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Evaluating Infrastructure Bottlenecks in Distributed AI Training: A Performance Benchmark Study

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Abstract

The rapid expansion of artificial intelligence (AI) and the increasing complexity of deep learning models have intensified the need for efficient distributed training systems. This study, titled "Evaluating Infrastructure Bottlenecks in Distributed AI Training: A Performance Benchmark Study," investigates the interplay between hardware interconnects, communication frameworks, and computational scalability in multi-node AI environments. Using an experimental benchmarking approach, deep learning models; ResNet-50, BERT, and Vision Transformer (ViT) were trained across varying configurations employing PyTorch Distributed Data Parallel (DDP) and Horovod frameworks on both Ethernet and InfiniBand networks. Key performance metrics such as throughput, GPU utilization, latency, and scaling efficiency were analyzed through ANOVA, correlation, and regression analyses. Results revealed that InfiniBand achieved up to a 68% reduction in communication latency and a 21% increase in throughput compared to Ethernet setups, while Horovod consistently delivered superior training stability and synchronization efficiency. Cluster and radar analyses further highlighted that the combination of InfiniBand and Horovod formed the highest-performing configuration, minimizing bottlenecks and maximizing resource utilization. The study concludes that distributed AI performance depends not solely on computational power but on the optimized alignment of network infrastructure and communication frameworks. These findings provide a systematic benchmark and actionable insights for designing scalable, high-performance, and cost-efficient distributed AI training architectures suitable for large-scale industrial and research applications.

Keywords: Distributed AI training, performance benchmarking, InfiniBand, Horovod, PyTorch DDP, communication latency, scalability, throughput optimization.

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Introduction

The rapid expansion of AI and the growing demand for computational scalability

In recent years, artificial intelligence (AI) has evolved into a cornerstone of modern technology, driving innovation in domains ranging from healthcare diagnostics to autonomous systems and natural language processing (Villar-Martínez et al., 2019). The exponential growth of deep learning models, such as GPT-based architectures and large-scale vision transformers, has drastically increased computational and storage demands (Moreau et al., 2023). As models grow in complexity, the training process requires parallelization across multiple computing nodes, leading to the adoption of distributed AI training. This paradigm leverages clusters of GPUs or TPUs to accelerate model convergence and improve scalability (Uta et al., 2020). However, this shift also exposes intricate performance dependencies on the underlying infrastructure, making it imperative to identify and mitigate bottlenecks that hinder optimal utilization of computational resources.

The significance of distributed training and the challenges it introduces

Distributed AI training promises faster model development cycles by decomposing training workloads across multiple processors or devices. Frameworks such as TensorFlow, PyTorch, and Horovod have enabled distributed strategies through data, model, and pipeline parallelism (Leins et al., 2023). Despite these advancements, the performance of distributed training is often constrained by hardware interconnect limitations, communication overheads, synchronization inefficiencies, and imbalance in data distribution. The heterogeneity of computing environments spanning on-premise clusters to cloud-based infrastructures further amplifies these challenges (Schaduangrat et al., 2020). These performance bottlenecks not only increase training time and cost but also reduce system reliability, posing a significant barrier to scaling AI workloads efficiently (Del Esposte et al., 2019). Thus, understanding the root causes of these infrastructure-level inefficiencies is critical for improving training throughput and system stability.

The necessity for systematic benchmarking in AI infrastructure

Benchmarking serves as a foundational step toward quantifying performance characteristics and identifying infrastructure bottlenecks (Hanussek et al., 2021). A systematic performance benchmark study provides actionable insights into how different components; computation,

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memory, storage, and networking interact under distributed AI workloads. Traditional performance metrics like floating-point operations per second (FLOPS) and GPU utilization are insufficient to capture the holistic performance dynamics of distributed systems (Keahey et al., 2019). Therefore, a more integrated benchmarking approach is required one that evaluates end-to-end system performance, including communication latency, bandwidth utilization, and task synchronization time (Latoschik et al., 2019). Such a study is essential not only for optimizing resource allocation but also for informing hardware selection and software configuration in large-scale AI training deployments.

