Enhancing Multi-Fidelity Optimization using Proxy and Evolution

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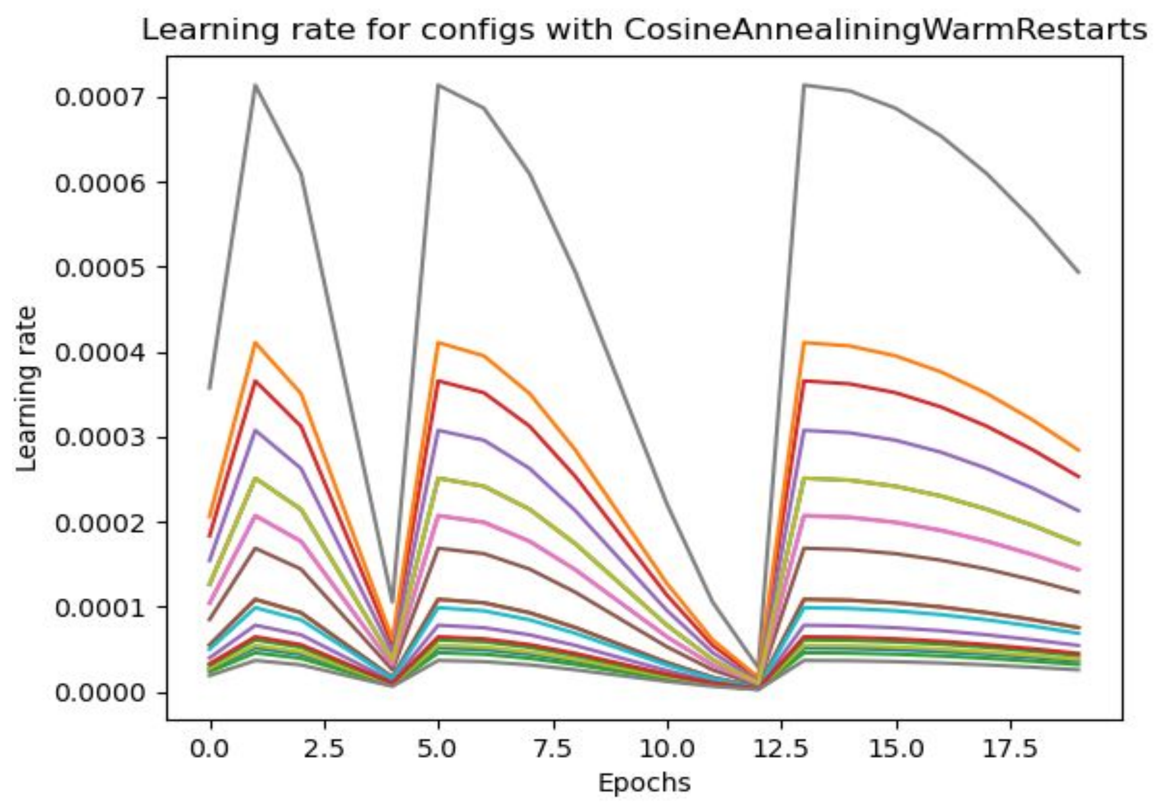
Abstract

We present a multi-fidelity method designed for optimizing CNN configurations within constrained computational resources. Warm starting, dynamic learning rates, early termination, and proxy-driven optimization are all integrated into our approach. Our approach considerably improves CNN performance by utilizing data augmentation, Regularized Evolution, and a smooth transition from proxy to target function. This novel strategy exhibits the capability to increase CNN effectiveness while adhering to resource constraints.

Configuration space Refinement and Optimization Strategies



Configuration space refinement - Incorporates prior knowledge based on known architectures and evidence based trials experimented on varying configuration spaces.

