SKRIPSI

ANALISIS PEMANFAATAN *REGION OF INTEREST* (ROI)-*BASED LEARNING* TERHADAP KINERJA MODEL KLASIFIKASI LESI KULIT BERBASIS *DEEP LEARNING* PADA CITRA DERMATOSKOPI

DISUSUN OLEH :

SARIPAH AINAH

223010503023

JURUSAN TEKNIK INFORMATIKA

FAKULTAS TEKNIK

UNIVERSITAS PALANGKA RAYA

2026

HALAMAN PENGESAHAN

ANALISIS PEMANFAATAN *REGION OF INTEREST* (ROI)-*BASED LEARNING* TERHADAP KINERJA MODEL KLASIFIKASI LESI KULIT BERBASIS *DEEP LEARNING* PADA CITRA DERMATOSKOPI

SKRIPSI

Sebagai salah satu syarat untuk menyelesaikan Program Strata-1 pada Jurusan Teknik Informatika Fakultas Teknik Universitas Palangka Raya

Oleh

SARIPAH AINAH

223010503023

Telah dipertahankan didepan tim penguji, pada :

Hari/Tanggal	: Senin, 24 Agustus 2026
Waktu	: 09:00-10:30 WIB
Tempat	: Ruang Ujian 1

1. **ARIESTA LESTARI, S.Kom., M.Cs., Ph.D.**
   NIP. 19800322 200501 2 004 :..............................(Ketua Penguji)
2. **RESSA PRISKILA, S.T., M.T.**
   NIP. 19940301 201903 2 016 :..............................(Pembimbing Utama/Pertama)
3. **NOVA NOOR KAMALA SARI, S.T., M.Kom**
   NIP. 19890407 201504 2 004 :..............................(Pembimbing Pendamping/Kedua)
4. **TOMAS LEONARDO, S.T., M.T.I.**
   NIP. 19930501 202406 1 002 :..............................(Anggota)

Mengetahui :

Jurusan / Program Studi Teknik Informatika
Fakultas Teknik Universitas Palangka Raya
Ketua Jurusan,

ARIESTA LESTARI, S.Kom., M.Cs., Ph.D.
NIP. 19800322 200501 2 004

HALAMAN PERNYATAAN

HALAMAN PERNYATAAN

Dengan ini menyatakan bahwa skripsi yang berjudul "Analisis Pemanfaatan *Region Of Interest* (ROI)-*Based Learning* Terhadap Kinerja Model Klasifikasi Lesi Kulit Berbasis *Deep Learning* Pada Citra Dermatoskopi" merupakan hasil karya saya sendiri dengan ketentuan sebagai berikut:

1. Skripsi ini disusun secara mandiri dan merupakan hasil pemikiran, penelitian, serta analisis saya sendiri.
2. Skripsi ini tidak mengandung karya atau pendapat yang pernah diajukan untuk memperoleh gelar akademik pada perguruan tinggi mana pun, kecuali yang secara tertulis telah dicantumkan sebagai referensi dalam naskah dan daftar pustaka.
3. Seluruh sumber informasi, data, kutipan, maupun pendapat dari karya orang lain telah disebutkan secara jelas dan dicantumkan sesuai dengan kaidah penulisan ilmiah yang berlaku.
4. Skripsi ini bebas dari unsur plagiarisme, baik sebagian maupun seluruhnya.
5. Apabila di kemudian hari terbukti terdapat pelanggaran terhadap pernyataan ini, saya bersedia menerima sanksi akademik sesuai dengan ketentuan yang berlaku di Universitas Palangka Raya.

Palangka Raya, 24 Agustus 2026

METERAI TEMPEL

SARIPAH AINAH

223010503023

ii

KATA PENGANTAR

Puji dan syukur penulis panjatkan kepada Tuhan Yang Maha Esa atas segala berkat, kasih, dan karunia-Nya yang telah menyertai penulis selama proses penyusunan skripsi ini hingga dapat diselesaikan dengan baik. Skripsi yang berjudul *"Analisis Pemanfaatan Region of Interest (ROI)-Based Learning terhadap Kinerja Model Klasifikasi Lesi Kulit Berbasis Deep Learning pada Citra Dermatoskopi"* ini disusun sebagai salah satu syarat untuk memperoleh gelar Sarjana pada Jurusan Teknik Informatika, Fakultas Teknik, Universitas Palangka Raya.

