I/O Patterns and Bottlenecks in Deep Learning Workloads

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This report analyzes I/O performance in deep learning workloads using the DLIO benchmark on NVIDIA GH200 nodes. We measured accelerator utilization (AU) and I/O throughput while varying process count, data format, read threads, batch size, and shuffling strategy. Results show that HDF5 format achieved 97.5% AU compared to 58.9% for NPZ, 6 processes yielded peak throughput of 10.5 GB/s, and 8 read threads provided 3x improvement over single-threaded reads. Shuffling had no measurable impact on performance.

Additional Key Words and Phrases: Deep Learning, I/O Performance, HPC, DLIO Benchmark

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1 Introduction

Deep learning training requires continuous data transfer from storage to accelerators. When data loading cannot match computation speed, accelerators remain idle, reducing training efficiency. [Paul et al. 2021] characterized I/O patterns in over 23,000 ML jobs on the Summit supercomputer, showing that ML workloads generate small, random reads across many files—contrasting with traditional HPC applications that perform large sequential accesses.

[Dryden et al. 2021] reported that I/O can consume up to 85% of training time in distributed deep learning. Given that training represents a significant cost in ML pipelines [Lewis et al. 2025], understanding I/O bottlenecks is essential for optimization.

This report measures how configuration parameters affect I/O performance in the UNet3D workload using the DLIO benchmark. We focus on two metrics: Accelerator Utilization (AU), the percentage of time accelerators spend computing rather than waiting for data, and I/O throughput in MB/s.

2 Background

Previous work has analyzed I/O patterns in deep learning. [Párraga et al. 2021] presented a methodology for characterizing I/O in TensorFlow and PyTorch applications. [Gainaru et al. 2022] examined I/O challenges in ML workflows for scientific data analysis and demonstrated optimization techniques.

The Deep Learning I/O (DLIO) benchmark [Devarajan et al. 2021] emulates I/O behavior of deep learning models without actual training, allowing isolation of I/O performance from computation overhead.

3 Experimental Setup

Experiments ran on PCAD cluster nodes equipped with NVIDIA GH200 Grace Hopper Superchips. Each node contains a 72-core ARM Neoverse-V2 CPU, 480 GiB RAM, and one NVIDIA GH200 GPU with 96 GB HBM3 memory. Storage uses a parallel filesystem.

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We configured the UNet3D workload with NPZ format, 32 training files, 1 sample per file, 262 KB record length, batch size 2, and 1 read thread as baseline. We then varied individual parameters: process count (1, 2, 4, 6, 8), data format (NPZ, PNG, HDF5), read threads (1, 8, 16), batch size (1, 4, 14), shuffling (file and sample shuffle on/off), and record size (10 MB, 512 MB).

4 Results

4.1 Process Scaling

Table 1 shows AU and throughput as process count increases.

Table 1. Process Scaling

Processes	AU (%)	I/O (MB/s)
1	33.67	974
2	36.37	2,001
4	58.85	5,699
6	86.52	10,475
8	77.94	9,437

Peak performance occurred at 6 processes (86.5% AU, 10.5 GB/s). At 8 processes, both metrics decreased. Throughput scaled approximately linearly from 1 to 6 processes.

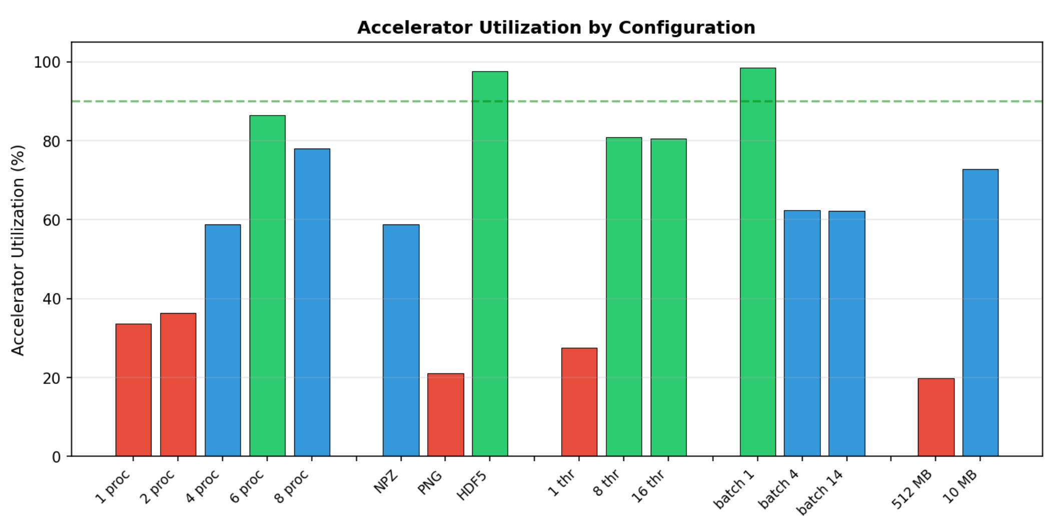

Fig. 1. Accelerator utilization across parameter configurations.

