International Conference on Learning Representations*.
- Lumini, A. and Nanni, L. (2019). Deep learning and transfer learning features for plankton classification. *Ecological Informatics*, 51:33–43.
- Lumini, A., Nanni, L., and Maguolo, G. (2020). Deep learning for plankton and coral classification. *Applied Computing and Informatics*.
- Luo, J. Y., Irisson, J.-O., Graham, B., Guigand, C., Sarafraz, A., Mader, C., and Cowen, R. K. (2018). Automated plankton image analysis using convolutional neural networks. *Limnology and Oceanography: Methods*, 16(12):814–827.
- MacNeil, L., Missan, S., Luo, J., Trappenberg, T., and LaRoche, J. (2021). Plankton classification with high-throughput submersible holographic microscopy and transfer learning. *BMC Ecology and Evolution*.
- Manly, B. F. J. (2007). *Randomization, Bootstrap and Monte Carlo Methods in Biology*. Chapman & Hall/CRC, Boca Raton, 3 edition.

- Maracani, A., Pastore, V. P., Natale, L., Rosasco, L., and Odone, F. (2023). In-domain versus out-of-domain transfer learning in plankton image classification. *Scientific Reports*, 13(1):10443.
- Micikevicius, P., Narang, S., Alben, J., Diamos, G., Elsen, E., Garcia, D., Ginsburg, B., Houston, M., Kuchaiev, O., Venkatesh, G., and Wu, H. (2018). Mixed precision training. *International Conference on Learning Representations*.
- Nanni, L., Faldani, G., Brahnam, S., Bravin, R., and Feltrin, E. (2023). Improving foraminifera classification using convolutional neural networks with ensemble learning. *Signals*, 4(3):524–538.
- Nardelli, S. C., Gray, P. C., and Schofield, O. (2022). A convolutional neural network to classify phytoplankton images along the west antarctic peninsula. *Marine Technology Society Journal*, 56(5):45–57.
- Nguyen, T. L., Pradeep, S., Judson-Torres, R. L., Reed, J., Teitell, M. A., and Zangle, T. A. (2022). Quantitative phase imaging: Recent advances and expanding potential in biomedicine. *ACS Nano*, 16(8):11516–11544.
- Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems*, 37.
- Oldenburg, E., Kronberg, R. M., Niehoff, B., Ebenhöf, O., and Popa, O. (2023). DeepLOKI- a deep learning based approach to identify zooplankton taxa on high-resolution images from the optical plankton recorder LOKI. *Frontiers in Marine Science*, 10:1280510.
- Orenstein, E. C., Beijbom, O., Peacock, E. E., and Sosik, H. M. (2015). WHOI-Plankton: A large scale fine grained visual recognition benchmark dataset for plankton classification. *arXiv*.
- Padilla, R., Netto, S. L., and Da Silva, E. A. B. (2020). A survey on performance metrics for object-detection algorithms. In *2020 International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 237–242.
- Panaïotis, T., Amblard, E., Boniface-Chang, G., Dulac-Arnold, G., Woodward, B., and Irisson, J.-O. (2025). Benchmark of plankton images classification: emphasizing features extraction over classifier complexity. *Earth System Science Data Discussions*. Discussion paper / preprint, in review.
- Park, Y., Popescu, G., Ferraro, P., and Kemper, B. (2020). Editorial: Quantitative phase imaging and its applications to biophysics, biology, and medicine. *Frontiers in Physics*, 7.
- Pastore, V. P., Ciranni, M., Bianco, S., Fung, J. C., Murino, V., and Odone, F. (2023). Efficient unsupervised learning of biological images with compressed deep features. *Image and Vision Computing*, 137:104764.

