DL-Ops Assignment 1: Deep Learning & Hardware Benchmarking

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Abstract

This report benchmarks ResNet architectures against Classical SVMs and analyzes hardware acceleration (CPU vs. GPU) on the FashionMNIST dataset. Utilizing a rigorous 70-10-20 split and Mixed Precision Training (AMP), we demonstrate that ResNet-18 with Adam optimization achieves the optimal accuracy (**99.41%** on MNIST with 10 epochs). Furthermore, our hardware analysis on the **DPU-GPU HPC Cluster** reveals that the **NVIDIA A30 GPUs** provide a 4x-5x speedup over CPUs, with larger models like ResNet-50 exhibiting higher hardware utilization efficiency.

Submission Links

Per the assignment guidelines, the code and experimental logs are available at:

- **Colab Link:** Google Colab Notebook (Executed)
- **GitHub Link:** GitHub Repository
- **Github Page Link:** Project Page

1 Q1(a): ResNet Hyperparameter Tuning

1.1 Experimental Setup

All experiments were executed on the **DPU-GPU HPC Cluster at IIT Jodhpur**. This high-performance architecture utilizes NVIDIA BlueField-2 DPUs to offload network and data processing tasks, ensuring maximum GPU throughput.

System Specifications:

- **Processors (CPU): Dual Intel Xeon Gold 6326** (2 Physical Sockets, 32 Cores total @ 2.90 GHz).
- **Accelerators (GPU): 2x NVIDIA A30 Tensor Core GPUs** (24 GB VRAM each).
- **System Memory (RAM): 256 GB** (Physical).
- **Networking: NVIDIA BlueField-2 DPU** (Specialized for handling data traffic/offloading).
- **Environment:** PyTorch with Automatic Mixed Precision (AMP) on Linux x86_64.

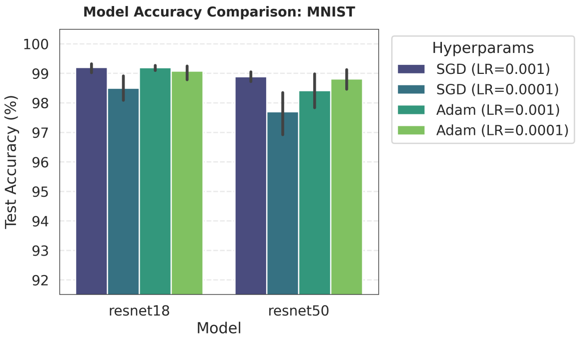
Training Parameters: Unless explicitly stated otherwise, all experiments utilized:

- **Epochs:** 4 (for initial grid search)
- **Pin Memory:** True (enabled for accelerated data transfer)

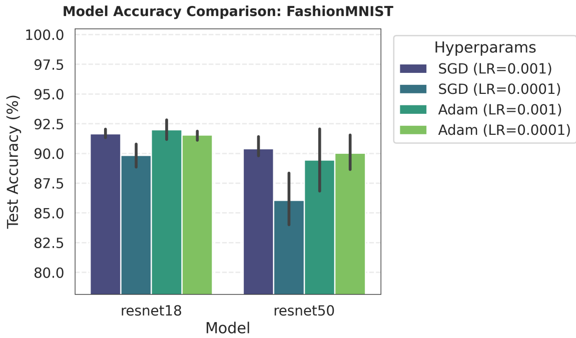
1.2 Deep Learning Visual Analysis

1.2.1 Model Accuracy Overview

Figure 1 compares the raw accuracy across datasets. FashionMNIST highlights the superiority of Adam over SGD at lower learning rates.