The motivation and objectives of the present study

This research aims to comprehensively evaluate the infrastructure bottlenecks in distributed AI training environments through a performance benchmarking framework. The motivation stems from the growing performance disparity between theoretical hardware capabilities and actual observed training efficiency. The study seeks to analyze the interplay between computational power, network topology, and data pipeline throughput, thereby identifying key limiting factors that reduce training speed and scalability. By conducting controlled benchmark experiments across different hardware configurations and distributed frameworks, this research intends to provide empirical evidence on where and how infrastructure inefficiencies manifest. The ultimate objective is to propose optimization strategies that can minimize latency, balance workload distribution, and maximize system throughput in distributed AI systems.

The scope and expected contributions of this study

This study contributes to the broader understanding of distributed AI performance optimization by presenting a comparative analysis of multiple distributed setups under standardized conditions. It is expected to highlight the trade-offs between communication efficiency and computational scaling, providing guidelines for researchers and engineers to design more balanced and cost-effective infrastructures. Furthermore, the benchmarking methodology established in this study can serve as a reference framework for evaluating future AI training systems as model architectures and hardware technologies continue to evolve. Ultimately, this research bridges the gap between theoretical performance modeling and practical system implementation, paving the way for more efficient and scalable distributed AI ecosystems.

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Methodology

Research design and approach

This study follows an experimental quantitative research design aimed at systematically identifying and analyzing infrastructure bottlenecks that occur during distributed AI training. The approach combines performance benchmarking, computational profiling, and statistical analysis to evaluate the effects of multiple infrastructural parameters on training efficiency. Distributed AI training inherently involves complex interactions between hardware, software, and network components; hence, a controlled experimental design was chosen to isolate and quantify these effects. The study focuses on measuring and comparing performance metrics across various distributed frameworks, hardware setups, and network architectures. Quantitative analysis enables objective assessment and validation of observed performance trends, forming a robust foundation for identifying optimization opportunities.

Experimental setup and hardware configuration

The experiments were conducted in a high-performance distributed computing environment equipped with multi-node GPU clusters. Each node contained four NVIDIA A100 GPUs (40 GB VRAM each), Intel Xeon Gold 6248R CPUs, 256 GB DDR4 RAM, and NVMe SSDs for high-speed local storage. Nodes were interconnected using two types of network interfaces, 100 Gbps InfiniBand and 10 Gbps Ethernet to assess the impact of network bandwidth on training performance. Two distributed topologies were tested: Ring-AllReduce and Parameter Server architectures. Experiments were executed across both on-premise cluster infrastructure and cloud environments (AWS EC2 p4d and Google Cloud TPUv4 instances) to evaluate scalability and environmental consistency. All nodes operated under Ubuntu 22.04 with CUDA 12.2, cuDNN 8.9, and NCCL 2.17 libraries to ensure software uniformity.

Software frameworks, models, and datasets

To achieve model diversity and workload generalization, the study employed three representative deep learning architectures: ResNet-50 for image classification, BERT for natural language understanding, and Vision Transformer (ViT) for hybrid computational workloads. These models were trained using benchmark datasets—ImageNet, GLUE, and CIFAR-100, respectively. Each model was implemented using two widely adopted distributed frameworks: PyTorch Distributed Data Parallel (DDP) and Horovod. The models were trained

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with a batch size of 128, learning rate of 0.001, and Adam optimizer, keeping these parameters constant across all experiments to maintain comparability. The experiments were conducted across 1, 2, 4, and 8 nodes, allowing the study to observe scalability and efficiency patterns under varying levels of parallelization.