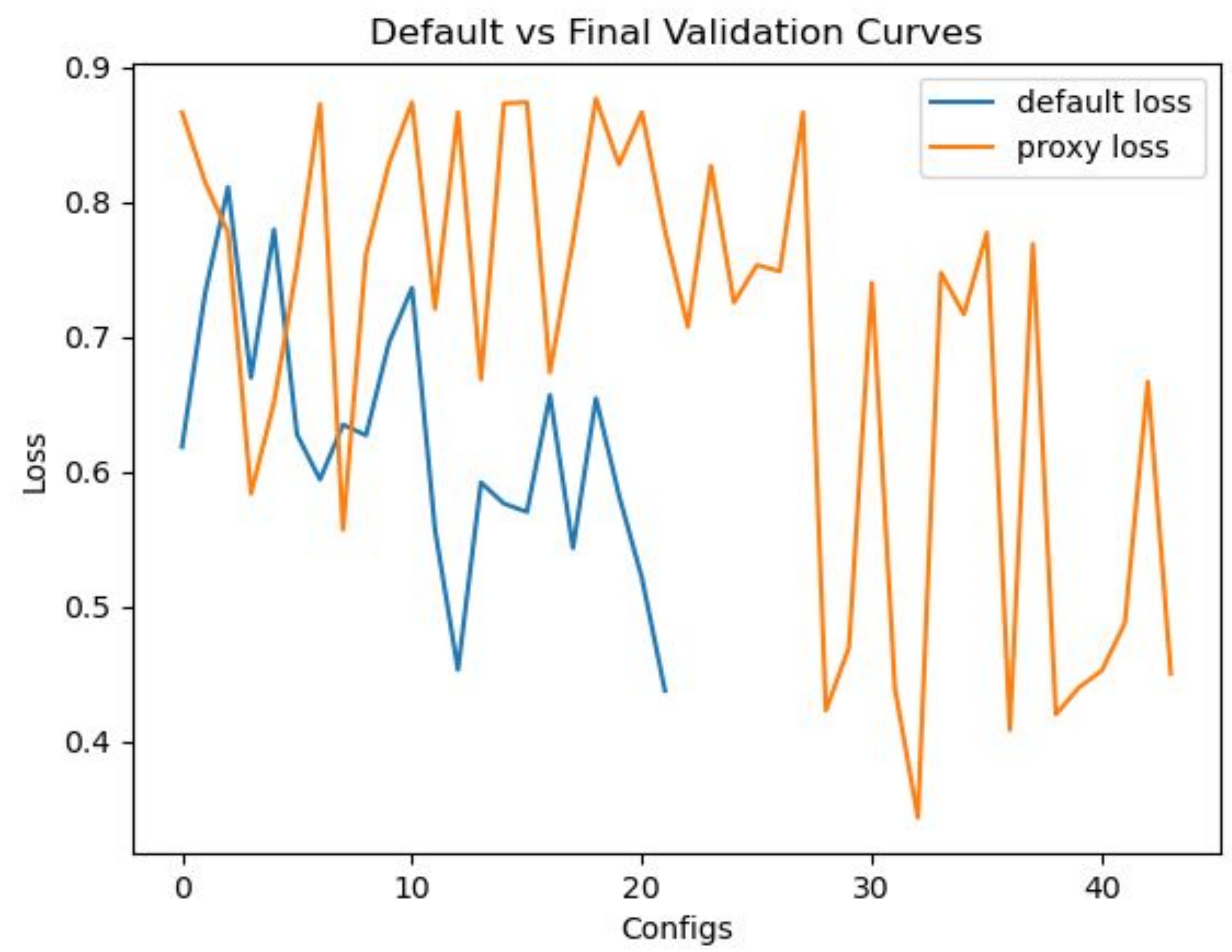
Cosine Annealing Warm Restarts: We use adaptive learning rates with Cosine Annealing Warm Restarts, boosting model training efficiency and convergence.

Effective Regularization: Early stopping with six epochs and data augmentation enhance generalization, preventing overfitting.

Proxy based optimization and warmstart

Proxy: We devised a proxy function, a lower-fidelity representation of the target function, employing reduced image sizes and limited epochs on a subset of the dataset. This proxy efficiently estimates configuration performance, triggering the real function evaluation only for configurations surpassing a predetermined loss threshold. By filtering out suboptimal configurations early, our approach focuses on validating configurations with promising ones, effectively streamlining the optimization process and conserving computational resources.