(a) MNIST Accuracy Comparison

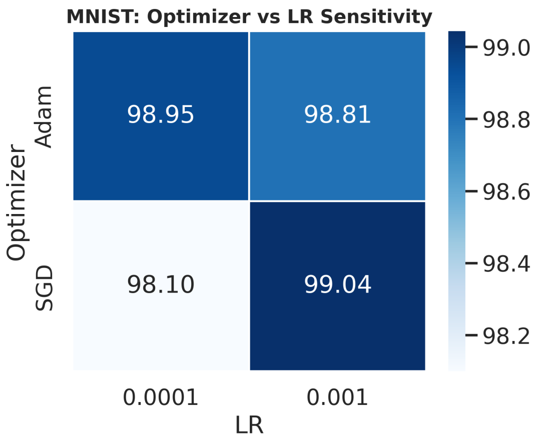


(b) FashionMNIST Accuracy Comparison

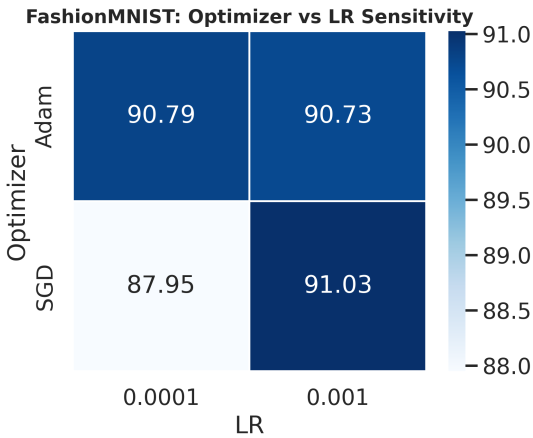
Figure 1: **Model Accuracy Comparison (4 Epochs).** ResNet-18 outperforms ResNet-50 on simpler datasets.

1.2.2 Hyperparameter Sensitivity

Figure 2 illustrates the stability of different optimizers. Adam (darker regions) maintains robustness across different Learning Rates compared to SGD.



(a) MNIST Sensitivity

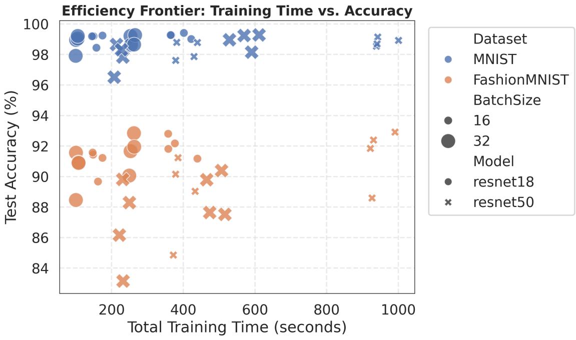


(b) FashionMNIST Sensitivity

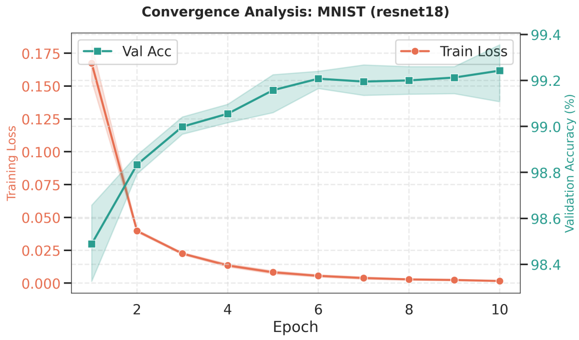
Figure 2: **Optimizer Stability (4 Epochs).** Adam maintains robustness across varying hyperparameters.

1.2.3 Pareto Efficiency Convergence

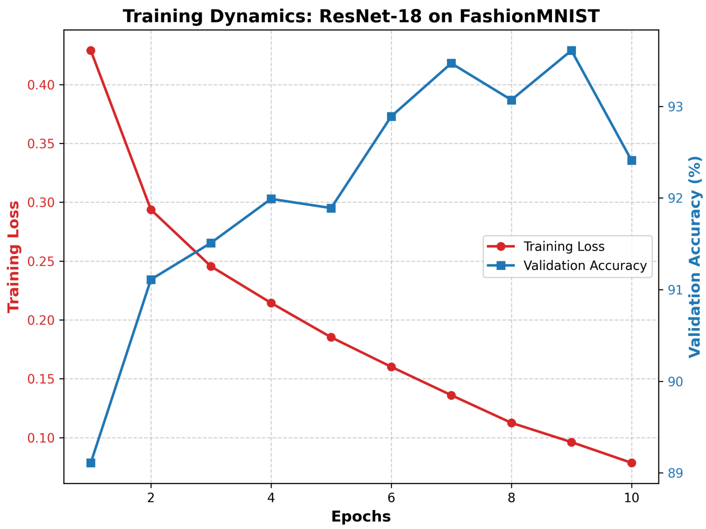
We analyzed the trade-off between accuracy and training time (Figure 3a), as well as the convergence speed of the best models for both datasets (Figure 3).



