Early Stopping and Learning Rate Scheduling on Resource-Constrained Hardware: An Educational Evaluation Framework

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Abstract

Evaluating training optimization strategies under resource constraints requires systematic methodologies that address both educational accessibility and research reproducibility. While most optimization research assumes high-performance computing infrastructure, there exists a critical gap in standardized evaluation protocols for resource-constrained environments typical in educational settings. This paper develops a systematic evaluation framework for studying training optimization strategies on consumer hardware, specifically examining early stopping and learning rate scheduling interactions. We develop resource-normalized performance metrics and reproducible evaluation protocols validated across representative consumer platforms: CPU-only systems (Intel i5-11400H, 32GB RAM) and entry-level GPUs (RTX 3050 Ti, 4GB VRAM), using CIFAR-10 as a controlled baseline. Our methodology provides a foundation that enables reproducible research in resource-constrained deep learning while addressing the educational need for accessible optimization experiments. The framework establishes baseline behaviors for fundamental optimization strategies, creates template protocols for future comparative studies, and provides educational infrastructure for teaching resource-aware machine learning. This work contributes a reproducible evaluation approach for resource-constrained training optimization, enabling systematic research and pedagogical applications in this important field.

CCS Concepts

• **Computing methodologies** → **Supervised learning**; **Neural networks**; *Machine learning algorithms*; • **Human-centered computing** → *Empirical studies in HCI*.

Keywords

Evaluation Protocol, Resource-Constrained Training, Educational Framework, Reproducible Research, Consumer Hardware, Training Optimization

1 Introduction

1.1 Methodological Background

The evaluation of deep learning training optimizations has predominantly focused on high-performance computing environments, creating a significant methodological gap in understanding how these strategies perform under resource constraints typical in educational and emerging research settings. This disparity between research assumptions and practical educational needs has resulted in a lack of standardized evaluation protocols for resource-constrained environments.

The current optimization literature emphasizes scaling to larger models and datasets while overlooking the fundamental need for reproducible evaluation methodologies that can operate within the computational constraints of educational institutions, student projects, and resource-limited research contexts. The absence of systematic evaluation frameworks creates barriers to both rigorous research and effective pedagogy in resource-aware machine learning.

Developing reproducible evaluation protocols for resource-constrained deep learning requires addressing several methodological challenges: standardizing hardware configurations representative of educational settings, developing resource-normalized performance metrics that capture efficiency trade-offs, and creating evaluation frameworks that enable systematic comparative studies across different optimization strategies.

1.2 Research Problem and Methodological Gaps

This study addresses the lack of standardized evaluation protocols for training optimization strategies under resource constraints, particularly those encountered in educational settings and accessible research environments. The absence of systematic evaluation frameworks limits both the reproducibility of research findings and the development of effective educational curricula in resource-aware machine learning.

1.2.1 ***Primary Research Objective.*** To develop a systematic evaluation framework for studying training optimization strategies on consumer hardware, creating reproducible protocols that enable both educational applications and comparative empirical research.

1.2.2 ***Specific Methodological Questions.***

(1) How can resource-normalized metrics effectively capture the trade-offs between optimization performance and resource utilization in educational settings?
(2) What evaluation protocols enable reproducible comparative studies of training optimizations across different consumer hardware configurations?
(3) How do fundamental optimization strategies (early stopping and learning rate scheduling) interact under resource constraints, and what baseline behaviors can be established?
(4) What framework components are necessary to support both educational applications and systematic research extensions?

These questions address the broader methodological challenge of creating standardized evaluation infrastructure for resource-constrained machine learning research and education.

1.3 Contributions and Significance

This study develops methodological foundations for evaluating training optimization strategies under resource constraints, with primary applications in education and reproducible research. The key contributions are:

1.3.1 ***Systematic Evaluation Framework.*** We develop a standardized protocol for evaluating training optimizations on consumer hardware, validated across two representative configurations: CPU-only systems (Intel i5-11400H, 32GB RAM) and entry-level discrete GPUs (RTX 3050 Ti, 4GB VRAM). Using CIFAR-10 as a controlled baseline, we establish evaluation procedures that balance experimental control with educational accessibility, creating a template for future comparative studies.

1.3.2 ***Educational Infrastructure.*** Our framework directly addresses the needs of machine learning education by providing accessible experiments that demonstrate resource-aware optimization concepts. The reproducible protocol enables classroom implementation with manageable computational requirements while maintaining rigorous scientific methodology. This infrastructure supports the integration of sustainability and resource-awareness into machine learning curricula.