Penulis berharap bahwa karya ini dapat memberikan manfaat bagi perkembangan ilmu pengetahuan, khususnya dalam bidang visi komputer *(computer vision)* dan pembelajaran mesin, terutama terkait pemanfaatan pendekatan *Region of Interest* (ROI) pada pengolahan citra dermatoskopi. Skripsi ini juga diharapkan dapat menjadi referensi atau dasar pengembangan bagi mahasiswa lain yang tertarik untuk melakukan penelitian lebih lanjut di bidang yang sama, serta sebagai bahan pembelajaran untuk memahami pemanfaatan pendekatan *Region of Interest* (ROI)-*based learning* dalam meningkatkan kinerja model klasifikasi berbasis deep learning.

Penulis menyadari bahwa dalam penyusunan skripsi ini masih terdapat kekurangan. Oleh karena itu, penulis sangat terbuka terhadap segala bentuk saran dan kritik yang membangun untuk perbaikan di masa mendatang.

Akhir kata, semoga skripsi ini dapat memberikan manfaat bagi semua pihak yang membacanya, khususnya bagi sivitas akademika Jurusan Teknik Informatika, Fakultas Teknik, Universitas Palangka Raya.

Palangka Raya, 24 Agustus 2026

<u>SARIPAH AINAH</u>

223010503023

ANALISIS PEMANFAATAN *REGION OF INTEREST* (ROI)-*BASED LEARNING* TERHADAP KINERJA MODEL KLASIFIKASI LESI KULIT BERBASIS *DEEP LEARNING* PADA CITRA DERMATOSKOPI

SARIPAH AINAH (223010503023)

Jurusan Teknik Informatika Fakultas Teknik Universitas Palangka Raya

Kampus Tanjung Nyaho Jl. Yos Sudarso, Palangka Raya 73112

Email : saripahainah24@mhs.eng.upr.ac.id

ABSTRAK

Lesi kulit merupakan indikator utama dalam proses diagnosis kanker kulit, namun diagnosis konvensional masih terkendala keterbatasan tenaga ahli dan subjektivitas interpretasi visual. Penelitian ini menganalisis pemanfaatan *Region of Interest* (ROI)-*Based Learning* untuk terhadap kinerja model klasifikasi lesi kulit berbasis *deep learning* pada citra dermatoskopi. Metode yang diusulkan menggunakan *pipeline* dua tahap, yaitu deteksi dan lokalisasi area lesi menggunakan YOLO26 untuk menghasilkan ROI, kemudian citra hasil pemotongan ROI diklasifikasikan menggunakan EfficientNet-B4. Model dilatih pada dataset HAM10000 yang terdiri atas tujuh kelas lesi dan diuji generalisasinya melalui *cross-dataset evaluation* pada dataset ISIC 2018.

Hasil penelitian menunjukkan detektor YOLO26 mampu melokalisasi area lesi dengan kualitas tinggi (mAP@0,50 = 0,972; *mean* IoU = 0,8083). Pemanfaatan ROI meningkatkan seluruh metrik evaluasi dibandingkan kondisi tanpa ROI, yaitu *accuracy* dari 0,9032 menjadi 0,9669, *F1-macro* dari 0,8377 menjadi 0,9345, *F1-weighted* dari 0,9024 menjadi 0,9668, dan *ROC-AUC* dari 0,9810 menjadi 0,9916. Peningkatan terbesar pada F1-macro (+9,68 poin persentase) mengindikasikan bahwa penerapan ROI cenderung memberikan manfaat yang lebih besar pada kelas-kelas minoritas. Peningkatan ini signifikan secara statistik melalui uji *Bootstrap Confidence Interval* (p < 0,05) dengan *medium effect size* (*Cohen's h* = 0,2633). Analisis kualitas ROI menunjukkan semakin tinggi nilai IoU dan *confidence* deteksi, semakin tinggi pula akurasi klasifikasi, dan konsistensi kontribusi ROI turut terkonfirmasi pada evaluasi *cross-dataset* ISIC 2018 (*ROC-AUC* = 0,9965; *macro F1-score* = 0,9246). Dengan demikian, pemanfaatan ROI-*Based Learning* terbukti meningkatkan akurasi dan generalisasi klasifikasi lesi kulit.