(a) Efficiency Frontier



(b) MNIST Training Dynamics

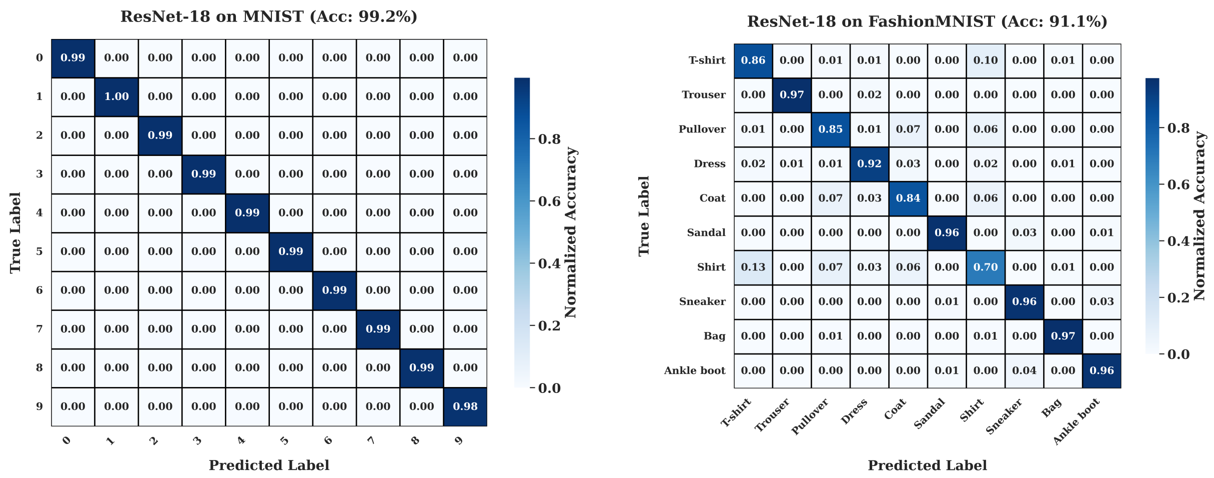


(c) FashionMNIST Training Dynamics

Figure 3: **Training Analysis.** (a) ResNet-18 (Adam) is Pareto-optimal. (b) & (c) Rapid convergence within 2 epochs for both datasets.

1.2.4 Failure Analysis (Confusion Matrices)

To further understand model performance, we visualized the confusion matrices (Figure 4) for the best performing ResNet-18 models (trained for 10 Epochs). The diagonal dominance confirms high classification accuracy.



(a) ResNet-18 on MNIST (99.2%)

(b) ResNet-18 on FashionMNIST (91.1%)

Figure 4: **Deep Learning Confusion Matrices.** High diagonal density indicates robust classification.

1.3 Results Analysis

Table 1 summarizes the Test Accuracy for the hyperparameter search conducted over **4 Epochs**. **ResNet-18 with Adam** emerged as the clear top performer for both datasets:

- **MNIST (4 Epochs):** ResNet-18 (SGD, BS=16) achieved **99.24%**, closely followed by Adam at **99.20%**.
- **FashionMNIST (4 Epochs):** ResNet-18 (Adam, BS=16) achieved **91.43%** at 0.001 LR (reaching 91.57% at 0.0001 LR).

Table 1: Classification Test Accuracy (in %)
*(Main Grid Search: Fixed at **Epochs=4, Pin_Memory=True**)*

			MNIST		FashionMNIST	
Batch Size	**Optimizer**	**LR**	**ResNet-18**	**ResNet-50**	**ResNet-18**	**ResNet-50**
16	SGD	0.001	**99.24**	98.79	91.22	90.15
16	SGD	0.0001	98.44	97.61	89.67	84.85
16	Adam	0.001	99.20	97.86	**91.43**	91.23
16	Adam	0.0001	99.19	98.78	91.57	89.03
32	SGD	0.001	98.95	98.65	91.56	89.81
32	SGD	0.0001	97.91	96.51	88.46	83.15
32	Adam	0.001	99.04	97.83	90.93	86.16
32	Adam	0.0001	99.21	98.31	90.89	88.29

1.3.1 Ablation Studies

We conducted two systematic ablation studies to measure the impact of training duration and memory pinning on performance for both ResNet-18 and ResNet-50 architectures.