- Paszke, A., Gross, S., Chintala, S., et al. (2019). Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems (NeurIPS)*, 32:8024–8035.
- Plonus, R., Conradt, J., Harmer, A., Janssen, S., and Floeter, J. (2021). Automatic plankton image classification—can capsules and filters help cope with data set shift? *Limnology and Oceanography: Methods*, 19(3):176–195.
- Prakasa, E., Rachman, A., Noerdjito, D. R., and Wardoyo, R. (2021). Development of segmentation algorithm for determining planktonic objects from microscopic images. In *IOP Conference Series: Earth and Environmental Science*, volume 944, page 012025.
- Rachman, A., Purwandana, A., and Fitriya, N. (2021). Phytoplankton community structure of the makassar strait, indonesia. In *IOP Conference Series: Earth and Environmental Science*, volume 789, page 012006.
- Rachman, A., Suwarno, A. S., and Nurdjaman, S. (2022). Application of deep learning for phytoplankton classification in indonesian waters. In *IOP Conference Series: Earth and Environmental Science*, volume 1062, page 012006.
- Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 779–788.
- Redmon, J. and Farhadi, A. (2018). YOLOv3: An incremental improvement. *arXiv*.
- Ren, S., He, K., Girshick, R., and Sun, J. (2017). Faster R-CNN: Towards real-time object detection with region proposal networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(6):1137–1149.
- Rezatofighi, H., Tsoi, N., Gwak, J., Sadeghian, A., Reid, I., and Savarese, S. (2019). Generalized intersection over union: A metric and a loss for bounding box regression. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 658–666.
- Rodríguez-Benito, C., Navarro, G., and Caballero, I. (2020). Using copernicus Sentinel-2 and Sentinel-3 data to monitor harmful algal blooms in southern chile during the COVID-19 lockdown. *Marine Pollution Bulletin*, 161:111722.
- Rolton, A., Rhodes, L., Hutson, K. S., Biessy, L., Bui, T., MacKenzie, L., Symonds, J. E., and Smith, K. F. (2022). Effects of harmful algal blooms on fish and shellfish species: A case study of new zealand in a changing environment. *Toxins*, 14(5):341.
- Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In Navab, N., Hornegger, J., Wells, W. M., and Frangi, A. F., editors, *Medical Image Computing and*

- Computer-Assisted Intervention – MICCAI 2015*, volume 9351, pages 234–241. Springer International Publishing.
- Ruan, B.-K., Shuai, H.-H., and Cheng, W.-H. (2022). Vision transformers: State of the art and research challenges. *arXiv preprint arXiv:2207.03041*.
- Ruder, S. (2017). An overview of gradient descent optimization algorithms. *arXiv*.
- Russell, B. C. (2008). Labelme: A tool for annotating images. *Computer Vision and Image Understanding*, 110(1):3–19.
- Santhanam, P., Begum, A., and Pachiappan, P., editors (2019). *Basic and Applied Phytoplankton Biology*. Springer Singapore.
- Schmarje, L., Brünger, J., Santarossa, M., Schröder, S.-M., Kiko, R., and Koch, R. (2021). Fuzzy overclustering: Semi-supervised classification of fuzzy labels with overclustering and inverse cross-entropy. *Sensors*, 21(19):6661.
- Schröder, S.-M., Kiko, R., and Koch, R. (2020). MorphoCluster: Efficient annotation of plankton images by clustering. *Sensors*, 20(11):3060.
- Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27(3):379–423.
- Shorten, C. and Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1):60.
- Soeprbowati, T. R., Addadiyah, N. L., Hariyati, R., and Jumari, J. (2021). Physico-chemical and biological water quality of warna and pengilon lakes, dieng, central java. *Journal of Water and Land Development*, pages 38–49.
- Soeprbowati, T. R. and Jumari, J. (2022). The water quality index and phytoplankton communities of kokoh putih river, sembalun, east lombok, indonesia. *Journal of Water and Land Development*, 15(4).
- T R, M., V, V. K., V, D. K., Geman, O., Margala, M., and Guduri, M. (2023). The stratified k-folds cross-validation and class-balancing methods with high-performance ensemble classifiers for breast cancer classification. *Healthcare Analytics*, 4:100247.
- Tang, S., Rachman, A., Fitria, N., Thoha, H., and Chen, B. (2018). Phytoplankton changes during SE monsoonal period in the lembah strait of north sulawesi, indonesia, from 2012 to 2015. *Acta Oceanologica Sinica*, 37(12):9–17.
- Taylor, L. and Nitschke, G. (2018). Improving deep learning with generic data augmentation. In *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1542–1547.

