PIPELINE REPORT

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1. Overview of the Sweep

The parameter sweep was conducted on the CIFAR-100 dataset using a grid search strategy, systematically exploring hyperparameters by varying model architecture, data augmentation techniques, optimizer settings, and learning rate scheduler configurations. In total, **32 unique experiments** were performed, covering all combinations of the selected parameters.

2. Parameter Configuration

The sweep involved both **fixed parameters** (constants across all experiments) and **variable parameters** (tested with different values). The following sections outline each set of parameters in detail.

2.1 Fixed Parameters

The following parameters were kept constant across all experiments:

- **Training Parameters**
  - Epochs: 50
  - Early Stopping: Enabled
  - Early Stopping Patience: 3
  - Early Stopping Min Delta: 0.01
- **Dataset Parameters**
  - Dataset Name: CIFAR-100
  - Batch Size: 256
  - Cache: Enabled
- **Data Augmentation**
  - Basic Augmentation: Enabled (random horizontal flips, crops, rotations, color jitter)

- **Optimizer**
  - Weight Decay: 0.001
  - Momentum: 0.9
  - Nesterov: True
- **Learning Rate Scheduler (ReduceLROnPlateau)**
  - Step Size: 10
  - Gamma: 0.1
  - Patience: 5
- **Learning Rate Scheduler (CosineAnnealingLR)**
  - T_max: 50

2.2 Variable Parameters

The following parameters were varied in the grid search, leading to 32 unique configurations:

- **Model Architecture**
  - Model Name: ResNet-18, PreAct ResNet-18
- **Data Augmentation Techniques**
  - Additional Augmentation (CutMix/MixUp): Enabled or Disabled
- **Optimizer**
  - Type: SGD, Adam
  - Learning Rate: 0.0001, 0.01
- **Learning Rate Scheduler**
  - Type: ReduceLROnPlateau, CosineAnnealingLR

3. Total Number of Experiments

The grid sweep included the following combinations of parameters:

$$2\text{ (Models)}\times 2\text{ (Augmentations)}\times 2\text{ (Optimizers)}\times 2\text{ (Learning Rates)}\times 2\text{ (Schedulers)} = 32\text{ experiments} \tag{1}$$

Each experiment utilized a unique configuration, providing insights into the impact of each parameter's variation on model performance.

Results

This section provides an overview and analysis of the parameter sweep results for both PreAct ResNet-18 and ResNet-18 models.

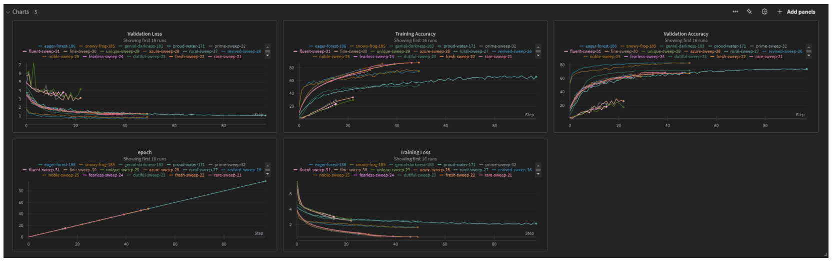

Figure 1: Combined accuracy and loss plots for all runs of PreAct ResNet-18 and ResNet-18.

4. Results for PreAct ResNet-18

In this section, we discuss the results of the PreAct ResNet-18 model based on two best-performing runs in the sweep: **Fearless-Sweep-24** and **Azure-Sweep-28**.

4.1 Run: Fearless-Sweep-24

Parameter	Value
Optimizer Type	Adam
Learning Rate	0.0001
Weight Decay	0.001
Additional Augmentations Enabled	Yes
Scheduler Type	CosineAnnealingLR
T_max	50
Early Stopping Enabled	Yes
Early Stopping Patience	3

Table 1: Relevant parameter configuration for run Fearless-Sweep-24.