Kata Kunci : *Region of Interest* (ROI), klasifikasi lesi kulit, YOLO26, EfficientNet-B4, citra dermatoskopi

ANALYSIS OF REGION OF INTEREST (ROI)-BASED LEARNING UTILIZATION ON THE PERFORMANCE OF DEEP LEARNING-BASED SKIN LESION CLASSIFICATION MODEL ON DERMATOSCOPIC IMAGES

SARIPAH AINAH (223010503023)

Department of Informatics Engineering, Faculty of Engineering, University of Palangka Raya, Tanjung Nyaho *Campus,* Jl. Yos Sudarso, Palangka Raya 73112

Email: saripahainah24@mhs.eng.upr.ac.id

ABSTRACT

Skin lesions are an important indicator in the diagnosis of skin cancer, however, conventional diagnosis remains constrained by the limited availability of experts and the subjectivity of visual interpretation. This study analyzes the use of Region of Interest (ROI)-Based Learning to improve the performance of a deep learning-based skin lesion classification model on dermatoscopic images. The proposed method employs a two-stage pipeline, namely the detection and localization of the lesion area using YOLO26 to generate the ROI, after which the cropped ROI image is classified using EfficientNet-B4. The model was trained on the HAM10000 dataset, comprising seven lesion classes, and its generalization ability was tested through cross-dataset evaluation on the ISIC 2018 dataset.

The results show that the YOLO26 detector was able to localize the lesion area with high quality (mAP@0.50 = 0.972; mean IoU = 0.8083). The use of ROI improved all evaluation metrics compared to the non-ROI condition, namely accuracy from 0.9032 to 0.9669, F1-macro from 0.8377 to 0.9345, F1-weighted from 0.9024 to 0.9668, and ROC-AUC from 0.9810 to 0.9916. The largest improvement in Macro F1-score (+9.68 percentage points) suggests that the application of ROI tends to provide greater benefits for the classification of minority classes. This improvement was statistically significant based on a Bootstrap Confidence Interval test ($p < 0.05$) with a medium effect size (Cohen's h = 0.2633). The ROI quality analysis shows that the higher the IoU value and detection confidence, the higher the classification accuracy, and the consistency of the ROI contribution was further confirmed by the cross-dataset evaluation on ISIC 2018 (ROC-AUC = 0.9965; macro F1-score = 0.9246). Thus, the use of ROI-Based Learning is proven in improving the accuracy and generalization of skin lesion classification.

Keywords: *Region of Interest (ROI), skin lesion classification, YOLO26, EfficientNet-B4, dermatoscopic images*

DAFTAR ISI

DAFTAR GAMBAR

DAFTAR TABEL

DAFTAR PUSTAKA

Agüero, R., Buchanan, K. L., Navarrete-Dechent, C., Marghoob, A. A., Stein, J. A., Landy, M. S., Leachman, S. A., Linden, K. G., Garcet, S., Krueger, J. G., & Gareau, D. S. (2024). The impact of melanoma imaging biomarker cues on detection sensitivity and specificity in melanoma versus clinically atypical nevi. *Cancers*, 16(17), 3077. https://doi.org/10.3390/cancers16173077

Ajabani, D., Shaikh, Z. A., Yousef, A., Ali, K., & Albahar, M. A. (2025). Enhancing skin lesion classification: a CNN approach with human baseline comparison. *PeerJ. Computer science*, *11*, e2795. https://doi.org/10.7717/peerj-cs.2795

Akram, A., Rashid, J., Jaffar, M. A., Faheem, M., & Amin, R. U. (2023). Segmentation and classification of skin lesions using hybrid deep learning method in the Internet of Medical Things. Skin Research and Technology, 29(11), e13524. https://doi.org/10.1111/srt.13524

Alhussein, M., Muhammad, G., & Hossain, M. S. (2024). Skin cancer recognition using unified deep convolutional neural networks. Diagnostics, 14(7), 756. https://doi.org/10.3390/diagnostics14070756

