PHENIKAA UNIVERSITY

FACULTY OF ELECTRICAL AND ELECTRONICS ENGINEERING

FINAL REPORT

Advanced Reinforcement Learning

Topic: DRL for optimizer selection in deep learning training process

Student:	Phạm Tuấn Anh
ID:	22011107
Class:	K16 AIRB
Instructor:	TS. Vũ Hoàng Diệu

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1. INTRODUCTION

1.1. Problem

Selecting an appropriate optimizer is crucial in training deep neural networks efficiently. However, there is no universally optimal optimizer for every training scenario. Traditional optimizers like SGD achieve good generalization but may converge slowly, whereas newer techniques such as Sharpness-Aware Minimization (SAM) improve generalization at the expense of increased computational cost. Consequently, manually choosing and fine-tuning optimizers is time-consuming, labor-intensive, and may not guarantee optimal performance. Thus, there exists a significant need for automated methods to dynamically select optimizers during training to maximize performance and minimize computational resources.

1.2. Motivation

The motivation behind integrating a Deep Q-Network (DQN) into the optimizer selection process arises from the inherent strengths and weaknesses of various optimization algorithms. While adaptive optimizers like Adam or SAM can rapidly converge in initial phases, their computational overhead and limited generalization potential in the final phases pose challenges. Conversely, traditional methods like SGD are more computationally efficient and typically provide better generalization but may take longer to converge initially. Leveraging reinforcement learning to dynamically adjust optimizer selection can potentially exploit the complementary strengths of different optimizers throughout the training process, enhancing efficiency and effectiveness.

1.3. My Idea

The core idea proposed in this work is to use reinforcement learning, specifically a Deep Q-Network (DQN), to dynamically select between optimizers such as SGD and SAM during training of a ResNet model on the CIFAR-10 dataset. The DQN observes various training indicators including loss, validation accuracy, gradient norms, and training epoch information as its state representation. At each epoch, the DQN agent chooses the optimizer that maximizes a designed reward function, balancing validation accuracy improvements and computational efficiency. This adaptive strategy aims to automatically harness the best properties of each optimizer, achieving high validation accuracy with fewer epochs and reduced computational time compared to static optimizer approaches.

1.4. Workflow

1.4.1. DQN trainning process

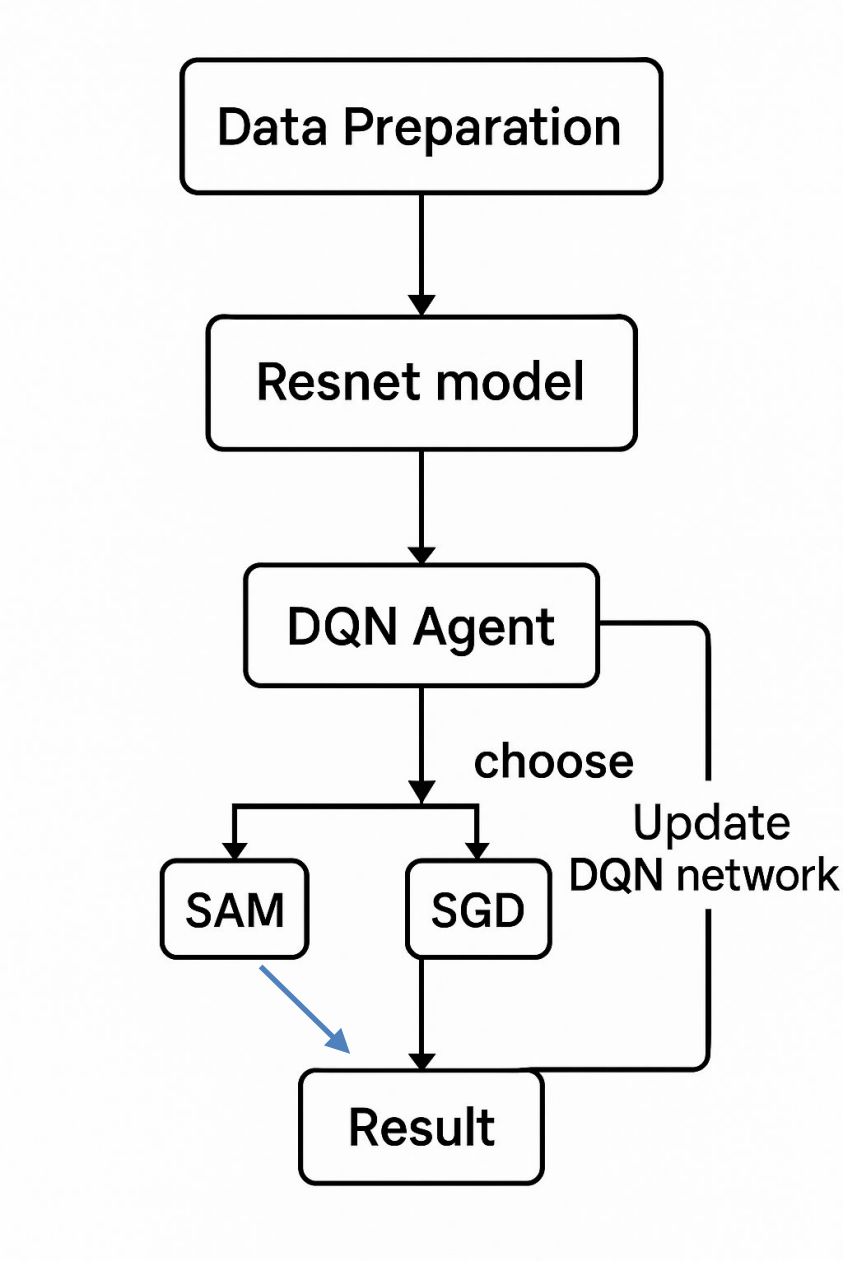

Figure 1:Workflow DQN

This is the flowchart of the training process where a the optimizer:

1. **Data Preparation**
   – The first block performs data preprocessing (loading the data, augmentation, normalization, etc.).
2. **ResNet Model**
   – The preprocessed data is fed into the ResNet model for forward computation and to gather metrics (loss, accuracy, gradient norms, etc.).
3. **DQN Agent**
   – The DQN agent observes the current state (e.g. loss, validation accuracy, gradient norms) and decides which optimizer to use for the next epoch.
4. **Optimizer Selection**
   – From the DQN Agent there are two branches:
   - **SAM** (Sharpness-Aware Minimization)
   - **SGD** (Stochastic Gradient Descent)
5. **Result**
   – The training result using the chosen optimizer (SAM or SGD) is recorded.
6. **Update DQN Network**
   – After computing the reward (based on the training result), a feedback arrow goes back to the DQN Agent to update its Q-network.

