

BAB VI KESIMPULAN DAN SARAN

A. Kesimpulan

Berdasarkan hasil implementasi, pengujian, dan analisis yang telah dilakukan, penelitian ini berhasil mengembangkan dan mengevaluasi sistem klasifikasi penyakit paru-paru berbasis *deep learning* dengan optimasi *hyperparameter* Bayesian menggunakan kerangka kerja Optuna. Secara keseluruhan, penelitian ini telah menjawab rumusan masalah dan mencapai seluruh tujuan penelitian, yaitu mengimplementasikan metode *Tree-structured Parzen Estimator* (TPE) dan *Gaussian Process* (GP) dalam optimasi *hyperparameter*, serta menganalisis dampaknya terhadap performa klasifikasi pada tiga arsitektur CNN yang berbeda (EfficientNetB2, DenseNet121, dan ResNet50). Adapun kesimpulan utama yang diperoleh adalah sebagai berikut:

1. Implementasi Optimasi *Hyperparameter* Berbasis Optuna

Optimasi *hyperparameter* berhasil diterapkan melalui *framework* Optuna dengan memanfaatkan dua algoritma Bayesian, yaitu *Tree-structured Parzen Estimator* (TPE) dan *Gaussian Process* (GP). Proses optimasi dilakukan dalam dua fase (*two-phase optimization*). GP dilakukan dengan 20 *trials* dan TPE dilakukan dengan 30 *trials*. Proses ini berhasil mengidentifikasi perubahan signifikan pada beberapa *hyperparameter* utama seperti *weight_decay* (+1102.8%), *dropout_rate* (+40%), dan *dense_units* (+25%), yang menunjukkan bahwa pendekatan Optuna efektif dalam menjelajahi ruang *hyperparameter* secara adaptif dan sistematis.

2. Dampak Optimasi *Hyperparameter* terhadap Performa Klasifikasi

Analisis komparatif antara model *default* dan model hasil optimasi Bayesian menunjukkan bahwa optimasi *hyperparameter* dalam kasus ini tidak berdampak yang signifikan dalam meningkatkan performa klasifikasi.

- EfficientNetB2, konfigurasi *default* memberikan hasil sedikit lebih unggul dari hasil optimasi (98.38% vs 98.36%), meskipun waktu pelatihan model optimal meningkat 24.9%.
- DenseNet121, model *default* juga lebih baik (97.70% vs 96.83%) karena optimasi yang terlalu agresif justru menghambat mekanisme *feature reuse*.

- ResNet50, perbedaan performa lebih mencolok (98.20% vs 97.03%), menunjukkan bahwa kombinasi hyperparameter hasil optimasi mengganggu *gradient flow* pada *residual blocks*.

Dengan demikian, terlihat dampak optimasi hyperparameter yang bisa di implementasikan dengan baik pada arsitektur tertentu tetapi tidak bisa universal di semua arsitektur model CNN. Oleh karena itu, bisa disimpulkan bahwa arsitektur model bersifat arsitektur spesifik.

3. Perbandingan Arsitektur CNN dan Efisiensi Model

Ketiga arsitektur CNN menunjukkan karakteristik dan keunggulan masing-masing. EfficientNetB2_Default memberikan akurasi tertinggi (98.38%) dengan reliabilitas klinis sangat baik, ResNet50_Default menunjukkan efisiensi pelatihan tertinggi dengan waktu 40% lebih cepat, sedangkan DenseNet121_Default unggul dalam stabilitas generalisasi. Perbandingan ini menunjukkan dampak arsitektur terhadap hasil optimasi, di mana setiap model memiliki sensitivitas berbeda terhadap perubahan *hyperparameter*.

B. Saran

Berdasarkan hasil penelitian yang menunjukkan bahwa konfigurasi *default* masih mengungguli hasil optimasi Bayesian pada ketiga arsitektur CNN, penelitian selanjutnya disarankan untuk mengembangkan strategi optimasi hyperparameter Bayesian yang lebih mendalam, adaptif, dan spesifik terhadap karakteristik arsitektur model (*architecture-specific optimization*). Tujuannya adalah agar setiap model seperti EfficientNetB2, DenseNet121, dan ResNet50 dapat memperoleh *Best Parameter Configuration* yang benar-benar sesuai dengan struktur internal dan mekanisme pembelajaran masing-masing, bukan hasil generalisasi lintas arsitektur.