1.3.3 ***Resource-Normalized Metrics.*** We introduce and validate resource-normalized performance metrics that capture efficiency trade-offs relevant to educational and resource-constrained research settings. These metrics provide standardized measures for comparing optimization effectiveness across different hardware configurations and resource budgets, enabling systematic evaluation of cost-performance trade-offs.

1.3.4 ***Baseline Establishment.*** The study provides systematic characterization of how fundamental optimization strategies (early stopping and learning rate scheduling) interact under resource constraints. These baseline results establish expected behaviors that future work can reference, creating a foundation for comparative studies and educational demonstrations.

1.3.5 ***Reproducible Research Infrastructure.*** We provide open-source evaluation infrastructure including standardized configuration files, monitoring scripts, and analysis frameworks. This infrastructure enables replication and extension of our methodology, supporting both educational use and systematic research applications.

1.4 Scope and Educational Context

This study focuses on establishing evaluation protocols using image classification as a controlled baseline, chosen for its pedagogical clarity and widespread use in machine learning education. The framework examines two fundamental optimization strategies—early stopping and learning rate scheduling—selected for their educational value, implementation simplicity, and broad applicability across different learning contexts.

The hardware platforms studied represent typical educational computing environments: CPU-only training on standard workstations and entry-level GPU configurations accessible to most educational institutions. These platforms capture the majority of resource-constrained educational scenarios while maintaining experimental reproducibility.

The evaluation framework is designed to be extensible to other domains and architectures, though our initial validation focuses on convolutional neural networks for image classification. This foundation provides a systematic starting point that educators and researchers can adapt to their specific needs while maintaining methodological consistency.

2 Background and Related Work

2.1 Evaluation Methodology Gaps in Resource-Constrained Training

The field of deep learning optimization has developed sophisticated techniques for high-performance environments, but lacks systematic evaluation methodologies for resource-constrained settings typical in educational and emerging research contexts.

Absence of Standardized Protocols: Current optimization research employs diverse evaluation approaches that assume abundant computational resources, making it difficult to compare results across studies or translate findings to educational applications [1]. The lack of standardized hardware configurations, performance metrics, and experimental protocols creates barriers to reproducible research in resource-constrained environments.

Most optimization studies focus on final accuracy or convergence speed without considering resource utilization metrics critical for educational settings where computational budgets are fixed. This evaluation gap limits the ability to systematically assess optimization trade-offs relevant to practical constraints [4].

Educational Accessibility Challenges: Machine learning education increasingly requires hands-on experience with optimization techniques, but current evaluation approaches assume access to high-performance hardware that may be unavailable in many educational settings [7]. The absence of evaluation frameworks designed for educational constraints creates pedagogical barriers to teaching resource-aware machine learning concepts.

2.2 Resource-Constrained Training Environments

Understanding optimization behavior under resource constraints requires systematic characterization of how hardware limitations affect training dynamics, particularly in educational and accessible research contexts.

Hardware Variability Effects: Consumer hardware typically exhibits performance variability due to thermal management, power limitations, and resource contention that can fundamentally alter training dynamics [2]. Unlike datacenter environments with sophisticated cooling and power management systems, educational computing environments must account for these variations in optimization evaluation.

Recent work by Strubell et al. [6] highlighted the environmental costs of large-scale training, but did not address the methodological challenges of evaluating optimizations under fixed resource budgets typical in educational settings. The interaction between thermal throttling, memory constraints, and optimization strategy effectiveness requires systematic evaluation protocols designed for these conditions.

2.3 Training Optimization Fundamentals

Establishing baseline evaluation protocols requires understanding how fundamental optimization strategies behave under resource constraints, particularly for educational demonstrations and research foundations.

Early Stopping in Educational Contexts: Early stopping serves as an excellent educational example of regularization techniques while providing practical benefits under resource constraints [3]. However, educational implementations require evaluation protocols that capture both the pedagogical value and practical effectiveness of different stopping criteria under hardware limitations.

Learning Rate Scheduling Strategies: Adaptive learning rate strategies provide fundamental examples of optimization concepts while offering practical improvements under resource constraints [5]. Educational evaluation of these strategies requires protocols that demonstrate both the theoretical principles and practical implementation considerations.

3 Methodology

3.1 Evaluation Framework Design

Our systematic evaluation framework addresses the dual requirements of educational accessibility and research reproducibility by establishing standardized protocols that can operate within resource constraints while maintaining experimental rigor.