1.4.1. PPO trainning process

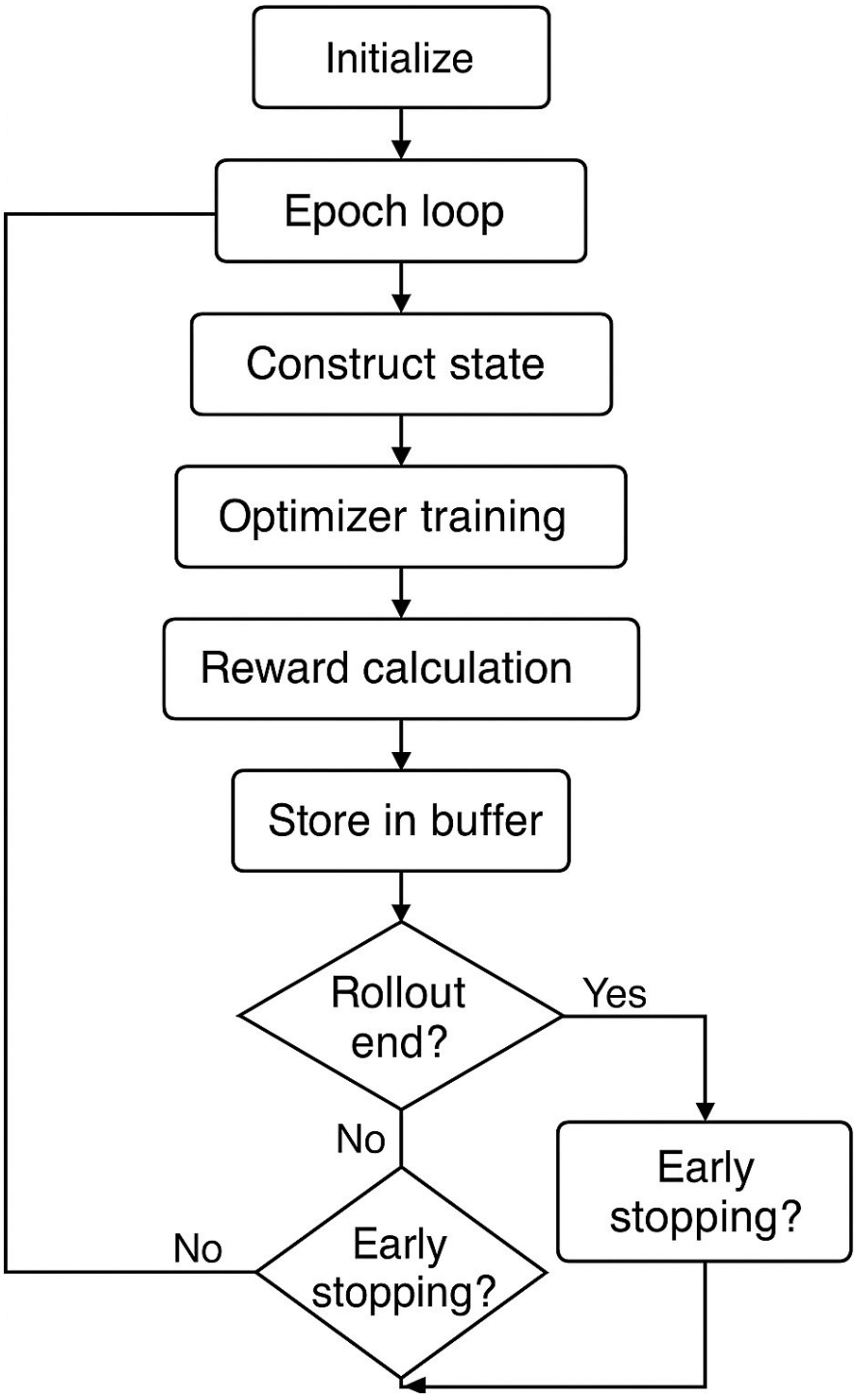

Figure 2: Workflow using PPO

Initialize: Initialize parameters for ResNet-18, Policy & Value networks, RolloutBuffer, and tracking variables.

Epoch Loop: For each epoch:

1. **Construct State**: Aggregate previous metrics into an 8-dimensional vector.
2. **Optimizer Training**: Sample an action from the policy, train ResNet-18 for one epoch with SGD or SAM.
3. **Reward Calculation**: Compute the reward based on changes in validation accuracy/loss and time.
4. **Store in Buffer**: Store the transition in the RolloutBuffer.
5. **Rollout End?**: If ROLLOUT_STEPS have been collected or the final epoch is reached, proceed to PPO update; otherwise, continue the epoch loop.
6. **Early Stopping?**: After each checkpoint, check the early stopping condition. If met, exit the loop; otherwise, return to the epoch loop.

PPO Update: At the end of a rollout, compute advantages (GAE), then perform actor-critic updates using the clipped surrogate and value loss steps.

Finish: Load the best checkpoint and evaluate on the test set.