1. Optimalisasi Bayesian yang Lebih Komprehensif dan Architecture-Specific

Eksperimen lanjutan perlu memperluas ruang pencarian (*search space*) dan menyesuaikan ruang tersebut dengan karakteristik setiap arsitektur.

- EfficientNetB2, eksplorasi perlu difokuskan pada *compound coefficient* (width, depth, resolution multipliers), *drop connect rate*, serta *learning rate decay* yang sesuai dengan scaling law-nya.

- DenseNet121, eksplorasi sebaiknya mencakup *growth rate*, *compression factor*, dan *bottleneck ratio* yang memengaruhi efisiensi *feature reuse*.
- ResNet50, perlu dilakukan pengaturan regularisasi yang lebih lembut (*gentle regularization*) dengan *weight_decay* di kisaran 1×10^{-6} hingga 5×10^{-4} dan *dropout* 0.2–0.4 agar *gradient flow* tetap stabil. Selain itu, kombinasi algoritma optimasi seperti *multi-objective Bayesian optimization* dengan 100–200 *trials* dapat digunakan untuk menghasilkan *Pareto-optimal solutions* yang mempertimbangkan trade-off antara akurasi, efisiensi komputasi, dan waktu inferensi, sesuai kebutuhan deployment di lapangan.

2. Pengayaan Hyperparameter dan Strategi Pelatihan yang Lebih Adaptif

Untuk memperoleh *best architecture-specific configuration*, penelitian lanjutan sebaiknya memasukkan hyperparameter penting yang belum dioptimasi, seperti:

- *Batch size optimization* (range 8–64) dengan *gradient accumulation* untuk menjaga stabilitas pelatihan,
- *Learning rate scheduling strategies* seperti Cosine Annealing, Warm Restarts, dan OneCycleLR,
- Eksperimen *optimizer alternatives* seperti Lion, AdaBelief, atau Ranger,
- *Stage-specific hyperparameters* untuk menentukan alokasi *epoch* yang optimal antara *Stage 1* (feature extraction) dan *Stage 2* (fine-tuning). Optimalisasi modul perhatian (CBAM) juga penting dilakukan dengan menyesuaikan *reduction ratio* (4–16), *kernel size* pada *spatial attention*, serta *pooling strategy* yang paling sesuai bagi tiap arsitektur.

3. Peningkatan Akurasi pada Kelas Minoritas dan Kelas yang Masih Tertukar

Untuk menekan tingkat kesalahan klasifikasi (terutama antara *Bacterial Pneumonia* dan *Viral Pneumonia* dengan *error rate* 11.5%), disarankan penerapan augmentasi lanjutan berbasis adaptasi domain, seperti Mixup, CutMix, AutoAugment, atau domain-specific augmentation yang mensimulasikan variasi protokol klinis (posisi pasien, paparan sinar, kondisi demografis).

Pendekatan class-conditional augmentation dengan *elastic deformation*, *morphological operations*, atau *synthetic lesion injection* juga diharapkan dapat meningkatkan kemampuan model dalam membedakan pola patologi yang mirip secara visual.

4. Eksplorasi Arsitektur Modern dan Pembelajaran Multi-Tugas (Multi-Task Learning)

Penelitian lanjutan dapat mengeksplorasi arsitektur baru seperti Vision Transformers (ViT, Swin Transformer), hybrid models (CoAtNet, ConvNeXt), dan efficiency-optimized CNNs (EfficientNetV2, MobileNetV4) untuk memaksimalkan *feature representation*. Selain itu, implementasi multi-task learning dengan *auxiliary tasks* seperti *lung segmentation*, *lesion detection*, dan *severity grading* berpotensi meningkatkan interpretabilitas klinis dan kualitas fitur yang dihasilkan model.

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