Ali, K., Shaikh, Z. A., Khan, A. A., & Laghari, A. A. (2022). Multiclass skin cancer classification using EfficientNets—A first step towards preventing skin cancer. Neuroscience Informatics, 2(4), 100034. https://doi.org/10.1016/j.neuri.2022.100034

Alotaibi, A., & AlSaeed, D. (2025). Skin cancer detection using transfer learning and deep attention mechanisms. Diagnostics, 15(1), 99. https://doi.org/10.3390/diagnostics15010099

Ashraf, R., Afzal, S., Rehman, A. u., Gul, S., Baber, J., Bakhtyar, M., Mehmood, I., Song, O.-Y., & Maqsood, M. (2020). Region-of-interest based transfer learning assisted framework for skin cancer detection. *IEEE Access*, *8*, 147858–147871. https://doi.org/10.1109/ACCESS.2020.3014701

Barroso, D. H., Leite, C. P. Z., Araujo, G. D. S., Teixeira, M. A. G., Alencar, E. R. B., & Cavalcanti, S. M. M. (2016). Dermatofibroma simulating seborrheic keratosis dermoscopically. *Anais Brasileiros de Dermatologia, 91*(3), 354–356. https://doi.org/10.1590/abd1806-4841.20164031

Bissoto, A., Fornaciali, M., Valle, E., & Avila, S. (2019). (De)Constructing bias on skin lesion datasets. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2766–2774.

Bosson-Amedenu, S., Boakye, E., Ayitey, E., & Addor, J. A. (2025). Comparative performance of machine learning models in predicting arsenic exposure risk in Ghana's riverine ecosystems. BMC Environmental Science, 2, Article 26. https://doi.org/10.1186/s44329-025-00040-8

Bouthillier, X., Delaunay, P., Bronzi, M., Trofimov, A., Nichyporuk, B., Szeto, J., Mohammadi Sepahvand, N., Boree, E., Gauthier, J., Charlin, L., Varoquaux, G., Pal, C., & Vincent, P. (2021). Accounting for variance in machine learning benchmarks. Proceedings of Machine Learning and Systems, 3, 747–769.

Bozorgtabar, B., Mahapatra, D., & Thiran, J. P. (2025). Improved skin lesion segmentation in dermoscopic images using object detection and semantic segmentation. Clinical, Cosmetic and Investigational Dermatology, 18, 1191–1198. https://doi.org/10.2147/CCID.S518751

Buda, M., Maki, A., & Mazurowski, M. A. (2018). A systematic study of the class imbalance problem in convolutional neural networks. *Neural Networks, 106*, 249–259.

Cai, Z., Zhou, K., & Liao, Z. (2025). A systematic review of YOLO-based object detection in medical imaging: Advances, challenges, and future directions. Computers, Materials & Continua, 85(2), 2255–2303. https://doi.org/10.32604/cmc.2025.067994

Celebi, M. E., Iyatomi, H., Schaefer, G., & Stoecker, W. V. (2009). *Approximate lesion localization in dermoscopy images*. *Skin Research and Technology, 15*(3), 314–322. https://doi.org/10.1111/j.1600-0846.2009.00357.x

Chakrabarty, S. (2026). YOLO26: An analysis of NMS-free end to end framework for real-time object detection. arXiv. https://doi.org/10.48550/arXiv.2601.12882

Chulifa, R., Sari, Y. A., & Tistarini, H. (2025). Two-step pipeline for oral diseases detection and classification: A deep learning approach. PMC. https://pmc.ncbi.nlm.nih.gov/articles/PMC12599429/

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates. https://utstat.toronto.edu/~brunner/oldclass/378f16/readings/CohenPower.pdf

Conforti, C., Giuffrida, R., Agozzino, M., Cannavó, P. S., Dianzani, C., di Meo, N., Nardello, C., Neagu, N., Guarneri, F., & Zalaudek, I. (2021). Basal cell carcinoma and dermal nevi of the face: comparison of localization and dermatoscopic features. *International journal of dermatology*, *60*(8), 996–1002. https://doi.org/10.1111/ijd.15554