2. DATASET AND PREPROCESSING

2.1. Dataset

Introduction to the CIFAR-10 Dataset

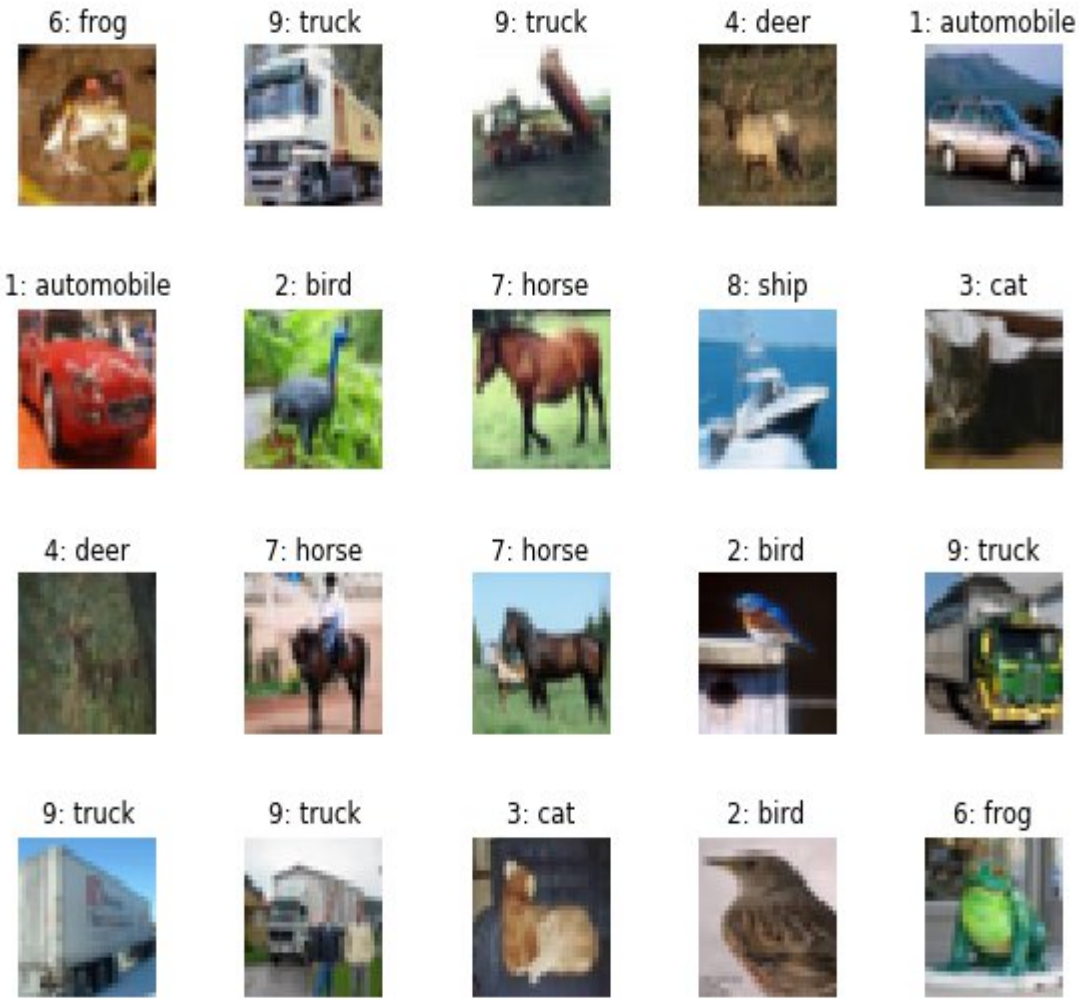

Figure 3: Cifar - 10 Dataset

- **Purpose**: CIFAR-10 is a widely used benchmark in computer vision research and education for evaluating image classification models.
- **Size**: 60,000 color images at 32×32 pixels.
- **Split**: 50,000 training images and 10,000 test images.

- **Classes (10)**:
    1. Airplane
    2. Automobile
    3. Bird
    4. Cat
    5. Deer
    6. Dog
    7. Frog
    8. Horse
    9. Ship
    10. Truck
- **Characteristics**:
    - Low resolution (32×32) poses a feature-extraction challenge.
    - Significant intra-class variation in pose, background, and lighting.
    - Commonly used with data augmentation techniques (random crops, flips, color jitter).

Introduction to the Fashion-MNIST Dataset

Figure 4: Fashion - MNIST Dataset

- **Purpose**: Fashion-MNIST was created as a more challenging drop-in replacement for the original MNIST, focusing on clothing item classification.
- **Size**: 70,000 grayscale images at 28×28 pixels.
- **Split**: 60,000 training images and 10,000 test images.
- **Classes (10)**:
    1. T-shirt/top
    2. Trouser
    3. Pullover
    4. Dress
    5. Coat
    6. Sandal
    7. Shirt
    8. Sneaker
    9. Bag
    10. Ankle boot

2.3. Intrinsic Challenges and Architectural Impact

Table 1: Comparison of Dataset Characteristics for CIFAR-10 vs. Fashion-MNIST

Aspect	CIFAR-10	Fashion-MNIST
Resolution	32×32 pixels (low resolution; limited fine-detail)	28×28 pixels (low resolution)
Color	3-channel color images (color cues present)	Single-channel grayscale (no color cues; emphasizes shape & texture)
Intra-class variability	High (diverse backgrounds, lighting, viewpoints)	Moderate (consistent backgrounds; garment style variations)
Inter-class similarity	Fine-grained (e.g., cat vs. dog)	Subtle boundaries (e.g., pullover vs. coat vs. dress)
Benchmark / Architectural drive	Drove rapid architectural innovation: LeNet → AlexNet → VGG → ResNet → DenseNet → Capsule networks	A more challenging "toy" dataset than MNIST for quick prototyping of simple MLPs/CNNs before full-color datasets

3. MODEL vs Algorithm

3.1. Resnet 18

CNN is a neural network model specialized in processing grid-like data such as images, audio, and time serie. CNN helps automatically extract features, minimize manual processing.The model we use has the following structure:

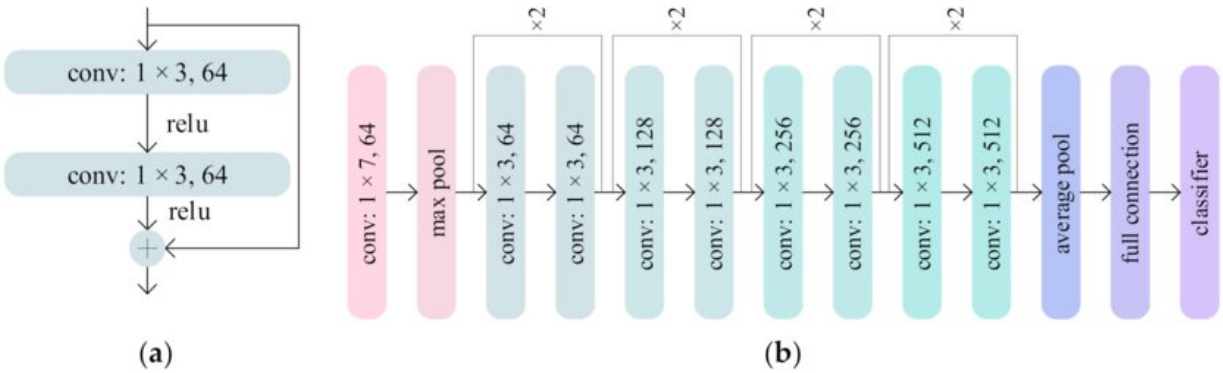

Figure 5: Model Resnet 18

ResNet-18 is a convolutional neural network architecture from the family of "Residual Networks" introduced by He et al. in 2015. It consists of 18 weight layers organized into a series of **residual blocks**, each of which contains two 3×3 convolutional layers with batch normalization and ReLU activations. What sets ResNet apart is the **shortcut (skip) connection** that bypasses these two layers, adding the input of the block directly to its output. This design mitigates the problem of vanishing gradients and enables training of much deeper networks.

The overall structure of ResNet-18 is:

1. **Initial Stem**

   A 7×7 convolution with 64 output channels, stride 2, followed by batch-norm, ReLU, and a 3×3 max-pooling (stride 2).

2. **Four Residual Stages**

   Stage 1: 2 blocks with 64 filters

   Stage 2: 2 blocks with 128 filters (the first block uses stride 2 to downsample)

   Stage 3: 2 blocks with 256 filters (downsample in first block)

   Stage 4: 2 blocks with 512 filters (downsample in first block)

3. **Classification Head**

   A global average pooling reduces each feature map to a single value.

   A final fully-connected layer maps to the number of target classes (e.g., 10 for CIFAR-10 or 1,000 for ImageNet).

With roughly 11 million parameters, ResNet-18 offers a good balance of depth and computational efficiency. Its residual design has become foundational in modern computer vision, inspiring numerous follow-up architectures.