Metric	Value
Training Accuracy	87.89%
Training Loss	0.41383
Validation Accuracy	67.97%
Validation Loss	1.24532
Epochs to Convergence	46

Table 2: Performance metrics for run Fearless-Sweep-24.

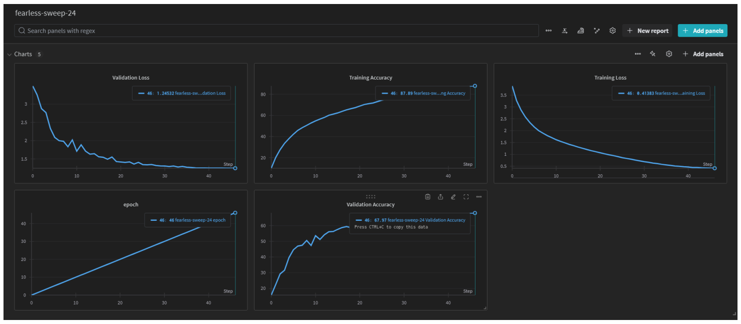

Figure 2: Combined plots for Fearless-Sweep-24.

4.2 Run: Azure-Sweep-28

Parameter	Value
Optimizer Type	SGD
Learning Rate	0.01
Momentum	0.9
Nesterov	True
Weight Decay	0.001
Additional Augmentations Enabled	Yes
Scheduler Type	CosineAnnealingLR
T_max	50
Early Stopping Enabled	Yes
Early Stopping Patience	3

Table 3: Relevant parameter configuration for run Azure-Sweep-28.

Metric	Value
Training Accuracy	86.31%
Training Loss	0.44401
Validation Accuracy	68.49%
Validation Loss	1.22456
Epochs to Convergence	34

Table 4: Performance metrics for run Azure-Sweep-28.

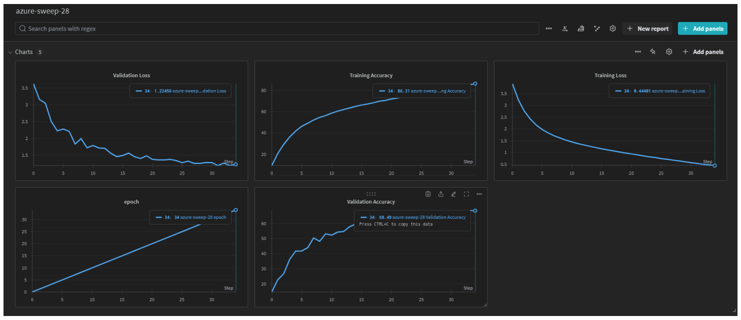

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Figure 3: Combined plots for Azure-Sweep-28.

4.3 New Run with Extended Epochs and Adjusted T_max

After analyzing the results of **Fearless-Sweep-24** and **Azure-Sweep-28**, a new run named proud-water-171 was conducted to explore the potential of improved model performance with an increased number of epochs and a larger ‘T_max‘ value for the learning rate scheduler. This new run maintains the same parameters as **Azure-Sweep-28** but with the following modifications:

- **Epochs**: Increased from 50 to 100
- **T_max**: Increased from 50 to 100
- **Early Stopping Patience**: Increased to allow for extended training

Parameter	**Value**
Optimizer Type	SGD
Learning Rate	0.01
Momentum	0.9
Nesterov	True
Weight Decay	0.001
Additional Augmentations Enabled	Yes
Scheduler Type	CosineAnnealingLR
T_max	100
Early Stopping Enabled	Yes
Early Stopping Patience	Adjusted
Epochs	100

Table 5: Relevant parameter configuration for the new extended run.

Metric	**Value**
Training Accuracy	66.004
Training Loss	2.14712
Validation Accuracy	73.99
Validation Loss	1.03582
Epochs to Convergence	97

Table 6: Performance metrics for the new extended run.