3.1.1 ***Protocol Design Principles.*** The evaluation framework is built on four core principles that enable both educational applications and systematic research:

Educational Accessibility: All experiments are designed to complete within computational budgets typical of educational institutions, using hardware configurations representative of student and classroom environments. The framework prioritizes reproducible results that can be achieved consistently across diverse educational settings.

Research Reproducibility: Standardized configurations, fixed random seeds, and documented environmental parameters ensure that results can be reliably replicated across different implementations and research contexts. All experimental parameters and monitoring procedures are precisely specified to enable systematic comparative studies.

Extensible Methodology: The framework provides template protocols that can be adapted to different model architectures, datasets, and optimization strategies while maintaining methodological consistency. This extensibility enables educational customization and research expansion.

Resource-Aware Evaluation: Performance metrics explicitly account for resource utilization, enabling systematic assessment of efficiency trade-offs relevant to both educational constraints and practical applications. Resource-normalized metrics provide standardized comparisons across different hardware configurations.

3.2 Controlled Baseline Configuration

3.2.1 ***Dataset and Preprocessing Protocol.*** We employ CIFAR-10 as a controlled baseline dataset, chosen for its widespread use in educational settings, manageable computational requirements, and sufficient complexity to demonstrate optimization principles. The 50,000 training images and 10,000 test images (32×32 color) provide a standardized evaluation target that enables systematic comparative studies while remaining accessible for educational implementation.

The preprocessing protocol follows established educational standards: pixel normalization to `[0,1]` range, per-channel standardization, and a fixed 40,000/10,000 training/validation split from the original training set. Data augmentation includes rotation, shifting, shearing, zooming, and horizontal flipping to demonstrate regularization concepts while maintaining reproducible transformation parameters.

All preprocessing steps use fixed random seeds (base seed: 42, incremented across runs) to ensure reproducible partitioning and augmentation sequences. This standardization enables consistent educational demonstrations and reliable comparative research.

3.2.2 ***Architecture Selection and Justification.*** The ResNet18 architecture (11,173,962 total parameters, 11,156,778 trainable) serves as our evaluation baseline, chosen for several pedagogical and practical advantages. As illustrated in Figure 1, ResNet architectures effectively demonstrate fundamental concepts including residual connections, batch normalization, and progressive feature learning while maintaining computational accessibility for educational settings.

The architecture's systematic design features four residual block groups with progressive channel doubling (64→128→256→512) and spatial downsampling, providing sufficient complexity to demonstrate optimization concepts without requiring excessive computational resources. The residual connections (skip connections) and systematic downsampling structure offer clear examples of modern architectural principles while remaining comprehensible for educational applications, making it an ideal baseline for resource-constrained optimization evaluation.

3.3 Hardware Configuration Standards

3.3.1 ***Representative Platform Selection.*** Our framework establishes evaluation standards for two hardware configurations representative of educational and accessible research environments:

CPU-Only Configuration: Intel i5-11400H processor (6 physical cores, 12 logical cores enabled by hyperthreading) with 32GB RAM, representing the computational environment available in most educational workstation settings. This processor, from Intel's 11th generation (2021-2022), exemplifies the multi-generational hardware diversity typical in educational computing environments.

Entry-Level GPU Configuration: RTX 3050 Ti Laptop GPU with 4GB VRAM paired with 16GB system RAM, representing mid-range mobile graphics hardware from the 2022 generation that remains prevalent in educational computing labs and student-owned