3.2. Reinforcement learning algorithm

3.2.1. DQN

DQN Agent Model Description

1. Architecture

The Deep Q-Network (DQN) agent is implemented as a multi-layer perceptron that approximates the action-value function $Q(s,a)$. Given a state vector $s \in \mathbb{R}^d$, the network outputs a Q-value for each action $a \in \mathcal{A}$, where $\mathcal{A} = \{\text{SGD}, \text{SAM}\}$. The typical architecture is:

- **Input layer:** Dimension d, corresponding to all state features (loss, accuracy, gradient norm, epoch index, etc.).
- **Hidden layers:** Two fully connected layers, each with H units (e.g., $H = 64$), followed by ReLU activations:

$$h_1 = \text{ReLU}(W_1 s + b_1), \quad h_2 = \text{ReLU}(W_2 h_1 + b_2).$$

- **Output layer:** Fully connected layer with $|\mathcal{A}| = 2$ units, producing Q-values:

$$Q(s,a;\theta) = W_3 h_2 + b_3, \quad a \in \{1,2\}.$$

Here, $\theta = \{W_1, b_1, W_2, b_2, W_3, b_3\}$ are the network parameters.

3.2.1.1 Training Algorithm

The DQN training follows the standard procedure:

1. **Experience Replay:** Store transitions (s_t, a_t, r_t, s_{t+1}) in a replay buffer of fixed capacity. During learning, sample random minibatches to break temporal correlations.
2. **Target Network:** Maintain a separate target network with parameters θ^-. Every C steps, update $\theta^- \leftarrow \theta$.
3. **Bellman Updates:** For each sampled transition, compute the target

$$y_t = r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-),$$

and minimize the mean squared error

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - Q(s_i,a_i;\theta))^2$$

via gradient descent on θ.

4. **ϵ-Greedy Policy:** During training, choose actions according to:

$$a_t = \begin{cases} \text{random action}, & \text{with probability } \epsilon, \\ \underset{a}{\text{argmax}} Q(s_t,a;\theta), & \text{with probability } 1-\epsilon. \end{cases}$$

Decay ϵ from an initial value down to a minimum (e.g., 0.05) over time.

3.2.1.2. Hyperparameters

Hidden units H: 64
Learning rate α: 0.001
Discount factor γ: 0.99
Replay buffer capacity: 5000 transitions
Minibatch size: 32
Target network update frequency C: 20 updates
Exploration decay: $\epsilon \leftarrow \max(\epsilon_{\min}, \epsilon \times 0.995)$

3.2.1.3. Integration Points

State input: Concatenate ResNet-extracted feature statistics and training metrics into a vector of dimension d.
Action output: Two Q-values corresponding to optimizers SGD and SAM.
Training schedule: After each epoch, compute reward and store transition, then perform one or more DQN updates.

3.2.1.4. Benefits and Considerations

Benefits:

Balances exploration of optimizer options with exploitation of learned policy.
Uses off-policy learning (experience replay) for data efficiency.
Stabilized by a fixed target network to prevent training divergence.

Considerations:

Additional overhead from DQN updates on top of main training loop.
Requires careful tuning of DQN hyperparameters to ensure convergence.

High-dimensional state vectors may lead to overfitting

3.2.2 PPO

3.2.2.1. Architecture

The PPO agent is implemented as an actor–critic model with two separate multi-layer perceptrons:

Policy (Actor) Network

Input Layer: Dimension d = STATE_DIM = 8, containing:

$$s = \left[\text{val\_acc},\ \text{val\_loss/LOSS\_SCALE},\ \Delta\text{acc},\ \Delta\text{loss},\ \text{epoch}/n_{\text{epochs}},\ \text{one\_hot(prev\_act)}\right],$$

where the one-hot now has 2 dimensions (SGD vs. SAM).

Hidden Layers:

$$h_1 = \tanh(W_1 s + b_1), \quad h_2 = \tanh(W_2 h_1 + b_2),$$

each of size $H = 64$.

Output Layer: 2 logits corresponding to {SGD, SAM}:

$$\text{logits} = W_3\, h_2 + b_3.$$

A Categorical distribution over these two logits is used to sample actions.

Parameters: $\theta_\pi = \{W_1, b_1, W_2, b_2, W_3, b_3\}_{\text{policy}}$.

- **Value (Critic) Network**

Input: Same 8-dimensional state vector

Hidden Layers: Two layers of size 64 with tanh activations

Output: Single scalar

$$V(s;\phi) = W_3' \tanh\left(W_2' \tanh(W_1' s + b_1') + b_2'\right) + b_3'.$$

Parameters: $\theta_v = \{W_1', b_1', W_2', b_2', W_3', b_3'\}_{\text{value}}$.

3.2.2.2. Training Algorithm

Rollout Collection

For each epoch t, build s_t, sample $a_t \sim \pi_\theta(\cdot\,|s_t)$ over {SGD, SAM}.

Train one epoch of ResNet-18 with the chosen optimizer.

Compute reward:

$$r_t = W_{\text{acc}}\,\Delta\text{acc} + W_{\text{loss}}\,\Delta\text{loss} - W_{\text{time}}\,(\text{epoch\_time})$$

plus, on the last epoch, $+\ W_{\text{final}} \times \text{val\_acc}$.

Store $(s_t, a_t, \log\pi_\theta(a_t|s_t), V_\phi(s_t), r_t, \text{done}_t)$.

Generalized Advantage Estimation (GAE) After every $K = 4$ epochs (or at end), compute

$$\widehat{A}_t = \sum_{l=0}^{T-t} (\gamma\lambda)^l \left[r_{t+l} + \gamma\, V_\phi(s_{t+l+1}) - V_\phi(s_{t+l})\right], \quad \widehat{R}_t = \widehat{A}_t + V_\phi(s_t).$$

Clipped Surrogate Objective Over $E = 4$ PPO epochs:

a. Recompute $\log\pi_\theta(a_t|s_t)$ and $V_\phi(s_t)$.

b. Ratio:

$$\rho_t = \exp\left(\log\pi_\theta(a_t|s_t) - \log\pi_{\theta_{\text{old}}}(a_t|s_t)\right).$$

c. Loss terms:

$$L_t^{\text{CLIP}} = \min\left(\rho_t\,\widehat{A}_t,\ \text{clip}(\rho_t, 1-\varepsilon, 1+\varepsilon)\,\widehat{A}_t\right),$$
$$L_t^{\text{ENT}} = \beta\,\mathscr{H}\left(\pi_\theta(\cdot\,|s_t)\right).$$

d. **Policy loss**: $L_\pi = -1/N \sum_t \left(L_t^{\text{CLIP}} + L_t^{\text{ENT}}\right)$.

e. **Value loss**: $L_v = 1/N \sum_t (\widehat{R}_t - V_\phi(s_t))^2$.

f. Update θ by $\nabla_\theta L_\pi$ and ϕ by $\nabla_\phi L_v$.