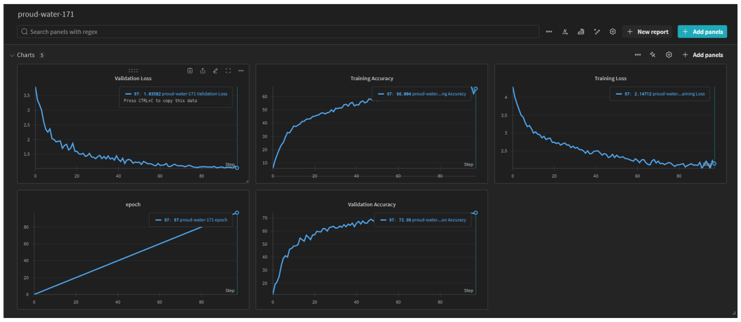

Figure 4: Combined accuracy and loss plot for the new extended run.

5. Results for ResNet-18

In the initial parameter sweep, ResNet-18 was used without any modifications to the input size, which may have impacted its performance since it was pretrained on the ImageNet dataset, where images are sized 224x224, compared to CIFAR-100's 32x32 images.

First, the results of one representative run from the initial sweep (named **rich-sweep-7**), followed by results of additional runs with the upsampling layer added.

5.1 ResNet-18 Sweep Run (rich-sweep-7)

Parameter	Value
Optimizer Type	Adam
Learning Rate	0.0001
Weight Decay	0.001
Additional Augmentations Enabled	Yes
Scheduler Type	ReduceLROnPlateau
Early Stopping Enabled	Yes
Early Stopping Patience	3
Epochs	50

Table 7: Relevant parameter configuration for ResNet-18 run (rich-sweep-7).

Metric	Value
Training Accuracy	56.88%
Training Loss	1.55725
Validation Accuracy	50.37%
Validation Loss	1.86905
Epochs to Convergence	45

Table 8: Performance metrics for ResNet-18 run (rich-sweep-7).

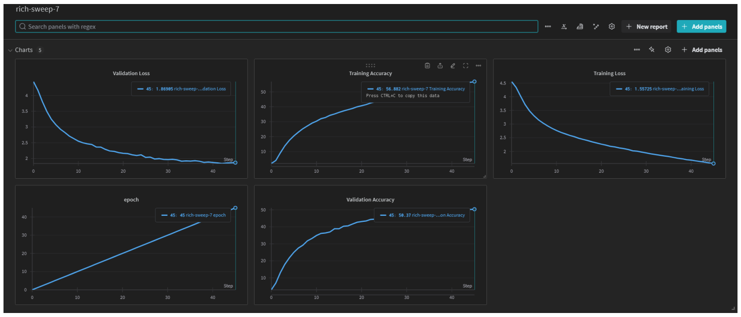
rich-sweep-7
Search panels with regex
New report
Add panels
Charts 5
Add panels
Validation Loss
45: 1.86905 rich-sweep-...dation Loss
Step
Training Accuracy
45: 56.882 rich-sweep-7 Training Accuracy
Step
Training Loss
45: 1.55725 rich-sweep-...aining Loss
Step
epoch
45: 45 rich-sweep-7 epoch
Step
Validation Accuracy
45: 50.37 rich-sweep-...on Accuracy
Step
0
10
20
30
40

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Figure 5: Combined plots for ResNet-18 run (rich-sweep-7)

5.2 Modified ResNet-18(Run: snowy-frog-185)

After observing the initial sweep, an upsampling layer was added to ResNet-18 to adapt CIFAR-100 images to a 224x224 resolution. This adjustment better aligns with the ImageNet-pretrained weights and improved overall performance by increasing the input size.

Parameter	**Value**
Optimizer Type	Adam
Learning Rate	0.001
Weight Decay	0.0001
Additional Augmentations Enabled	Yes
Scheduler Type	CosineAnnealingLR
T_max	50
Early Stopping Enabled	Yes
Early Stopping Patience	15
Epochs	50

Table 9: Relevant parameter configuration for modified ResNet-18 with upsampling layer (Run: snowy-frog-185).