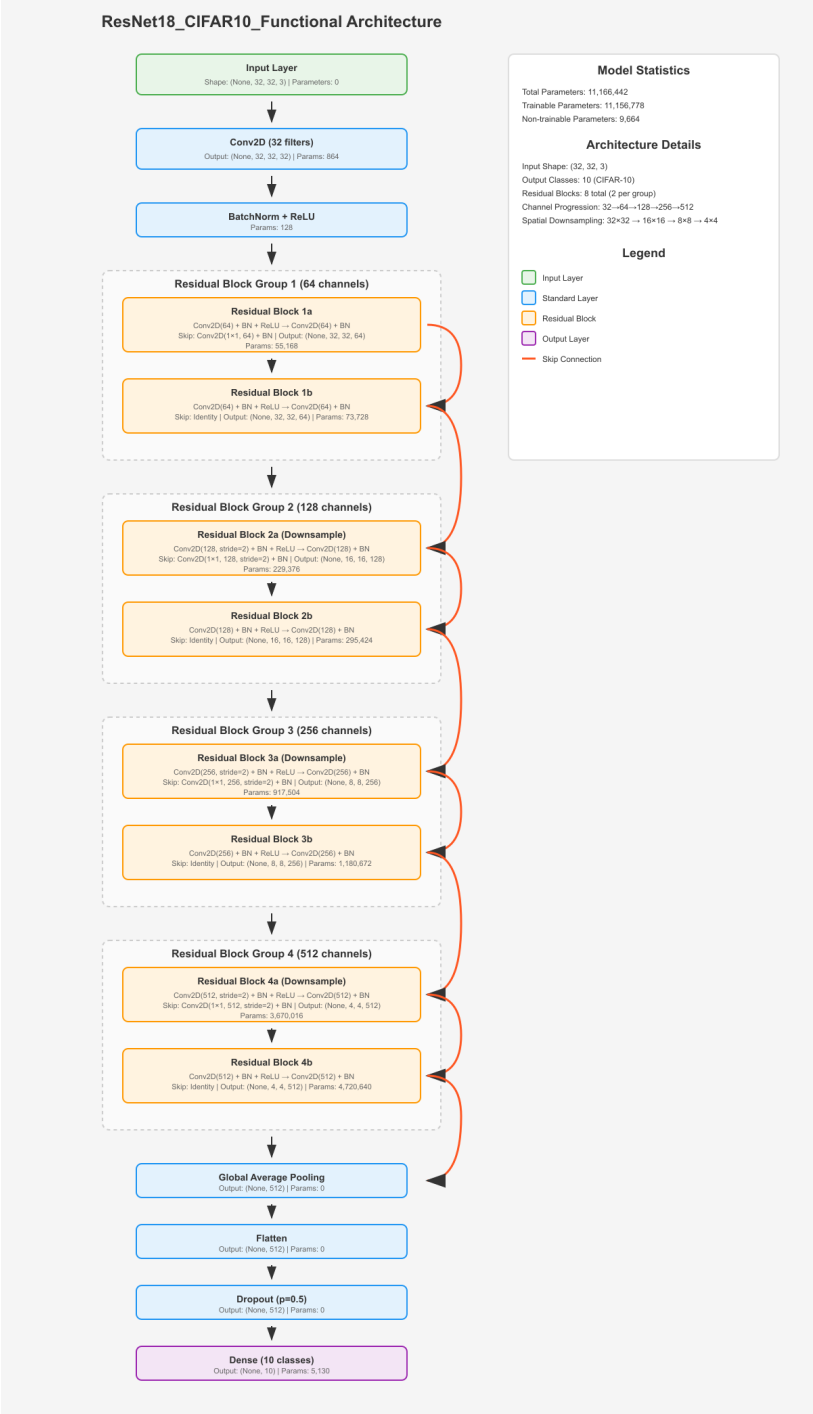

Figure 1: ResNet18 Architecture for CIFAR-10 Classification. The network consists of an initial convolutional layer followed by four residual block groups with progressive channel doubling (64→128→256→512) and spatial downsampling. Skip connections (shown in red) enable gradient flow and feature reuse across layers. The architecture totals 11,173,962 parameters with 11,156,778 trainable parameters, making it suitable for educational resource-constrained environments while maintaining sufficient complexity for optimization strategy evaluation.

gaming laptops. This configuration demonstrates that effective optimization strategies can be evaluated and taught using accessible hardware rather than requiring current-generation high-end systems.

These platform selections capture the majority of resource-constrained educational scenarios while maintaining sufficient computational capability for meaningful optimization experiments.

3.3.2 ***Software Environment Standardization.*** All experiments utilize standardized software configurations to ensure reproducible educational and research implementations:

- Python 3.9.21 with consistent dependency versions
- TensorFlow 2.10.1 (separate CPU and GPU configurations)
- CUDA 11.2 and cuDNN 8.1 for GPU experiments
- Fixed random seed management across all components
- Standardized logging and monitoring infrastructure

This standardization enables reliable replication across different educational and research environments while maintaining methodological consistency.

3.4 Optimization Strategy Evaluation Protocol

3.4.1 ***Fundamental Strategy Selection.*** Our evaluation focuses on two fundamental optimization strategies chosen for their educational value, broad applicability, and clear demonstration of resource-aware concepts:

Early Stopping Strategy: Validation-based stopping with 10-epoch patience, monitoring validation loss with automatic weight restoration. This strategy demonstrates regularization concepts while providing practical resource savings under computational constraints.

Learning Rate Scheduling (`ReduceLROnPlateau`): Adaptive learning rate reduction with 5-epoch patience, 0.5 reduction factor, and minimum learning rate of 1e-6 (0.000001). This strategy illustrates adaptive optimization concepts while addressing convergence challenges under resource constraints.