3.2.2.3. Hyperparameters

- Hidden units $H = 64$
- Discount $\gamma = 0.99$, GAE $\lambda = 0.95$
- Rollout length $K = 4$, PPO epochs $E = 4$
- Clip $\varepsilon = 0.2$, Entropy coeff. $\beta = 2 \times 10^{-2}$
- LR $_\pi = 3 \times 10^{-4}$, LR $_v = 1 \times 10^{-3}$
- LOSS_SCALE = 2.0 (for stability)
- Weight decay = 5×10^{-4}

3.2.2.4. Integration Points

State: 8-dim features per epoch.
Action: 2 logits → {SGD, SAM}.

Schedule: collect 1 transition/epoch; update every 4.
Reward: balances val-acc gain, loss drop, time cost, plus final bonus

5. EVALUATION

Table 2: Performance Metrics, Convergence Epochs, and Per-Epoch Time for Various Methods on CIFAR-10 and MiniFashion

Data	Methods	Acc %	F1 score %	Precision %	Recall %	Converges after	Time for one epoch (s)
CIFAR-10	**DQN for SAM vs SGD**	0.8115	0.8112	0.8121	0.8113	41	18.64-22.4
	PPO for Sam sgd adam	0.8532	0.8532	0.8546	0.8532	82	14.16-22.27
	Adam	0.8172	0.8167	0.8190	0.8172	65	14.7-16.12
	SAM	0.8261	0.8341	0.8302	0.8444	54	19-20.16
	SGD	0.8167	0.8149	0.8092	0.8250	52	7.96-8.13
	PPO for SAM vs SGD	0.8432	0.8441	0.8458	0.8432	40	14.4-22.90
Minisfashion	**SAM**	0.9268	0.9266	0.9269	0.9288	26	22.8-23.3
	SGD	0.9171	0.9151	0.9175	0.9171	33	15.7-16.5
	Adam	0.9102	0.9098	0.9098	0.9102	41	19.9-20.1
	PPO for SAM vs SGD	0.9271	0.9253	0.9253	0.9217	42	16.3-23.13
	PPO for Sam sgd adam	0.9262	0.9264	0.9268	0.9277	47	17.4-24.9

Below is an in-depth analysis of five optimizer methods—SGD, SAM, DQN (SGD vs SAM), PPO (SGD vs SAM), and PPO (SGD, Adam, SAM)—evaluated on CIFAR-10 and FashionMNIST. The report covers stability, performance vs. computation cost, data efficiency, hyperparameter sensitivity, generalization ability, practical deployment considerations, and conclusions.

Best Acuraccy:

MNIST FASHION using PPO (SAM, SGD):

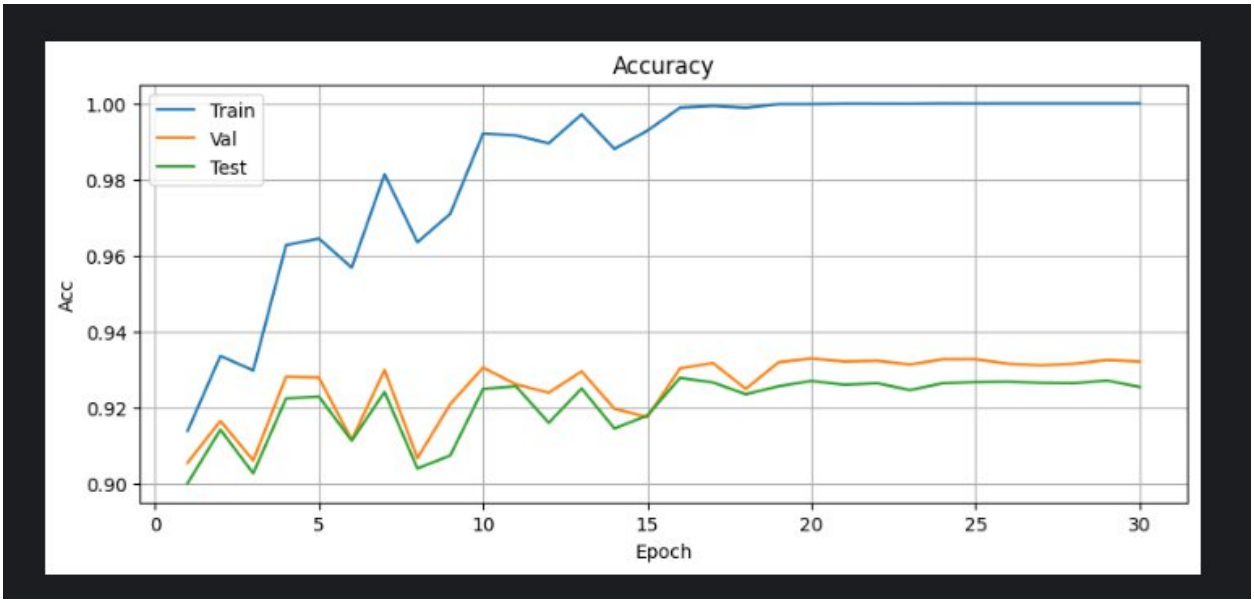

Figure 6: PPO Optimizer Selection: Accuracy over Epochs

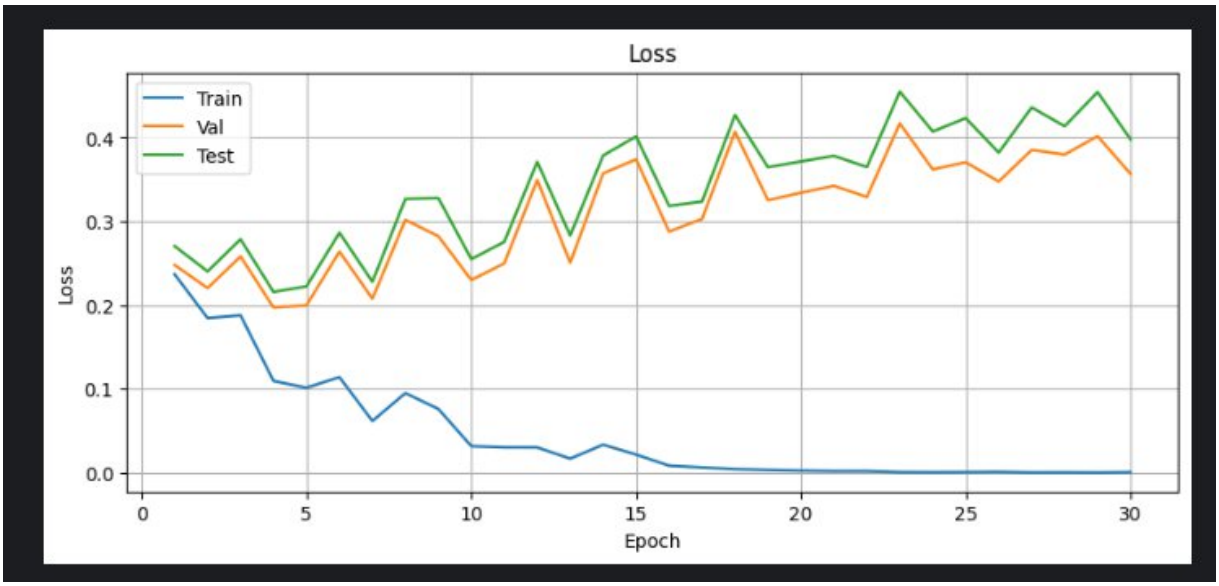

Figure 7: Training Loss of PPO Using Different Optimizers

CIFAR – 10 using PPO(SAM,SGD,ADAM):