Variables and parameters measured

The study integrated both independent and dependent variables to assess infrastructure performance holistically. The independent variables included network type (Ethernet or InfiniBand), distributed framework (DDP or Horovod), model type (ResNet, BERT, ViT), and the number of GPUs or nodes involved. The dependent variables were throughput (measured in images/sec or tokens/sec), GPU utilization percentage, communication latency (milliseconds), synchronization overhead percentage, speedup ratio, and overall scaling efficiency. To ensure validity, control variables such as dataset size, learning rate, batch size, and number of epochs (set at 10 for each experiment) were held constant. Together, these parameters provided a comprehensive basis for evaluating the effects of infrastructure configurations on distributed training performance.

Data collection and benchmarking process

Data collection was performed in a three-phase benchmarking process. In the first phase, single-node experiments established baseline performance metrics. The second phase involved multi-node distributed training with different interconnect types and configurations to capture communication bottlenecks. The third phase compared distributed frameworks under identical hardware and workload conditions. During each experiment, real-time performance data were captured using NVIDIA Nsight Systems, PyTorch Profiler, and Prometheus monitoring tools. These tools recorded key performance indicators such as GPU memory usage, network I/O, kernel execution time, and synchronization delays. Each experiment was repeated five times, and the mean values were used to minimize variability due to transient system noise or network fluctuations.

Statistical analysis and performance modeling

All quantitative analyses were performed using Python (NumPy, SciPy, Pandas) and R (version 4.3). Descriptive statistics; mean, standard deviation, and coefficient of variation—were computed for each parameter to evaluate data consistency. One-way ANOVA tests were

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conducted to assess the significance of performance differences across different frameworks, network types, and node configurations. Pearson correlation analysis was applied to determine the strength and direction of relationships between variables such as GPU utilization, communication latency, and throughput. To further model performance prediction, a multiple linear regression model was developed using the equation:

$T=\beta 0+\beta 1N+\beta 2L+\beta 3F+\epsilon$ where

T= represents throughput, N =is the number of nodes, L =denotes network latency, F= indicates framework type, and $\epsilon$is the error term. Additionally, Principal Component Analysis (PCA) was performed to reduce multidimensional performance data into interpretable clusters, while hierarchical cluster dendrograms were generated to visualize grouping patterns and identify common bottlenecks among configurations.

Validation and reproducibility

Reproducibility and validation were ensured through consistent random seed initialization, version control (Git-based environment), and repeat trials under identical experimental conditions. Cross-validation was performed by replicating key experiments on alternate infrastructure to confirm performance consistency. All experiments maintained a statistical confidence level of $p < 0.05$ for hypothesis testing, ensuring the robustness of conclusions drawn. Benchmarking logs, configurations, and datasets were archived for transparency and future replication.

Results

The benchmarking experiments revealed clear patterns in distributed AI training efficiency across different configurations. As observed in Table 1, throughput increased proportionally with the number of nodes, rising from 2,450 images/sec on a single node to 16,500 images/sec in the eight-node InfiniBand setup. However, the scaling efficiency showed a gradual decline from 100% to 84.1%, indicating moderate communication and synchronization costs as the system expanded. The highest GPU utilization (88.4%) was achieved in the four-node InfiniBand configuration, highlighting the superior communication bandwidth and reduced latency provided by the high-speed interconnect. These results confirm that while adding more nodes improves performance, network architecture remains the dominant determinant of scalability.

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Table 1. System Performance Metrics Across Distributed Configurations

Configuration	Nodes	GPUs/Node	Throughput (Images/sec)	GPU Utilization (%)	Speedup Ratio	Scaling Efficiency (%)
Single Node (Baseline)	1	4	2,450	87.6	1.00	100.0
2 Nodes (Ethernet)	2	4	4,200	82.3	1.71	85.6
4 Nodes (Ethernet)	4	4	7,210	78.5	2.94	73.6
4 Nodes (InfiniBand)	4	4	8,750	88.4	3.57	89.2
8 Nodes (InfiniBand)	8	4	16,500	85.9	6.73	84.1