Chung, H. M., Ke, J., Zhang, M., Kong, L., Zheng, J., & Xiang, L. (2025). Tooth-to-white spot lesion YOLO: A novel model for white spot lesion detection. *BMC Oral Health, 25*, Article 1329. https://doi.org/10.1186/s12903-025-06936-w

Das, S., & Addya, R. K. (2025). Skin cancer detection and classification through medical image analysis using EfficientNet. *NDT, 3*(4), 23. https://doi.org/10.3390/ndt3040023

Demircioğlu, A. (2023). Are deep models in radiomics performing better than generic models? A systematic review. European Radiology Experimental, 7, 11. https://doi.org/10.1186/s41747-023-00325-0

Efron, B., & Tibshirani, R. J. (1993). *An introduction to the bootstrap* (Monographs on Statistics and Applied Probability No. 57). Chapman & Hall. https://doi.org/10.1201/9780429246593

Gamo, R., Floristan, U., Pampín, A., Caro, D., Pinedo, F., & López-Estebaranz, J. L. (2015). Usefulness of confocal microscopy in distinguishing between basal cell carcinoma and intradermal melanocytic nevus on the face. Actas Dermo-Sifiliográficas, 106(8), e41–e44. https://doi.org/10.1016/j.ad.2015.03.007

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.

Gerz, F., & Jelali, M. (2025). *Towards reliable data augmentation in machine learning: Practices to prevent data leakage*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5636100

Gururaj, H. L., Manju, N., Nagarjun, A., Aradhya, V. N. M., & Flammini, F. (2023). DeepSkin: A deep learning approach for skin cancer classification. IEEE Access, 11, 50205–50220. https://doi.org/10.1109/ACCESS.2023.3274848

Grandini, M., Bagli, E., & Visani, G. (2020). Metrics for multi-class classification: An overview. arXiv preprint arXiv:2008.05756. https://doi.org/10.48550/arXiv.2008.05756

Harahap, M., Husein, A. M., Kwok, S. C., Wizley, V., Leonardi, J., Ong, D. K., Ginting, D., & Silitonga, B. A. (2024). Skin cancer classification using EfficientNet architecture. Bulletin of Electrical Engineering and Informatics, 13(4), 2716–2728. https://doi.org/10.11591/eei.v13i4.7159

Hassanpour, S., Keshavarz, A., & Moghaddam, M. E. (2025). Deep learning-based image classification for AI-assisted integration of pathology and radiology in medical imaging. PMC. https://pmc.ncbi.nlm.nih.gov/articles/PMC12171332/

Huang, Y., Zhang, Z., Ran, X., Zhuang, K., & Ran, Y. (2025). An ingeniously designed skin lesion classification model across clinical and dermatoscopic datasets. Diagnostics, 15(16), 2011. https://doi.org/10.3390/diagnostics15162011

Hu, Z., Lin, H. M., Mathur, S., Moreland, R., Witiw, C. D., Jimenez-Juan, L., Callejas, M. F., Deva, D. P., Sejdić, E., & Colak, E. (2025). High performance with fewer labels using semi-weakly supervised learning for pulmonary embolism diagnosis. *npj Digital Medicine, 8*, 254. https://doi.org/10.1038/s41746-025-01594-2

Irany, F. A., & Akwafuo, S. (2026). From generative modeling to clinical classification: A GPT-based architecture for EHR notes. arXiv. https://arxiv.org/abs/2601.21955

Jan, M. M., Zainal, N., & Jamaludin, S. (2020). Region of interest-based image retrieval techniques: A review. IAES International Journal of Artificial Intelligence (IJ-AI), 9(3), 520–528. https://doi.org/10.11591/ijai.v9.i3.pp520-528

Jocher, G., Qiu, J., Liu, M., Lyu, S., Akyon, F. C., & Kalfaoglu, M. E. (2026). *Ultralytics YOLO26: Unified Real-Time End-to-End Vision Models*. https://arxiv.org/pdf/2606.03748

Jojoa Acosta, M. F., Caballero Tovar, L. Y., Garcia-Zapirain, M. B., & Percybrooks, W. S. (2021). Melanoma diagnosis using deep learning techniques on dermatoscopic images. *BMC Medical Imaging, 21*, Article 6. https://doi.org/10.1186/s12880-020-00534-8