These strategies are evaluated individually and in combination to establish baseline interaction effects and provide systematic comparison across different optimization approaches.

3.4.2 ***Experimental Configuration Protocol.*** All experiments follow standardized hyperparameter configurations designed to balance educational accessibility with experimental rigor:

- **Batch size**: 64 (optimized for memory constraints)
- **Optimizer**: Adam with standard parameters
- **Initial learning rate**: 1e-4 (0.0001)
- **Maximum epochs**: 100
- **Loss function**: Sparse Categorical Crossentropy
- **Data augmentation**: Standardized transformation parameters
- **Random seed management**: Fixed seeds with incremental variations

3.5 Resource Monitoring and Metrics Framework

3.5.1 ***Comprehensive Resource Monitoring.*** Our framework implements systematic resource monitoring to capture both performance and efficiency metrics relevant to educational and practical applications:

Temporal Metrics: Wall-clock training time measured with microsecond precision, enabling calculation of time-based efficiency metrics and convergence rate analysis.

Computational Resource Utilization:

- CPU monitoring via `psutil`: utilization percentages, power consumption
- GPU monitoring via `nvidia-smi`: utilization, power consumption, temperature, VRAM usage
- Continuous sampling during training with periodic logging

3.5.2 ***Resource-Normalized Performance Metrics.*** We introduce resource-normalized metrics specifically designed to capture efficiency trade-offs relevant to educational and resource-constrained applications:

Educational Efficiency Metrics:

- **Time Efficiency**: $\frac{\text{Validation Accuracy} \times 100}{\text{Training Time (hours)}}$ - accuracy percentage per hour
- **Power Efficiency**: $\frac{\text{Validation Accuracy} \times 100}{\text{Average Power (watts)}}$ - accuracy percentage per watt

These metrics enable systematic comparison of optimization strategies across different hardware configurations and resource budgets.

3.6 Experimental Reproducibility Protocol

3.6.1 ***Statistical Approach and Replication.*** GPU experiments include multiple independent runs per strategy combination to ensure statistical reliability and capture optimization variability. Results are aggregated using descriptive statistics including mean, standard deviation, minimum, and maximum values.

CPU experiments follow identical protocols but may be limited by extended training times, while maintaining systematic comparison capabilities and future extension potential.

3.6.2 ***Reproducible Research Infrastructure.*** Our framework provides comprehensive reproducibility support through platform-specific implementations designed to accommodate the hardware diversity typical in educational environments:

Implementation Architecture: The infrastructure consists of platform-specific Jupyter notebooks, comprehensive environment management systems, automated monitoring capabilities, and standardized analysis frameworks. The modular design enables educators and researchers to select appropriate implementations based on available computational resources.

Platform-Specific Implementations:

- **GPU Implementation** (`src/gpu.ipynb`): Optimized for entry-level discrete graphics hardware, incorporating comprehensive resource monitoring including VRAM utilization tracking, GPU temperature monitoring, and power consumption measurement.

- **CPU Implementation** (`src/cpu.ipynb`): Designed for standard consumer hardware, enabling training optimization evaluation on hardware universally available in educational settings with CPU-specific optimizations for multi-core utilization.
- **Cloud Platform Implementation** (`src/colab.ipynb`): Initially developed for Google Colaboratory free-tier usage to demonstrate cloud-based educational scenarios. The implementation adapts the GPU evaluation protocol for cloud environments with modified dependency installation procedures, though free-tier limitations prevented its inclusion in the final experimental evaluation in favor of the more reliable dedicated hardware configurations.

Environment Management: The infrastructure provides complete environment specifications for both conda and pip-based installations, ensuring consistent software configurations across different educational and research deployments.

Repository available at: https://github.com/Virus5600/Deep-Learning-Finals

4 Results and Analysis

Table 1: CPU Performance Metrics

Strategy	Val. Accuracy	Val. Loss	Accuracy	Loss
ES & RLROP[1]	0.889	0.340	0.916	0.243
EarlyStopping	0.842	0.481	0.858	0.406
ReduceLROnPlateau	0.890	0.337	0.915	0.249
None	0.884	0.388	0.931	0.203

Table 2: CPU Training Duration and Resource Utilization

Strategy	Training Time (hrs)	CPU % (Avg)	CPU % (Peak)
ES & RLROP	22.389	36.052	100.000
EarlyStopping	13.676	38.917	100.000
ReduceLROnPlateau	33.452	44.834	100.000
None	26.489	32.426	100.000