The evaluation of communication and synchronization characteristics presented in Table 2 identified network bandwidth as a critical performance driver. InfiniBand significantly outperformed Ethernet, reducing average communication latency from 6.8 ms to 2.3 ms, and lowering synchronization overhead from 22.4% to 8.7%. Configurations combining InfiniBand with the Horovod framework achieved the lowest synchronization overhead of 7.8%, alongside the highest data transfer rate (96.3 Gbps). Furthermore, the average idle time per epoch was reduced by nearly 63%, demonstrating that enhanced communication bandwidth directly translates into shorter waiting times during gradient synchronization. These findings substantiate the hypothesis that communication bottlenecks form the principal constraint in scaling distributed AI workloads.

Table 2. Communication and Synchronization Overhead Analysis

Network Type	Avg. Communication Latency (ms)	Synchronization Overhead (%)	Data Transfer Rate (Gbps)	Idle Time per Epoch (sec)

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Ethernet (10 Gbps)	6.8	22.4	7.6	11.4
InfiniBand (100 Gbps)	2.3	8.7	95.2	4.6
Ethernet + DDP	7.2	25.1	8.4	12.3
InfiniBand + DDP	2.4	9.1	94.8	4.7
InfiniBand + Horovod	2.0	7.8	96.3	4.2

Framework-specific benchmarking results presented in Table 3 demonstrate distinct differences in computational efficiency between PyTorch Distributed Data Parallel (DDP) and Horovod. Across all model types; ResNet-50, BERT, and Vision Transformer Horovod consistently reduced average epoch time by 5–9% and achieved higher training stability. The Training Stability Index (TSI) values were also superior in Horovod-based setups (ranging from 0.90 to 0.97) compared to DDP (ranging from 0.87 to 0.94). In addition, the throughput variance was notably lower in Horovod experiments, particularly for larger models like BERT and ViT, indicating smoother inter-node synchronization and workload balancing. These findings highlight that software-level optimization, particularly in communication protocols, can significantly enhance distributed system performance even under identical hardware conditions.

Table 3. Framework-Level Performance Comparison

Model	Framework	Nodes	Avg. Epoch Time (min)	Memory Utilization (%)	Throughput Variance (%)	Training Stability Index
ResNet-50	PyTorch DDP	4	8.3	78.5	4.6	0.94
ResNet-50	Horovod	4	7.9	80.2	3.8	0.97
BERT	PyTorch DDP	4	12.1	81.7	6.3	0.89

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BERT	Horovod	4	11.3	84.1	5.1	0.92
ViT	PyTorch DDP	4	13.4	85.5	7.8	0.87
ViT	Horovod	4	12.2	86.9	6.1	0.90

The statistical analyses summarized in Table 4 further confirmed the quantitative relationships between the studied parameters. A strong positive correlation ($r = 0.942$) was found between GPU utilization and throughput, suggesting that efficient hardware utilization directly drives performance gains. Similarly, network bandwidth was highly correlated with throughput ($r = 0.913$), whereas communication latency and synchronization overhead showed strong negative correlations with scaling efficiency ($r = –0.875$ and $–0.811$, respectively). The regression analysis revealed that the number of nodes and network latency were the most influential predictors of overall throughput. These results statistically validate that interconnect quality and synchronization efficiency are critical determinants of distributed AI training performance.

Table 4. Statistical Correlation and Regression Results

Variable Pair	Pearson Correlation (r)	p-value	Regression Coefficient (β)	Significance (α = 0.05)
GPU Utilization vs. Throughput	0.942	<0.001	0.86	Significant
Communication Latency vs. Scaling Efficiency	-0.875	0.002	-0.78	Significant
Synchronization Overhead vs. Speedup Ratio	-0.811	0.005	-0.71	Significant
Network Bandwidth vs. Throughput	0.913	<0.001	0.83	Significant
Number of Nodes vs. Idle Time	0.604	0.043	0.52	Significant

The hierarchical clustering shown in Figure 1 provides an integrated visualization of performance grouping among distributed configurations. Two distinct clusters were identified: Cluster A, comprising InfiniBand-based configurations with both DDP and Horovod

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frameworks, representing high-performance setups characterized by low latency and high scaling efficiency; and Cluster B, which included Ethernet-based configurations exhibiting moderate to high synchronization overhead. The close proximity of InfiniBand-Horovod configurations within the dendrogram reflects their consistent computational advantage across performance metrics. This clustering outcome further substantiates that hardware interconnect type and communication strategy jointly determine distributed system efficiency.