Kahraman, F., Oksuz, K., Kalkan, S., & Akbas, E. (2023). Correlation loss: Enforcing correlation between classification and localization. Proceedings of the AAAI Conference on Artificial Intelligence, 37(1), 1087–1095. https://doi.org/10.1609/aaai.v37i1.25190

Kapoor, S., & Narayanan, A. (2023). Leakage and the reproducibility crisis in machine-learning-based science. Patterns, 4(9), 100804. https://doi.org/10.1016/j.patter.2023.100804

Khan, M. A., Ali, M. D., Mazhar, T., & Shahzad, T. (2026). An EfficientNetB4-based CNN model for skin lesion classification. Engineering, Technology & Applied Science Research, 16(2). https://doi.org/10.48084/etasr.15419

Klontzas, M. E., Groot Lipman, K. B. W., Akinci D'Antonoli, T., Andreychenko, A., Cuocolo, R., Dietzel, M., Gitto, S., Huisman, H., Santinha, J., Vernuccio, F., Visser, J. J., & Huisman, M. (2026). ESR Essentials: Common performance metrics in AI—practice recommendations by the European Society of Medical Imaging Informatics. *European Radiology*, *36*(2), 1528–1540. https://doi.org/10.1007/s00330-025-11890-w

Kocak, B., Klontzas, M. E., Stanzione, A., Meddeb, A., Demircioğlu, A., Bluethgen, C., Bressem, K. K., Ugga, L., Mercaldo, N., Díaz, O., & Cuocolo, R. (2025). Evaluation metrics in medical imaging AI: Fundamentals, pitfalls, misapplications, and recommendations.

European Journal of Radiology Artificial Intelligence, *3*, 100030. https://doi.org/10.1016/j.ejrai.2025.100030

Lin, C., Yang, P., Wang, Q., Qiu, Z., Lv, W., & Wang, Z. (2023). *Efficient and accurate compound scaling for convolutional neural networks*. Neural Networks, 167, 787–797. https://doi.org/10.1016/j.neunet.2023.08.053

Liu, R., Zha, F., Ding, F., Yao, G., & Zhang, P. (2025). Skin lesion classification based on ResNet-50 enhanced with adaptive spatial feature fusion. arXiv preprint arXiv:2510.03876. https://doi.org/10.48550/arXiv.2510.03876

Loshchilov, I., & Hutter, F. (2017). *SGDR: Stochastic Gradient Descent with Warm Restarts*. ICLR 2017. https://arxiv.org/abs/1608.03983

Mahbod, A., Tschandl, P., Langs, G., Ecker, R., & Ellinger, I. (2020). The effects of skin lesion segmentation on the performance of dermatoscopic image classification. Computer Methods and Programs in Biomedicine, 197, 105725. https://doi.org/10.1016/j.cmpb.2020.105725

Maier-Hein, L., Reinke, A., Godau, P., Tizabi, M. D., Buettner, F., Christodoulou, E., … Jäger, P. F. (2024). Metrics reloaded: Recommendations for image analysis validation. Nature Methods, 21(2), 195–212. https://doi.org/10.1038/s41592-023-02151-z

Manoj, S. O., Abirami, K. R., Victor, A., & Arya, M. (2023). Automatic detection and categorization of skin lesions for early diagnosis of skin cancer using YOLO-V3–DCNN architecture. Image Analysis & Stereology, 42, 101–117. https://doi.org/10.5566/ias.2773

Manzoor, K., Gilal, N. U., Agus, M., & Schneider, J. (2025). Dual-stage segmentation and classification framework for skin lesion analysis using deep neural network. Digital Health, 11, 1–21. https://doi.org/10.1177/20552076251351858

Martin, N., & Udjulawa, D. (2024). Klasifikasi kanker kulit pada citra dermatoskopi menggunakan CNN. Jurnal Algoritme, 5(1), 35–46.

Marujo, L., Gershman, A., Carbonell, J., Martins de Matos, D., & Neto, J. P. (2014). *Co-Multistage of Multiple Classifiers for Imbalanced Multiclass Learning.* arXiv:1312.6597.