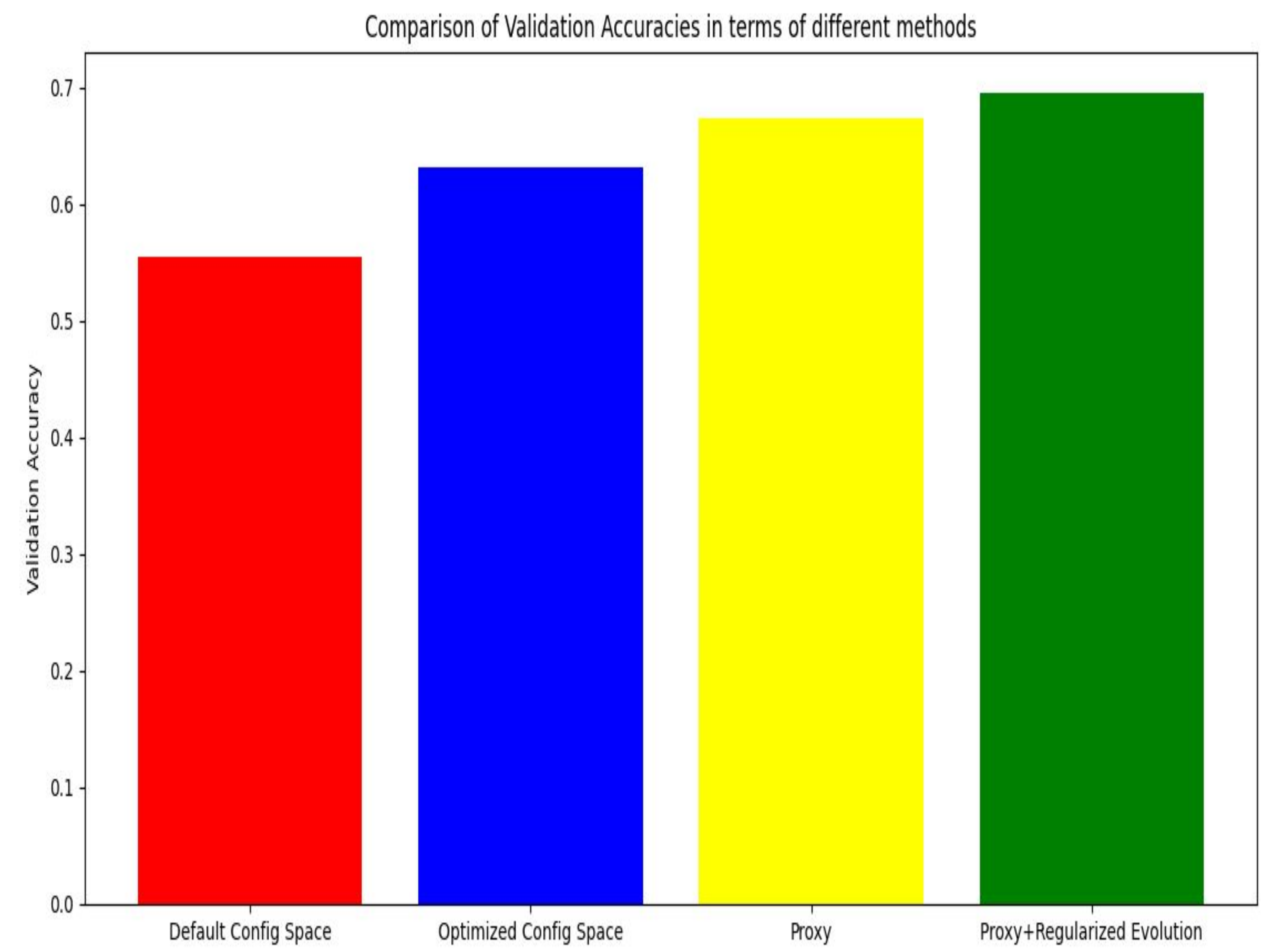
Warmstart: Through a 1000-second warm up phase, we intelligently sample and evaluate configurations using the proxy function. Configurations exceeding proxy validation accuracy thresholds are pre-warmed, boosting efficiency during subsequent SMAC optimization.

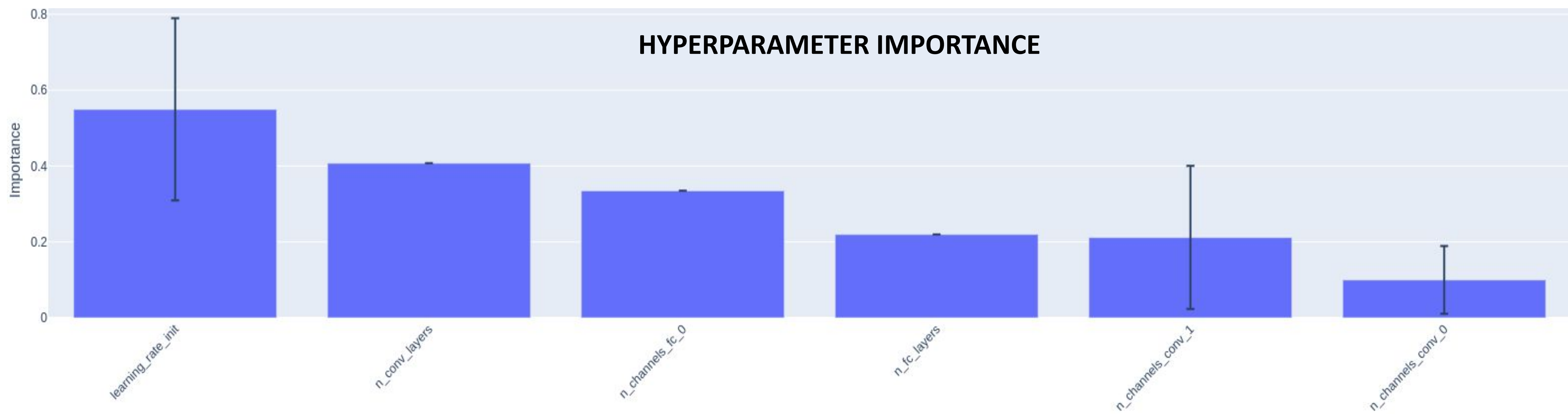


Regularized Evolution

After obtaining the incumbent through SMAC optimization, we extended our optimization efforts using the Regularized Evolution function over several generations. This approach, guided by a predefined population size, fitness function, and mutation rate rooted in evidence-based knowledge, fine-tuned the SMAC-optimized incumbent. By iteratively improving configurations, we enhanced the potential for discovering even more promising solutions, marking a pivotal stage in our optimization process.

The default configuration achieved a test accuracy of 55.55%. After optimizing the configuration space, accuracy increased to 63.2%, further boosted to 67.33% using proxy optimization. With the application of evolutionary techniques, the final accuracy reached an impressive 69.6%.





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