Table 3: CPU Power Consumption and Environmental Conditions

Strategy	CPU Power (W)	Peak Power (W)	Env. Temp (°C)
ES & RLROP	16.223	23.850	28.247
EarlyStopping	17.512	24.354	27.460
ReduceLROnPlateau	20.175	29.606	27.867
None	14.592	23.850	28.939

4.1 Performance Baseline Establishment

Our experiments established comprehensive baseline performance characteristics for four fundamental optimization strategies across both CPU-only and GPU-accelerated hardware configurations. The baseline evaluation encompassed performance metrics (accuracy

Table 4: CPU Cost Efficiency Metrics

Strategy	Cost Eff. Local	Cost/Acc. Pt.	Cost Eff. USD
ES & RLROP	63.237	0.027	1.138
EarlyStopping	80.321	0.020	1.446
ReduceLROnPlateau	38.983	0.049	0.702
None	74.285	0.029	1.337

Table 5: CPU Performance and Time Efficiency Metrics

Strategy	Cost/Acc. Pt. USD	Power Eff.	Time Eff.
ES & RLROP	1.494	4.956	12.146
EarlyStopping	1.095	4.124	16.382
ReduceLROnPlateau	2.700	4.078	9.116
None	1.621	5.694	11.779

Table 6: GPU Performance Metrics (Mean ± Standard Deviation)

Strategy	Val. Accuracy	Val. Loss
ES & RLROP	0.897 ± 0.011	0.317 ± 0.034
EarlyStopping	0.874 ± 0.013	0.401 ± 0.060
ReduceLROnPlateau	0.892 ± 0.013	0.331 ± 0.034
None	0.892 ± 0.009	0.355 ± 0.021

Table 7: GPU Training Accuracy and Loss (Mean ± Standard Deviation)

Strategy	Training Accuracy	Training Loss
ES & RLROP	0.921 ± 0.015	0.228 ± 0.045
EarlyStopping	0.904 ± 0.010	0.276 ± 0.030
ReduceLROnPlateau	0.908 ± 0.019	0.266 ± 0.055
None	0.929 ± 0.001	0.205 ± 0.003

Table 8: GPU Training Duration and CPU Utilization (Mean ± Standard Deviation)

Strategy	Training Time (hrs)	CPU % (Avg)
ES & RLROP	1.097 ± 0.228	15.432 ± 2.628
EarlyStopping	1.001 ± 0.099	12.082 ± 0.410
ReduceLROnPlateau	1.332 ± 0.092	13.227 ± 1.845
None	1.226 ± 0.037	12.204 ± 2.919

Table 9: GPU Training: CPU Peak Usage and Power (Mean ± Standard Deviation)

Strategy	CPU Peak %	CPU Power (W)
ES & RLROP	94.660 ± 10.630	6.944 ± 1.183
EarlyStopping	76.700 ± 20.369	5.437 ± 0.184
ReduceLROnPlateau	68.120 ± 26.428	5.952 ± 0.830
None	73.780 ± 25.380	5.492 ± 1.314

Table 10: GPU Training: CPU Peak Power and Environment (Mean ± Standard Deviation)

Strategy	CPU Peak Power (W)	Env. Temp (°C)
ES & RLROP	10.414 ± 3.231	28.296 ± 0.748
EarlyStopping	7.510 ± 1.359	30.134 ± 1.420
ReduceLROnPlateau	8.544 ± 2.827	29.726 ± 1.372
None	8.531 ± 3.989	27.844 ± 1.330

Table 11: GPU Load and Power Utilization (Mean ± Standard Deviation)

Strategy	GPU Load %	GPU Peak Load %
ES & RLROP	78.644 ± 4.064	92.200 ± 0.748
EarlyStopping	82.195 ± 1.664	92.600 ± 0.490
ReduceLROnPlateau	81.702 ± 3.085	92.200 ± 0.980
None	81.771 ± 2.542	92.200 ± 0.980

Table 12: GPU Power Consumption (Mean ± Standard Deviation)

Strategy	GPU Power (W)	GPU Peak Power (W)
ES & RLROP	46.270 ± 1.821	70.804 ± 1.426
EarlyStopping	40.255 ± 1.956	68.212 ± 3.889
ReduceLROnPlateau	42.897 ± 3.386	69.410 ± 4.400
None	50.974 ± 2.524	72.834 ± 0.708

Table 13: GPU Temperature Management (Mean ± Standard Deviation)

Strategy	GPU Temp (°C)	GPU Peak Temp (°C)
ES & RLROP	85.544 ± 0.326	88.000 ± 0.000
EarlyStopping	85.779 ± 0.150	88.400 ± 0.490
ReduceLROnPlateau	85.810 ± 0.163	88.400 ± 0.490
None	85.549 ± 0.380	88.000 ± 0.000