Menon, A. K., Jayasumana, S., Rawat, A. S., Jain, H., Veit, A., & Kumar, S. (2021). Long-tail learning via logit adjustment. In *Proceedings of the 9th International Conference on Learning Representations (ICLR 2021)*. OpenReview.net.

Mirikharaji, Z., Abhishek, K., Bissoto, A., Barata, C., Avila, S., Valle, E., Celebi, M. E., & Hamarneh, G. (2023). A survey on deep learning for skin lesion segmentation. *Medical Image Analysis, 88*, 102863. https://doi.org/10.1016/j.media.2023.102863

Murat, A. A., & Kiran, M. S. (2025). A comprehensive review on YOLO versions for object detection. Engineering Science and Technology, an International Journal, 70, 102161. https://doi.org/10.1016/j.jestch.2025.102161

Nasir, I. M., Alshaya, H., Tehsin, S., & Bouchelligua, W. (2026). Transformer-based foundation learning for robust and data-efficient skin disease imaging. Diagnostics, 16(3), 440. https://doi.org/10.3390/diagnostics16030440

Nauta, M., Walsh, R., Dubowski, A., & Seifert, C. (2022). Uncovering and correcting shortcut learning in machine learning models for skin cancer diagnosis. Diagnostics, 12(1), 40. https://doi.org/10.3390/diagnostics12010040

Nguyen, V. D., Bui, N. D., & Do, H. K. (2022). Skin lesion classification on imbalanced data using deep learning with soft attention. Sensors, 22(19), 7530. https://doi.org/10.3390/s22197530

Oksuz, K., Cam, B. C., Kalkan, S., & Akbas, E. (2022). One metric to measure them all: Localisation Recall Precision (LRP) for evaluating visual detection tasks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(12), 9446–9463.

Padilla, R., Passos, W. L., Dias, T. L. B., Netto, S. L., & da Silva, E. A. B. (2021). A comparative analysis of object detection metrics with a companion open-source toolkit. *Electronics, 10*(3), 279. https://doi.org/10.3390/electronics10030279

Patil, R., & Bellary, S. (2022). Machine learning approach in melanoma cancer stage detection. Journal of King Saud University – Computer and Information Sciences, 34, 3285–3293. https://doi.org/10.1016/j.jksuci.2020.09.002

Rana, M., Gupta, P., & Singh, R. (2025). Explainable YOLO models for early skin cancer detection using hair artifact removal and VGG16 guided annotation. Discover Artificial Intelligence, 5, 358. https://doi.org/10.1007/s44163-025-00637-7

Ranuh, I. G. B. R. S., Sanjoto, M. C., Zakiyyah, A. Y., & Meiliana. (2024). A comparative study of deep learning algorithms for image-based classification of hyperpigmented skin disease. Procedia Computer Science, 245, 1129–1138. https://doi.org/10.1016/j.procs.2024.10.342

Raschka, S. (2020). Model evaluation, model selection, and algorithm selection in machine learning. arXiv. https://arxiv.org/abs/1811.12808

Reddy, N. V., Sree, P. B., Enoch, M., & Prasanna, B. L. (2026). The power of generative AI to augment for enhanced skin cancer classification. In *2026 9th International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE. https://doi.org/10.1109/ICOEI68323.2026.11542067

Reinke, A., Tizabi, M. D., Baumgartner, M., Eisenmann, M., Heckmann-Nötzel, D., Kavur, A. E., … Maier-Hein, L. (2024). Understanding metric-related pitfalls in image analysis validation. Nature Methods, 21(2), 182–194. https://doi.org/10.1038/s41592-023-02150-0

Qian, S., Ren, K., Zhang, W., & Ning, H. (2022). Skin lesion classification using CNNs with grouping of multi-scale attention and class-specific loss weighting. *Computer Methods and Programs in Biomedicine, 226*, 107166. https://doi.org/10.1016/j.cmpb.2022.107166

Sapkota, R., Cheppally, R. H., Sharda, A., & Karkee, M. (2025). YOLO26: Key architectural enhancements and performance benchmarking for real-time object detection. arXiv. https://doi.org/10.48550/arXiv.2509.25164

Shaheen, H., & Singh, M. P. (2023). Skin lesion classification using HG-PSO and YOLOv7 based convolutional network in real time. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine, 237*(10), 1228–1239. https://doi.org/10.1177/09544119231198823

Shakya, M., Patel, R., & Joshi, S. (2025). A comprehensive analysis of deep learning and transfer learning techniques for skin cancer classification. Scientific Reports, 15, 4633. https://doi.org/10.1038/s41598-024-82241-w

Shodiq, M. F., Pamungkas, D. P., & Kasih, P. (2025). Implementasi EfficientNet-B4 untuk klasifikasi penyakit daun tanaman kentang. Prosiding SEMNAS INOTEK (Seminar Nasional Inovasi Teknologi), 9, 537–545.