4.2 Data Format

Table 2 compares storage formats at 4 processes.

HDF5 achieved 97.5% AU and 66% higher throughput than NPZ. PNG achieved only 21% AU due to decompression overhead.

Table 2. Data Format Comparison

Format	AU (%)	I/O (MB/s)
NPZ	58.85	5,699
PNG	21.08	2,042
HDF5	97.53	9,447

Table 3. Read Threads

Threads	AU (%)	I/O (MB/s)
1	27.51	2,664
8	80.87	7,833
16	80.50	7,797

4.3 Read Threads

Table 3 shows the effect of parallel read threads at 4 processes.

Increasing from 1 to 8 threads improved AU from 27.5% to 80.9%. No improvement occurred between 8 and 16 threads.

4.4 Batch Size

Table 4 shows batch size effects at 4 processes.

Table 4. Batch Size

Batch Size	AU (%)	I/O (MB/s)
1	98.44	1,661
4	62.36	3,834
14	62.26	7,538

Batch size 1 achieved 98.4% AU but only 1.7 GB/s throughput. Batch size 14 achieved 7.5 GB/s but 62.3% AU. The workload shifts from compute-bound (small batches) to I/O-bound (large batches).

4.5 Shuffling

Table 5 shows shuffling effects at 4 processes.

Table 5. Shuffling Strategies

Configuration	AU (%)	I/O (MB/s)
File shuffle off	57.64	5,583
File shuffle random	57.19	5,539
Sample shuffle off	57.58	5,577
Sample shuffle random	58.00	5,618

All configurations performed within 1% of each other. Shuffling did not degrade performance on this storage system.

4.6 Record Size

Table 6 shows record size effects at 4 processes.

Table 6. Record Size

Size	AU (%)	I/O (MB/s)
10 MB	72.87	505
512 MB	19.83	7,034

Larger records (512 MB) achieved 14x higher throughput than smaller records (10 MB) but lower AU (19.8% vs 72.9%).

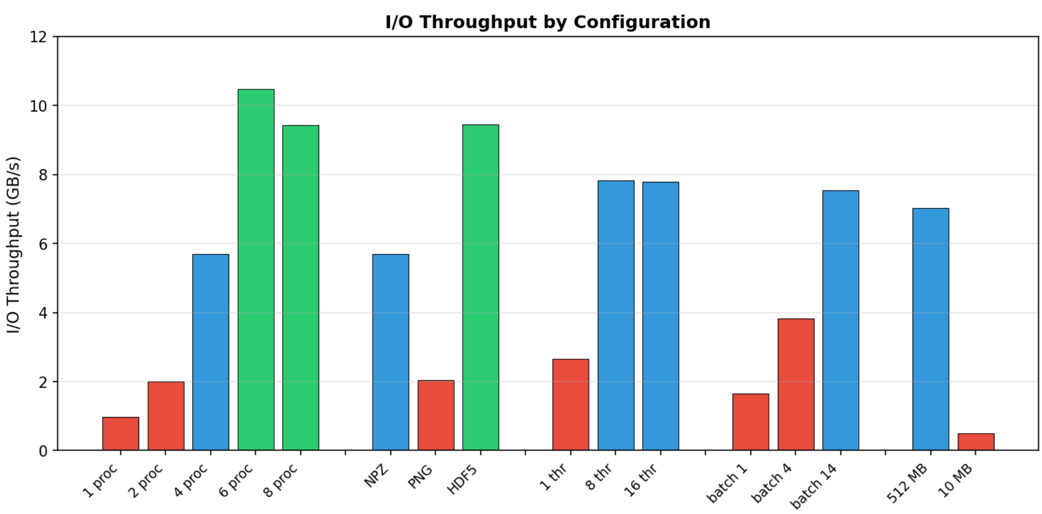

Fig. 2. I/O throughput across parameter configurations.

5 Discussion

The results show that I/O performance depends strongly on configuration. HDF5 format and 8 read threads provided the largest improvements. Process scaling beyond 6 reduced performance, suggesting resource contention. Batch size presents a trade-off: small batches maximize AU but limit throughput, while large batches do the opposite.

These measurements apply to the specific hardware and workload tested. Different storage systems, file sizes, or access patterns may yield different results.

6 Conclusions

We measured I/O performance of the UNet3D workload on NVIDIA GH200 nodes. Key findings: HDF5 format achieved 97.5% AU; 6 processes provided peak throughput; 8 read threads improved AU by 3x; shuffling had no measurable impact. Future work could extend this analysis to other workloads and storage configurations.

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