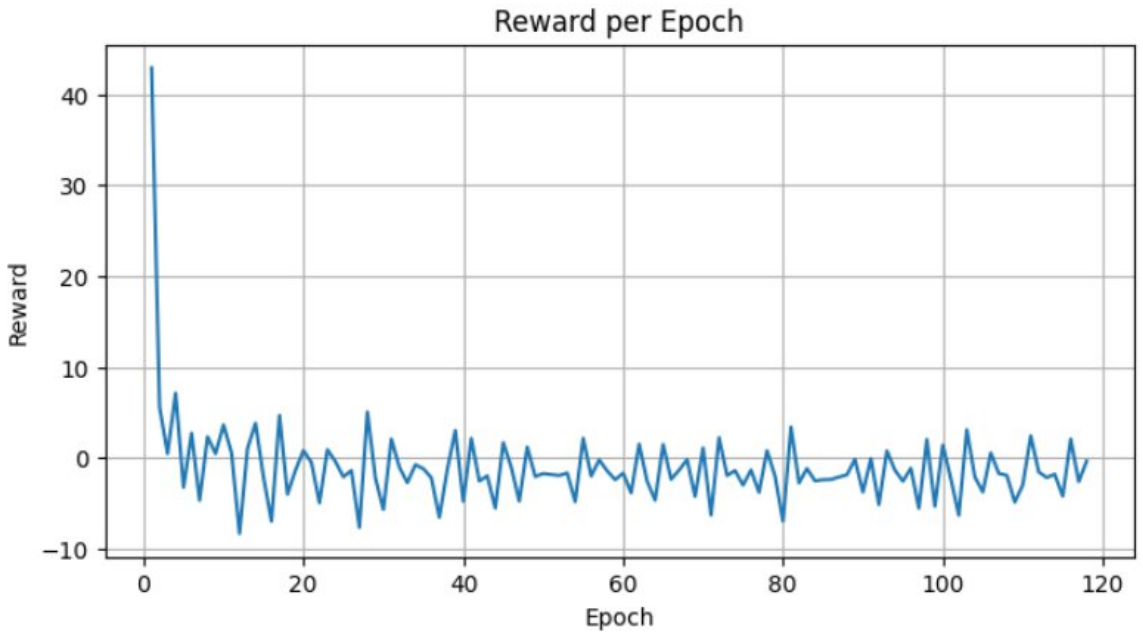

Figure 8: CIFAR-10 Reward Trajectory with PPO Optimizer Selection (SGD, SAM, Adam)