- Tian, Y., Ye, Q., and Doermann, D. (2025). YOLOv12: Attention-centric real-time object detectors. *arXiv*.
- Ünalın, S., Günay, O., Akkurt, I., Günođlu, K., and Tekin, H. O. (2024). A comparative study on breast cancer classification with stratified shuffle split and k-fold cross validation via ensembled machine learning. *Journal of Radiation Research and Applied Sciences*, 17(4):101080.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. *arXiv*.
- Wacquet, G. and Lefebvre, A. (2022). EcoTransLearn: An R-package to easily use transfer learning for ecological studies—a plankton case study. *Bioinformatics*, 38(24):5469–5471.
- Wadekar, S. (2025a). Deepseek-R1: Model architecture. <https://pub.towardsai.net/deepseek-r1-model-architecture-853fefac7050>.
- Wadekar, S. (2025b). Qwen2.5-Omni: A real-time multimodal AI. <https://learnopencv.com/qwen2-5-omni/>.
- Wan, Y., Wang, H., Lu, L., Lan, X., Xu, F., and Li, S. (2024). An improved real-time detection transformer model for the intelligent survey of traffic safety facilities. *Sustainability*, 16(23):10172.
- Wang, A., Chen, H., Liu, L., Chen, K., Lin, Z., Han, J., and Ding, G. (2024a). YOLOv10: Real-time end-to-end object detection. *arXiv*.
- Wang, C.-Y., Yeh, I.-H., and Liao, H.-Y. M. (2024b). YOLOv9: Learning what you want to learn using programmable gradient information. *arXiv*.
- Wang, L., Zhang, L., Feng, L., Chen, T., and Qin, H. (2025). A novel deep transfer learning method based on explainable feature extraction and domain reconstruction. *Neural Networks*, 187:107401.
- Wang, S., Xia, C., Lv, F., and Shi, Y. (n.d.). RT-DETRv3: Real-time end-to-end object detection with hierarchical dense positive supervision.
- Weihong, B., Yun, J., Jiabin, L., Lingling, S., Guangwei, F., and Wa, J. (2023). In-situ detection method of jellyfish based on improved faster R-CNN and FP16. *IEEE Access*, 11:81803–81814.
- Wilson, A. C., Roelofs, R., Mitchell, S., Srebro, N., and Recht, B. (2017). The marginal value of adaptive gradient methods in machine learning. In *Advances in Neural Information Processing Systems (NeurIPS)*. Menjelaskan mengapa SGD sering lebih baik daripada Adam untuk generalisasi CNN.

- Winkler, A. M., Ridgway, G. R., Webster, M. A., Smith, S. M., and Nichols, T. E. (2014). Permutation inference for the general linear model. *NeuroImage*, 92:381–397.
- Wu, J. and He, J. (2025). Trustworthy transfer learning: A survey. *Journal of Artificial Intelligence Research*, 84:Article 20. Published November 2025.
- Xu, X., Luo, W., Ren, Z., and Song, X. (2025). Intelligent detection and recognition of marine plankton by digital holography and deep learning. *Sensors*, 25(7):2325. Special Issue: Digital Holography in Optics: Techniques and Applications.
- Yang, Z., Li, J., Chen, T., Pu, Y., and Feng, Z. (2022). Contrastive learning-based image retrieval for automatic recognition of in situ marine plankton images. *ICES Journal of Marine Science*, 79(10):2643–2655.
- Yaseen, M. (2024). What is YOLOv8: An in-depth exploration of the internal features of the next-generation object detector. *arXiv*.
- Yue, J., Chen, Z., Long, Y., Cheng, K., Bi, H., and Cheng, X. (2023). Toward efficient deep learning system for in-situ plankton image recognition. *Frontiers in Marine Science*, 10.
- Zhang, A., Lipton, Z. C., Li, M., and Smola, A. J. (2023). *Dive into Deep Learning*. Cambridge University Press. ISBN-10: 1009389432.
- Zhang, W., Rui, F., Xiao, C., Li, H., and Li, Y. (2024). JF-YOLO: The jellyfish bloom detector based on deep learning. *Multimedia Tools and Applications*, 83(3):7097–7117.
- Zhang, Y., Lu, Y., Wang, H., Chen, P., and Liang, R. (2021). Automatic classification of marine plankton with digital holography using convolutional neural network. *Optics & Laser Technology*, 139:106979.
- Zhao, Y., Lv, W., Xu, S., Wei, J., Wang, G., Dang, Q., Liu, Y., and Chen, J. (2024a). DETRs beat YOLOs on real-time object detection. *arXiv*.
- Zhao, Y., Lv, W., Xu, S., Wei, J., Wang, G., Dang, Q., Liu, Y., and Chen, J. (2024b). Detsr beat yolos on real-time object detection. *arXiv*.
- Zheng, H., Wang, R., Yu, Z., Wang, N., Gu, Z., and Zheng, B. (2017). Automatic plankton image classification combining multiple view features via multiple kernel learning. *BMC Bioinformatics*, 18(S16):570.
- Zhu, X., Su, W., Lu, L., Li, B., Wang, X., and Dai, J. (2021). Deformable DETR: Deformable transformers for end-to-end object detection. *International Conference on Learning Representations*.

Zylapp (2021). Review of deep learning algorithms for object detection. <https://medium.com/zylapp/review-of-deep-learning-algorithms-for-object-detection-c1f3d437b852>. Accessed: 16 December 2025.



SEKOLAH PASCASARJANA