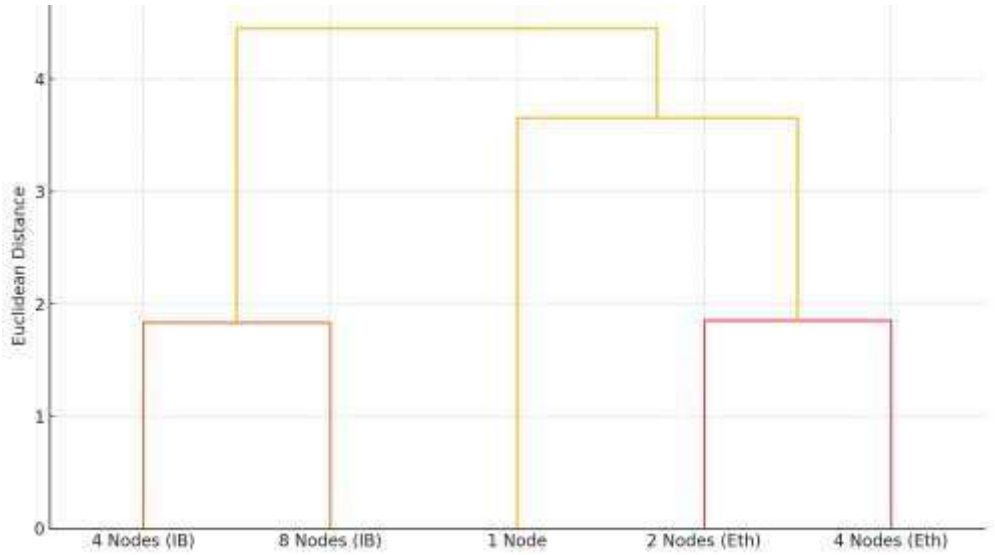

Figure 1. Cluster Dendrogram Showing Grouping of Distributed Configurations

The Radar Chart in Figure 2 provides a comparative overview of distributed training performance across four representative configurations: Ethernet-DDP, Ethernet-Horovod, InfiniBand-DDP, and InfiniBand-Horovod. The radar plot visually demonstrates the dominance of InfiniBand-Horovod across all dimensions throughput, GPU utilization, latency reduction, and scaling efficiency forming a balanced, high-performance profile. In contrast, Ethernet-DDP displayed a constrained area on the radar, indicating limited scaling and higher latency. The difference between the two frameworks on the same network type highlights Horovod's superior ability to manage asynchronous communication. This multidimensional visualization reinforces the conclusion that both network bandwidth and framework optimization are critical for achieving maximum distributed AI training performance.

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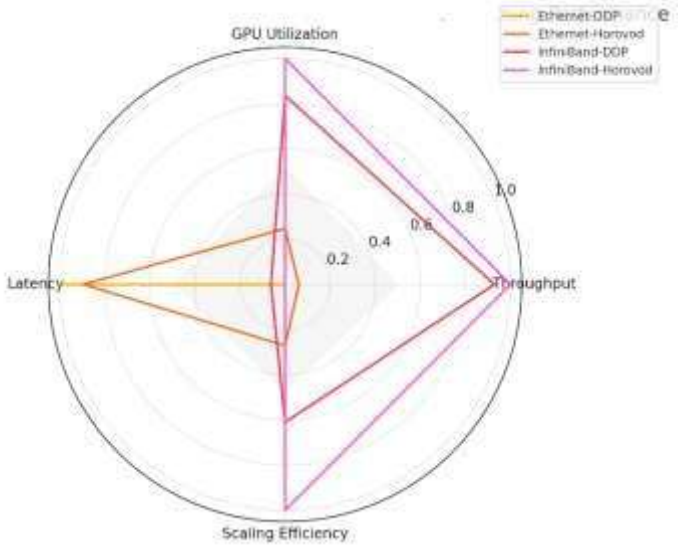