Metric	**Value**
Training Accuracy	74.29%
Training Loss	1.6735
Validation Accuracy	82.69%
Validation Loss	0.8434

Table 10: Performance metrics for modified ResNet-18 (Run: snowy-frog-185).

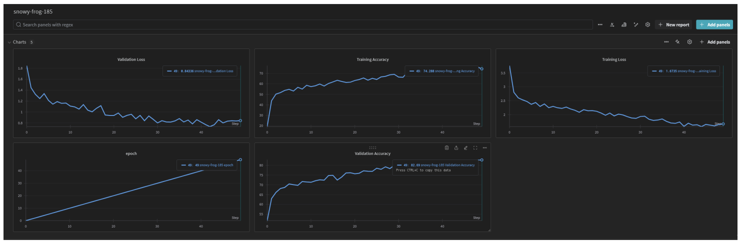

Figure 6: Combined plots for modified ResNet-18 run(Run: snowy-frog-185).

This modification led to significantly improved performance compared to the initial run. The validation accuracy reached 82.69%, with a validation loss of 0.8434, indicating effective learning and generalization with the modified setup.

6. Pipeline Overview

The training pipeline is designed for flexibility and efficiency, supporting multiple models, datasets, optimizers, schedulers, and augmentations. This section provides an overview of the key components, including supported configurations.

6.1 Supported Datasets and Data Augmentations

The pipeline supports the following datasets:

- **MNIST**: Grayscale image dataset with 28x28 resolution.
- **CIFAR-10**: RGB image dataset with 32x32 resolution, containing 10 classes.
- **CIFAR-100**: RGB image dataset with 32x32 resolution, containing 100 classes.

Each dataset can be augmented with a range of transformations to enhance generalization:

- **Random Horizontal Flip**: Flips images horizontally with a specified probability.
- **Random Crop**: Crops images randomly with padding to maintain image size (e.g., for CIFAR datasets).
- **Random Rotation**: Rotates images randomly by up to 15 degrees.
- **Color Jitter**: Adjusts brightness, contrast, saturation, and hue (applicable to RGB datasets like CIFAR-10 and CIFAR-100).
- **Random Choice between CutMix and MixUp**: Randomly applies either CutMix or MixUp augmentation, both of which blend images and labels in the dataset.
- **Normalization**: Standardizes pixel values; mean and standard deviation are dataset-specific

6.2 Models

The pipeline currently supports the following models:

- **ResNet-18**
- **PreAct ResNet-18**
- **LeNet**.
- **MLP (Multi-Layer Perceptron)**

6.3 Optimizers

The training pipeline supports a variety of optimizers, each with configurable parameters:

- **SGD (Stochastic Gradient Descent)**
- **Adam**
- **AdamW**
- **RMSProp**

6.4 Schedulers

Learning rate schedulers help adjust the learning rate over time for more stable training:

- **StepLR**
- **ReduceLROnPlateau**
- **CosineAnnealingLR**

7. Pipeline Efficiency Optimizations

To maximize computational efficiency, several key optimizations are implemented within the training pipeline:

- **Caching**: The data loader includes an option to cache the dataset in memory, significantly reducing data loading times during training.
- **Gradient Scaling with `GradScaler`**: The pipeline utilizes PyTorch's `GradScaler` for mixed precision training, reducing memory usage and speeding up training.
- **Optimized Data Loading with `num_workers` and `pin_memory`**: The data loader is configured with multiple workers (`num_workers` and `persistent_workers`) to parallelize data loading, improving CPU-GPU data transfer rates. Additionally, setting `pin_memory=True` enables page-locked memory, which speeds up memory transfers from CPU to GPU, especially beneficial for larger batch sizes.
- **cuDNN Benchmarking**: This optimization is particularly effective when input sizes are consistent.

8. Conclusion

I believe I deserve a score between 16 and 20 points depending on how well some aspect have been implemented.

For live tracking of metrics across different runs, visit project on Weights & Biases.