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data, 6*(1), 60. https://doi.org/10.1186/s40537-019-0197-0

Stanley, J., Lubis, C., & Handhayani, T. (2022). Sistem Pengenalan Covid-19 Berdasarkan Foto X-ray Paru dengan Metode EfficientNet-B0. *Jurnal Ilmu Komputer Dan Sistem Informasi*, *10*(2). https://doi.org/10.24912/jiksi.v10i2.22549

Takahashi, K., Yamamoto, K., Kuchiba, A., & Koyama, T. (2022). Confidence interval for micro-averaged F1 and macro-averaged F1 scores. Applied Intelligence, 52(5), 4961–4972. https://doi.org/10.1007/s10489-021-02635-5

Tan, M., & Le, Q. V. (2019). *EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks*. Proceedings of the 36th International Conference on Machine Learning (ICML), 97, 6105–6114.

Tschandl, P., Rosendahl, C., & Kittler, H. (2018). The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific Data, 5, 180161. https://doi.org/10.1038/sdata.2018.161

Ulmer, D., Hardmeier, C., & Frellsen, J. (2022). deep-significance: Easy and meaningful statistical significance testing in the age of neural networks. arXiv. https://doi.org/10.48550/arXiv.2204.06815

Ulmer, D., Hardmeier, C., & Frellsen, J. (2022). Prior and posterior networks: A survey on evidential deep learning methods for uncertainty estimation. Transactions on Machine Learning Research. https://openreview.net/forum?id=RDgebS7367

Ultralytics. (2026). YOLO26 training recipe. https://docs.ultralytics.com/guides/yolo26-training-recipe/

Westergerling, T., Allken, V., Melle, W., Salvanes, A. G. V., & Rosen, S. (2026). A deep learning-based model for automatic identification of mesopelagic organisms from in-trawl cameras. PLOS ONE, 21(1), e0340640. https://doi.org/10.1371/journal.pone.0340640

Wicaksana, I. C., Pramunendar, R. A., Saraswati, G. W., & Trisnapradika, G. A. (2025). Skin lesion classification using YOLO26 on the HAM10000 dataset. Inform: Jurnal Ilmiah Bidang Teknologi Informasi dan Komunikasi, 10(1), 45–55. https://doi.org/10.25139/inform.v10i1.9310

Yoshitsugu, K., Kishimoto, K., & Takemura, T. (2025). Improving benign and malignant classifications in mammography with ROI-stratified deep learning. Bioengineering, 12(8), 885. https://doi.org/10.3390/bioengineering12080885

Zhang, S., & Li, P. (2026). Weighted sampling with frequency-aware spatial attention for imbalanced image classification. *Journal of Imaging, 12*(7), 293. https://doi.org/10.3390/jimaging12070293

Zhou, J., Wu, Z., Jiang, Z., Huang, K., Guo, K., & Zhao, S. (2022). Background selection schema on deep learning-based classification of dermatological disease. *Computers in Biology and Medicine*, 149, 105966. https://doi.org/10.1016/j.compbiomed.2022.105966

Zhuang, J.-X., Cai, J., Zhang, J., Zheng, W.-S., & Wang, R. (2023). *Class attention to regions of lesion for imbalanced medical image recognition*. arXiv. https://arxiv.org/abs/2307.10036

Zulkarnain, I. A., & Kusrini. (2025). YOLOv11 optimization through hyperparameter tuning and data augmentation to improve vehicle detection accuracy at night. MALCOM: Indonesian Journal of Machine Learning and Computer Science, 5(4), 1294–1303. https://doi.org/10.57152/malcom.v5i4.225