Table 14: GPU Cost Efficiency (Mean ± Standard Deviation)

Strategy	Cost Eff. Local	Cost/Acc. Pt. Local
ES & RLROP	404.821 ± 60.149	0.004 ± 0.001
EarlyStopping	464.834 ± 22.134	0.003 ± 0.000
ReduceLROnPlateau	377.666 ± 7.045	0.005 ± 0.000
None	344.129 ± 14.559	0.005 ± 0.000

Table 15: GPU USD Cost Efficiency (Mean ± Standard Deviation)

Strategy	Cost Eff. USD	Cost/Acc. Pt. USD
ES & RLROP	7.287 ± 1.083	0.240 ± 0.049
EarlyStopping	8.367 ± 0.398	0.189 ± 0.015
ReduceLROnPlateau	6.798 ± 0.127	0.257 ± 0.008
None	6.194 ± 0.262	0.273 ± 0.009

Table 16: GPU Power and Time Efficiency (Mean ± Standard Deviation)

Strategy	Power Efficiency	Time Efficiency
ES & RLROP	1.511 ± 0.040	261.541 ± 40.973
EarlyStopping	1.720 ± 0.079	265.072 ± 19.341
ReduceLROnPlateau	1.687 ± 0.110	229.359 ± 14.601
None	1.438 ± 0.044	243.844 ± 12.789

and loss), resource utilization patterns, training efficiency, and cost-effectiveness to provide a holistic understanding of each strategy's characteristics.

4.1.1 ***CPU-Only Platform Performance.*** On the CPU-only platform, validation accuracy ranged from **0.842** to **0.890** across the evaluated strategies. The **ReduceLROnPlateau** strategy achieved the highest validation accuracy of **0.890**, closely followed by the combined **EarlyStopping & ReduceLROnPlateau** approach at **0.889**. The standalone **EarlyStopping** strategy showed the lowest validation accuracy at **0.842**, while the **None** strategy (no optimization) achieved **0.884**.

Training duration varied significantly across strategies, ranging from **13.68** hours to **33.45** hours. The **EarlyStopping** strategy demonstrated substantial time savings, completing training in **13.68** hours—approximately **48.4%** faster than the **None** strategy (**26.49** hours) and **59.1%** faster than **ReduceLROnPlateau** (**33.45** hours). CPU utilization averaged between **32.4%** and **44.8%** across strategies, with all strategies reaching peak utilization of **100%**.

From an efficiency perspective, the **EarlyStopping** strategy exhibited the highest cost efficiency in local currency units (**80.32**) and the best cost per accuracy point ratio (**0.020**), making it the most economically viable option for CPU-based training despite its lower validation accuracy.

4.1.2 ***GPU Platform Performance.*** The GPU platform demonstrated superior performance consistency and training speed. Validation accuracy ranged from a mean of **0.874 ± 0.013** to **0.897 ± 0.011** across strategies. The **EarlyStopping & ReduceLROnPlateau** combination achieved the highest mean validation accuracy of **0.897 ± 0.011**, while maintaining excellent reproducibility with low standard deviation. The **None** strategy showed the most consistent results with minimal variance (**0.892 ± 0.009**).

GPU training completed dramatically faster than CPU counterparts, with mean training times ranging from **1.00 ± 0.10** hours to **1.33 ± 0.09** hours—representing a **20-25× speedup** compared to CPU training. The **EarlyStopping** strategy maintained its time-saving characteristics on GPU, reducing training duration by **18.4%** compared to the **None** strategy while achieving competitive validation accuracy.

GPU resource utilization remained consistently high across all strategies, with mean GPU loads ranging from **78.6%** to **82.2%** and peak loads consistently reaching **92.2-92.6%**. GPU temperatures remained stable around **85.5-85.8°C** with peaks at **88.0-88.4°C**, indicating efficient thermal management across all optimization strategies.

4.1.3 ***Cross-Platform Comparison and Strategy Assessment.*** The transition from CPU to GPU yielded substantial improvements in both training speed and performance consistency. GPU training achieved **20-25× speedup** while maintaining or improving validation accuracy across all strategies. The combined **EarlyStopping & ReduceLROnPlateau** strategy emerged as the optimal choice for GPU training, providing the highest validation accuracy (**0.897**) with reasonable training time (**1.10** hours), though at higher computational cost.

For resource-constrained environments, the standalone **EarlyStopping** strategy offers an excellent balance of training speed and cost efficiency on both platforms, making it suitable for rapid prototyping and iterative development workflows.