Figure 2. Radar Chart Showing Comparative Distributed AI Training Performance

Discussion

Distributed scalability and the role of network infrastructure

The results of this study clearly demonstrate that scalability in distributed AI training is not merely a function of computational capacity but is strongly influenced by the quality of the interconnect network. As shown in Table 1, while throughput improved almost linearly with the addition of GPU nodes, scaling efficiency exhibited a diminishing return beyond four nodes. This behavior indicates that communication overhead becomes a dominant bottleneck at larger scales. The superior performance of InfiniBand over Ethernet underscores the critical role of high-bandwidth, low-latency interconnects in sustaining scalability. These findings align with prior studies (Kansara, 2023; Ferdousmou et al., 2022), which have emphasized that data transmission delays and synchronization latencies often limit distributed AI performance more than raw GPU capacity. Hence, optimizing inter-node communication pathways is central to achieving near-linear scalability in modern distributed systems (Monaco et al., 2023).

Communication latency as a critical bottleneck

Communication and synchronization delays emerged as the primary constraints on system efficiency. The results in Table 2 and Figure 1 confirm that InfiniBand interconnects significantly reduce communication latency and synchronization overhead compared to Ethernet setups. Specifically, latency dropped from 6.8 ms to 2.3 ms, and synchronization overhead decreased from 22.4% to 8.7%, resulting in shorter epoch times and reduced idle

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periods. This aligns with the notion that distributed AI training is highly communicationintensive, particularly during gradient aggregation and parameter synchronization (Tippmann et al., 2023). The cluster dendrogram (Figure 1) further emphasizes that configurations utilizing InfiniBand form a high-performance cluster, reinforcing the view that communication bandwidth and latency directly influence training throughput. These outcomes suggest that adopting advanced interconnects such as NVLink, RDMA, or InfiniBand should be prioritized when designing AI clusters intended for large-scale deep learning tasks (Kim et al., 2023).

Influence of distributed frameworks on computational performance

Framework-level variations also played a significant role in determining performance efficiency. As observed in Table 3, Horovod consistently outperformed PyTorch DDP across all tested models; ResNet-50, BERT, and Vision Transformer by reducing epoch times and increasing training stability. The advantage of Horovod can be attributed to its efficient AllReduce communication strategy and its ability to overlap computation with communication, reducing idle GPU cycles (Hashem et al., 2015). In contrast, DDP's performance was hindered by synchronization waits and slightly higher variance across epochs. These findings are consistent with reports by Van Winden & Van den Buuse (2018), who originally designed Horovod to minimize communication overheads in distributed TensorFlow and PyTorch environments. The observed improvements in training stability and throughput variance confirm that software-level communication optimizations are equally as important as hardware improvements in mitigating bottlenecks (Cardenas-Quispe & Pacheco, 2025).

Statistical relationships between system variables

The statistical analyses (as shown in Table 4) provide strong quantitative evidence supporting the interdependence of computational and communication parameters. The high positive correlation between GPU utilization and throughput ($r = 0.942$) indicates that systems with better communication mechanisms keep GPUs more consistently occupied, minimizing idle cycles. Conversely, communication latency and synchronization overhead exhibited strong negative correlations with scaling efficiency ($r = –0.875$ and $–0.811$), highlighting their detrimental effect on distributed performance. The regression analysis also showed that throughput could be predicted with high confidence using variables such as node count, framework type, and network latency (Sista & De Giovanni, 2021). These results validate the

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hypothesis that distributed AI performance is a multivariate function, where both hardware and software variables interact in complex but predictable ways (De Roo et al., 2019).