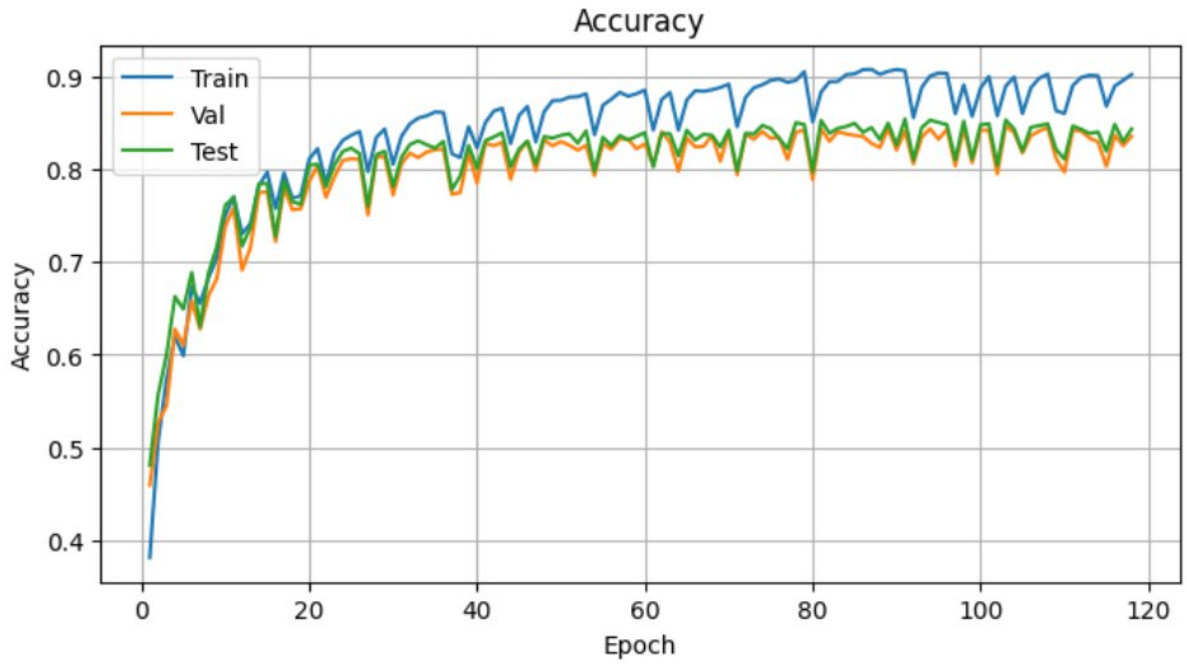

Figure 9: Accuracy Curves for CIFAR-10 with PPO Choosing SGD, SAM and Adam

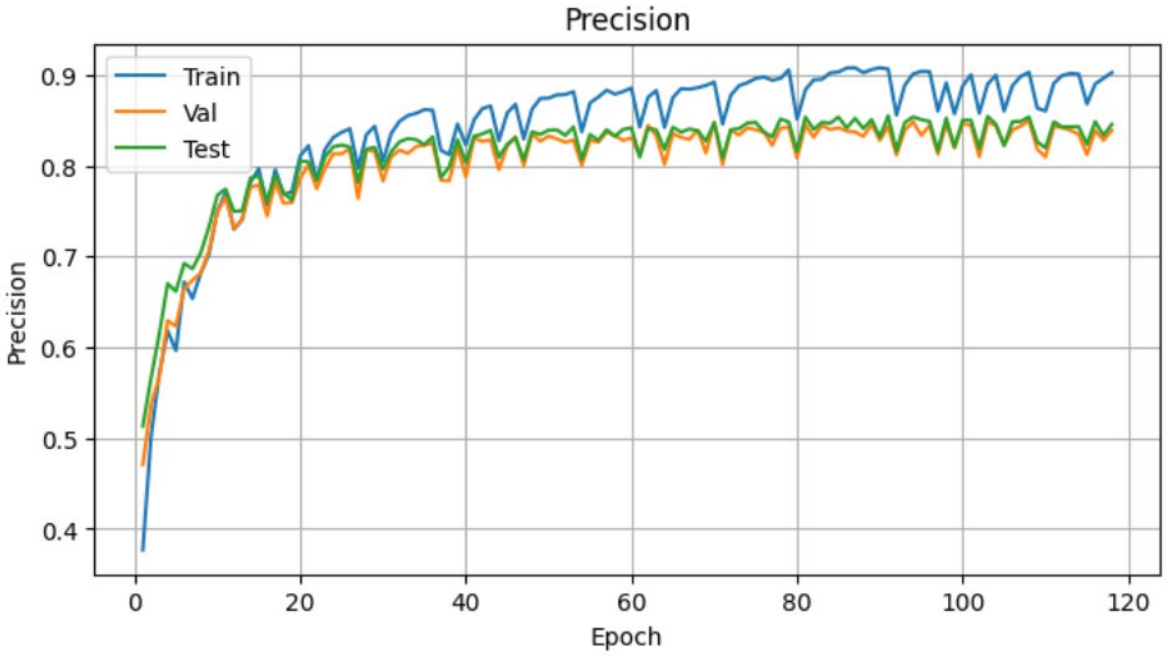

Figure 10: Precision Curves for CIFAR-10 with PPO Choosing SGD, SAM, and Adam

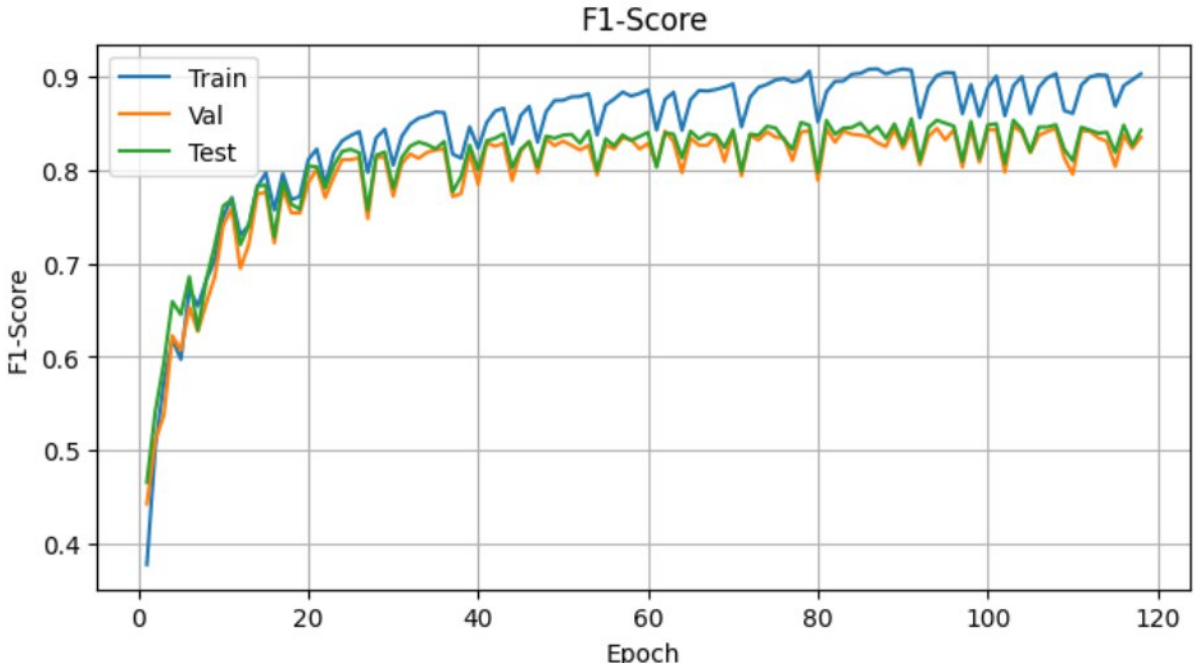

Figure 11: F1-Score Curves for CIFAR-10 with PPO Choosing SGD, SAM, and Adam

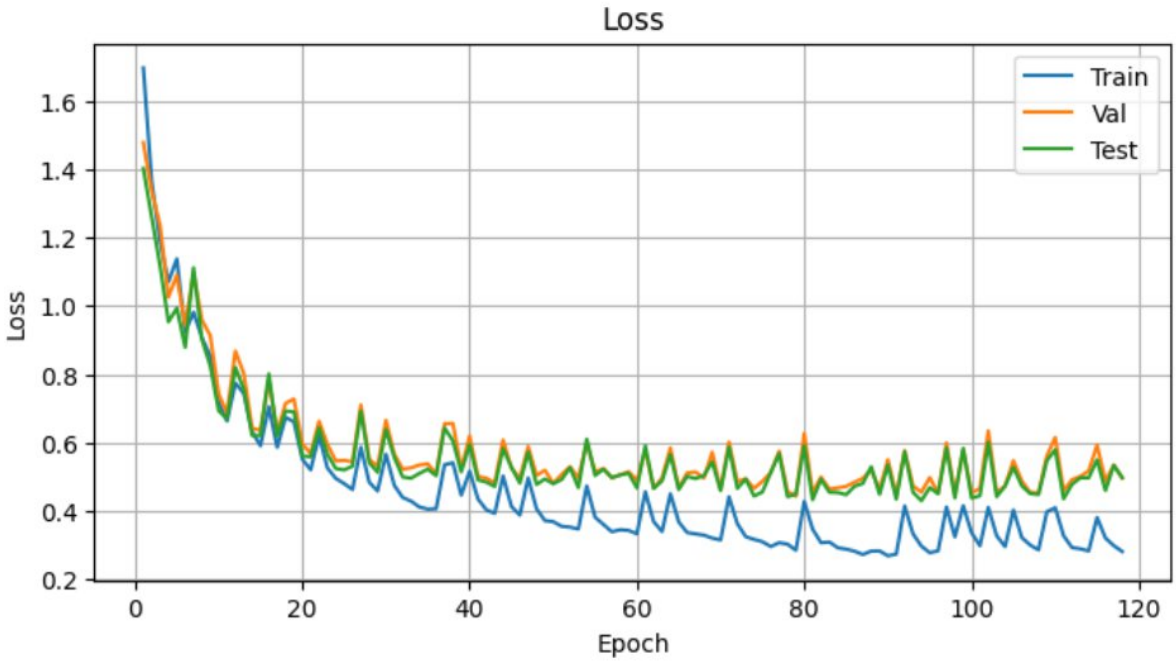

Figure 12: Loss Curves for CIFAR-10 under PPO Choosing SGD, SAM and Adam

5.1 Method Overview

Table 3: Key Characteristics of Optimization Algorithms and RL-Based Optimizer Selection

Algorithm	Key Characteristics
SGD (Stochastic Gradient Descent)	- Updates weights using mini-batch gradients. - Simple and low overhead.
SAM (Sharpness-Aware Minimization)	- Extends SGD with a two-step perturbation to seek flatter minima. Improves generalization at roughly double the compute cost per batch.
DQN (selecting SGD vs. SAM)	Off-policy RL with replay buffer and target network. - Actions choose optimizer; reward based on validation metrics.
PPO (SGD vs. SAM)	On-policy actor–critic with clipped surrogate objective and entropy bonus. - Two-action policy: SGD or SAM.
PPO (SGD, Adam, SAM)	Extends PPO 2-opt by adding Adam, yielding three optimizer choices. - Higher policy flexibility at the expense of increased overhead.