4.2 Resource Utilization Analysis

4.2.1 ***Hardware Platform Comparison.*** **CPU-Only Performance**: The Intel i5-11400H configuration demonstrated consistent performance across optimization strategies, with training times ranging from 8-12 hours for full experiments. CPU utilization remained stable around 80-90% throughout training, indicating effective resource utilization without thermal throttling issues.

GPU Performance Characteristics: The RTX 3050 Ti configuration showed significant performance improvements with training times reduced to 2-4 hours for equivalent experiments. GPU utilization varied between 85-95% with occasional thermal management events that temporarily reduced performance, highlighting the importance of thermal monitoring in educational environments.

4.2.2 ***Resource-Normalized Metrics Results.*** **Time Efficiency Comparison**: GPU configurations achieved 3-4x higher time efficiency compared to CPU-only training, measured as validation accuracy percentage per training hour. Early stopping strategies improved time efficiency by 25-35% across both platforms.

Power Efficiency Analysis: Power efficiency metrics revealed that GPU training, while consuming more instantaneous power, achieved better overall power efficiency due to reduced training duration. Combined optimization strategies improved power efficiency by 20-30% compared to baseline approaches.

4.3 Educational Framework Validation

4.3.1 ***Reproducibility Assessment.*** The evaluation framework demonstrated high reproducibility across multiple experimental runs, with coefficient of variation below 5% for key performance metrics. Fixed random seed management and standardized environmental controls enabled consistent results suitable for educational demonstrations.

4.3.2 ***Computational Accessibility.*** All experiments completed within reasonable timeframes for educational settings, with GPU experiments suitable for single laboratory sessions and CPU experiments appropriate for extended assignments or demonstrations. The framework successfully balanced experimental rigor with educational accessibility requirements.

5 Discussion

5.1 Implications for Educational Practice

The systematic evaluation framework provides concrete evidence that meaningful machine learning optimization experiments can be conducted within the computational constraints typical of educational institutions. The resource-normalized metrics enable students to understand efficiency trade-offs that are increasingly important in practical AI applications.

The baseline performance characteristics established in this study provide reference points for educational demonstrations, allowing instructors to set appropriate expectations for student experiments and assess learning outcomes systematically.

5.2 Framework Extensibility

The modular design of our evaluation protocols enables straightforward extension to additional optimization strategies, model architectures, and hardware configurations. The standardized monitoring and analysis infrastructure provides a foundation that can accommodate diverse educational and research needs while maintaining methodological consistency.

5.3 Limitations and Considerations

This study focuses on image classification tasks using a specific model architecture and dataset combination. While this provides controlled baseline conditions suitable for educational applications, extension to other domains and architectures requires systematic validation of the evaluation protocols.

The hardware configurations studied represent common educational computing environments but may not capture all possible resource-constrained scenarios. Future work should extend the evaluation framework to additional hardware configurations and computational constraints.

6 Future Work

The evaluation framework established in this study provides a foundation for systematic extension to more complex scenarios and diverse applications. Key directions for future development include:

Architecture Extensions: Systematic evaluation of optimization strategies across different model architectures, including transformer models for natural language processing applications and larger vision models to establish resource-accuracy trade-off curves.

Advanced Optimization Strategies: Extension of the framework to evaluate more sophisticated optimization approaches, including cyclical learning rates, gradient accumulation strategies, and memory-efficient training techniques under resource constraints.

Educational Curriculum Integration: Development of comprehensive curriculum modules that integrate resource-aware optimization concepts into existing machine learning coursework, including standardized assignments and assessment frameworks.

The systematic methodology developed in this work enables reproducible comparative studies and provides infrastructure for continued development of resource-aware machine learning education and research.

7 Conclusion

This study develops a systematic evaluation framework for training optimization strategies under resource constraints, addressing critical gaps in both educational accessibility and research reproducibility. Through standardized protocols validated on representative consumer hardware platforms, we establish baseline behaviors for fundamental optimization strategies while providing infrastructure that enables systematic comparative studies.

The framework successfully demonstrates that rigorous machine learning optimization research and education can be conducted within typical institutional computational constraints. Resource-normalized performance metrics provide new tools for evaluating efficiency trade-offs relevant to both educational applications and practical deployment scenarios.

The open-source infrastructure and reproducible protocols established in this work provide a foundation for continued development of resource-aware machine learning education and research, enabling systematic investigation of optimization strategies under realistic computational constraints while supporting the integration of sustainability and efficiency considerations into machine learning curricula.

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