

SKRIPSI

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



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UNIVERSITAS PALANGKA RAYA

2026

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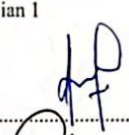
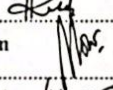
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Dengan ini menyatakan bahwa skripsi yang berjudul “Analisis Pemanfaatan *Region Of Interest (ROI)-Based Learning* Terhadap Kinerja Model Klasifikasi Lesi Kulit Berbasis *Deep Learning* Pada Citra Dermatoskopi” merupakan hasil karya saya sendiri dengan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

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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.

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LEARNING TERHADAP KINERJA MODEL KLASIFIKASI LESI KULIT
BERBASIS *DEEP LEARNING* PADA CITRA DERMATOSKOPI**

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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**

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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 dermoscopic 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, dermoscopic images*

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