5.2 Stability & Convergence

- SGD can oscillate in rugged loss landscapes; careful learning-rate scheduling is crucial for stability.
- SAM flattens the landscape, reducing validation loss variance, but an overly large ρ can cause instability.
- DQN's replay buffer decorrelates samples, yielding fast convergence (31–40 epochs) but can get stuck on outdated policies if ε-decay is too slow or target updates are sparse.

- PPO achieves strong stability via:
    - Clipped Surrogate Objective: bounds policy updates.
    - Entropy Bonus: maintains exploration and prevents premature collapse onto one optimizer.
    - 2-opt PPO typically converges in 29–40 epochs; 3-opt PPO needs 47–82 epochs due to the extra action choice.

5.3 Performance vs. Computation Cost

Table 4: Comparison of Optimization Methods

Method	Time/epoch	Total Cost ≈ time/epoch × epochs	Remarks
SGD	~8 s	Low	Best for rapid experimentation; accuracy 78–92 %.
SAM	~20–23 s	High	+1 % accuracy over SGD but ~2.5× compute per epoch.
DQN	~18–22 s	Moderate (31–40 epochs)	Fast convergence but lower accuracy than SAM or PPO.
PPO 2-opt	~15–23 s	Medium	Balanced speed & accuracy; actor–critic overhead ~1.5–2×.
PPO 3-opt	~14–25 s	Very high (82 epochs + overhead)	Highest accuracy but largest compute cost and complexity.

- SGD has the lowest epoch cost.
- SAM doubles or triples per-epoch time versus SGD.
- DQN adds buffer and target-network updates.
- PPO adds two networks (actor and critic) and uses multi-epoch updates per rollout.
- 3-opt PPO incurs the highest overhead due to three actions and longer rollouts.

5.4. Data Efficiency

DQN (off-policy) leverages replay buffer to reuse experiences, achieving high sample efficiency and fewer interactions (epochs) for convergence.

PPO (on-policy) discards old data, requiring fresh rollouts—sample efficiency is lower than DQN but gains stability and fewer hyperparameters (no buffer size or target update frequency).

SGD/SAM (baseline) each batch is used once; high data efficiency on training data but susceptible to overfitting.

5.5. Hyperparameter Sensitivity

SGD: sensitive to learning rate and momentum; scheduling strategy (step decay, cosine) is critical.

SAM: requires tuning ρ (perturbation radius) and learning rate; ρ too large → instability, too small → minimal benefit.

Table 5: Hyperparameter Sensitivity Comparison for DQN vs PPO

Algorithm	Hyperparameter	If value is too low	If value is too high
DQN	Epsilon-decay	Under-exploitation (insufficient exploitation)	Under-exploration (insufficient exploration)
	Buffer size	Limited variety, poor generalization	Stale transitions, reduced training efficiency
	Target update frequency	Less diverse training data	Outdated (stale) target network
	Q-network learning rate	Slow updates, slow convergence	May cause divergence (unstable training)
PPO	Clip ε	Slow updates, slow performance improvement	Training instability
	Entropy coefficient β	Premature convergence	Excessive randomness, slow convergence
	Rollout length K	High bias, low variance (poor estimation)	Low bias, high variance (careful advantage normalization needed)

5.6 Generalization Ability

SAM excels at flattening the loss surface, enhancing generalization to unseen data.

RL methods (DQN/PPO) learn adaptive optimizer-selection policies:

Switch optimizers based on training phase (e.g., SGD early for speed, SAM later for robustness).

PPO 3-opt offers the highest flexibility, dynamically leveraging SGD, Adam, and SAM as landscape evolves.

5.7 Practical Deployment

Research environments: use PPO 3-opt when GPU/time resources are abundant and maximum accuracy is the goal.

Industry pipelines:

For simplicity and maintainability, stick with SGD or SAM.

To automate optimizer selection across diverse projects, implement PPO 2-opt—it adds minimal overhead and integrates smoothly with existing training loops.

DQN is suitable when you already use off-policy RL frameworks and want to reuse buffers across experiments.

Conclusion:

1. SGD/SAM: fast and simple baselines.
2. DQN: high sample efficiency and quick convergence but limited top-end accuracy.
3. PPO 2-opt: balanced stability, speed, and accuracy with moderate compute overhead.
4. PPO 3-opt: highest accuracy and policy flexibility at the cost of significant compute and complexity.

Recommendation: Choose the method that best aligns with your accuracy requirements, computational resources, and desired automation level.

6. CONCLUSION

6.1 Key Takeaways

Adaptive Optimizer Selection:
Reinforcement-learning agents (DQN and PPO) dynamically switch between optimizers—SGD, SAM (and Adam)—to match the training phase, yielding better trade-offs between convergence speed and final accuracy than any static optimizer.

Effective Reward Engineering:
A composite reward that balances validation accuracy gains, loss reduction, and per-epoch compute cost steers the agent toward policies that optimize both performance and efficiency, rather than naively maximizing a single metric.

Seamless Integration with Minimal Overhead:
Embedding a lightweight actor–critic (PPO) or Q-network (DQN) into a standard ResNet-18 training loop requires only modest additional compute and code changes, making the approach easy to debug, extend, and deploy.

6.2 Future Directions

Broaden the Optimizer Portfolio:
Incorporate algorithms such as AdamW, RMSprop, AdaBelief, and LAMB to give the agent richer choices and adaptivity across diverse tasks.

Evaluate on Modern Architectures:
Apply the framework to DenseNet, Vision Transformers, EfficientNet, or mobile-optimized models to validate generality and discover architecture-specific optimizer strategies.

Multi-Objective Reward Design:
Extend the reward to include energy consumption, memory footprint, or gradient stability, driving "green" and resource-aware training for large-scale models.

Hierarchical or Meta-RL Schemes:
Develop a two-level controller where a high-level agent tunes hyperparameters (learning-rate schedules, weight decay) over long horizons, while a low-level agent selects the optimizer each epoch.

Real-World Deployment Studies:
Test on industrial benchmarks—robotics control, recommendation engines, or time-series forecasting—where dynamic optimizer choice can deliver robust, efficient training under highly nonstationary data distributions.

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