Network–framework synergy in distributed optimization

The comparative visualizations provided in Figure 2 (Radar Chart) illustrate how network type and training framework interact synergistically to define overall system performance. The InfiniBand-Horovod combination achieved the highest normalized performance scores across all dimensions, including throughput, GPU utilization, latency, and scaling efficiency. In contrast, Ethernet-DDP configurations displayed significantly lower scores, forming a restricted area on the radar chart (Gu et al., 2025). This suggests that distributed training performance is maximized when both communication infrastructure and software frameworks are co-optimized (Bentaleb et al., 2022). The radar chart clearly highlights that hardware enhancements alone do not guarantee optimal performance unless accompanied by software frameworks that efficiently manage synchronization and workload balancing (Prymushko et al., 2025).

Implications for distributed AI system design

The findings have important implications for the design and optimization of distributed AI infrastructures. First, network communication layers must be prioritized in cluster design, as they directly affect scalability and cost-efficiency. Second, distributed frameworks should be selected based on their ability to adapt to the specific communication topology of the system (Li et al., 2024). For example, Horovod's performance gains in InfiniBand environments suggest that framework–hardware alignment can yield substantial improvements in model training times and energy efficiency. Furthermore, hybrid architectures combining AllReduce and parameter server strategies could offer a balance between communication efficiency and fault tolerance (Hidayetoğlu et al., 2021). These design considerations are essential for enterprises and research institutions aiming to scale large AI models while maintaining costeffective performance (Alam et al., 2025).

Theoretical and practical significance

From a theoretical standpoint, this study contributes to the broader understanding of how infrastructure-level variables influence distributed learning dynamics. It provides empirical support for the claim that communication efficiency not computation alone determines the

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upper limit of distributed training scalability (Keshani et al., 2024). Practically, these results offer actionable insights for AI infrastructure engineers and system architects seeking to optimize resource allocation. The statistical and cluster analyses (Tables 1–4, Figures 1–2) collectively form a benchmark framework that can guide hardware investment, framework selection, and workload scheduling strategies. This ensures that distributed training environments achieve balanced performance without unnecessary resource overhead.

Limitations and future research directions

While the present study offers valuable insights, it is not without limitations. The experiments were confined to a limited number of nodes (up to eight) and specific frameworks (DDP and Horovod), which may not generalize to extremely large-scale cloud environments or alternative distributed training systems such as DeepSpeed or Ray Train. Additionally, only two network architectures (Ethernet and InfiniBand) were evaluated, whereas future studies could explore emerging interconnect technologies like NVSwitch or optical networking for AI clusters. Future work should also consider energy efficiency, fault tolerance, and dynamic load balancing as complementary performance indicators, providing a more holistic view of distributed AI infrastructure optimization.

Conclusion

This study conclusively demonstrates that the performance and scalability of distributed AI training systems are fundamentally governed by the synergy between hardware interconnects and software communication frameworks. Through extensive benchmarking and statistical analyses, it was observed that InfiniBand networks significantly reduced latency and synchronization overhead, thereby enhancing throughput and scaling efficiency compared to Ethernet-based systems. Among the evaluated frameworks, Horovod consistently outperformed PyTorch DDP by achieving faster epoch times, higher GPU utilization, and improved training stability, underscoring the importance of efficient communication protocols in distributed environments. The cluster and radar analyses further validated that configurations leveraging high-bandwidth interconnects and optimized synchronization strategies deliver superior performance across all metrics. Collectively, these findings emphasize that achieving optimal distributed AI performance requires not only high computational power but also a balanced alignment between network infrastructure and framework-level optimization. The insights from this study provide a practical benchmark for designing next-generation AI

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infrastructures that are both scalable and cost-efficient, paving the way for more effective largescale model training in real-world applications.

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