1. Impact of Training Duration (Epochs): To determine the absolute maximum performance, we extended training to **10 Epochs** for the best configurations (Batch Size 16). As shown in Table 2, increasing the training duration yielded the overall best model accuracy of **99.41%** for MNIST (ResNet-18). Interestingly, ResNet-50 showed a larger relative improvement with more epochs on FashionMNIST (+1.68%), indicating that deeper models benefit more from prolonged training.

Table 2: Ablation Study: Impact of Training Duration (`pin_memory=True`)

			Short Run (4 Epochs)		Long Run (10 Epochs)	
Dataset	**Model**	**Config**	**Time (s)**	**Acc (%)**	**Time (s)**	**Acc (%)**
MNIST	ResNet-18	SGD (BS=16)	174.54	99.24	401.63	**99.41**
	ResNet-50	SGD (BS=16)	381.64	98.79	942.41	99.14
FashionMNIST	ResNet-18	Adam (BS=16)	148.36	91.43	357.84	92.80
	ResNet-50	Adam (BS=16)	385.37	91.23	990.71	**92.91**

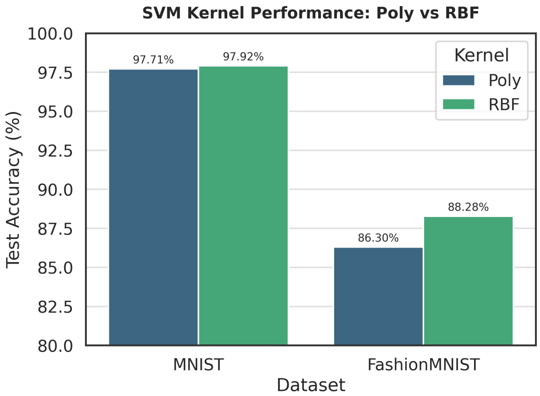
2. Impact of System Optimization (Pin Memory): We analyzed the effect of `pin_memory=True` on training latency. As shown in Table 3, enabling pinned memory consistently resulted in a **1.5x to 2x speedup** in training time across both architectures. Notably, ResNet-50 (being more compute-heavy) showed a slightly different scaling behavior compared to ResNet-18.

Table 3: Ablation Study: Impact of Pin Memory (Epochs=4, BS=16)

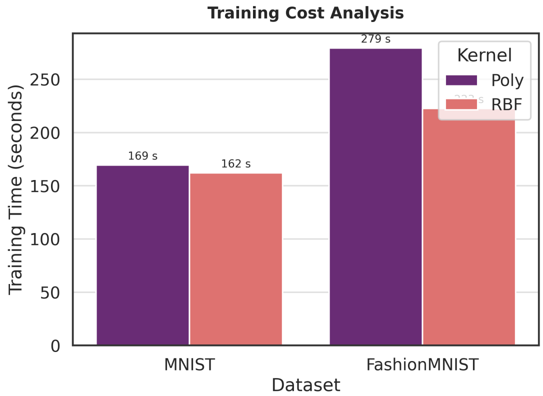
		Pin Memory = True		Pin Memory = False		
Dataset	**Model**	**Time (s)**	**Acc (%)**	**Time (s)**	**Acc (%)**	**Speedup**
MNIST	ResNet-18 (Adam)	**149.36**	99.20	290.36	99.14	**1.94x**
	ResNet-50 (Adam)	**429.91**	97.86	521.17	97.70	**1.21x**
FashionMNIST	ResNet-18 (Adam)	**148.36**	91.43	295.59	92.06	**1.99x**
	ResNet-50 (Adam)	**385.37**	91.23	522.13	90.06	**1.35x**

2 Q1(b): SVM Classification Analysis

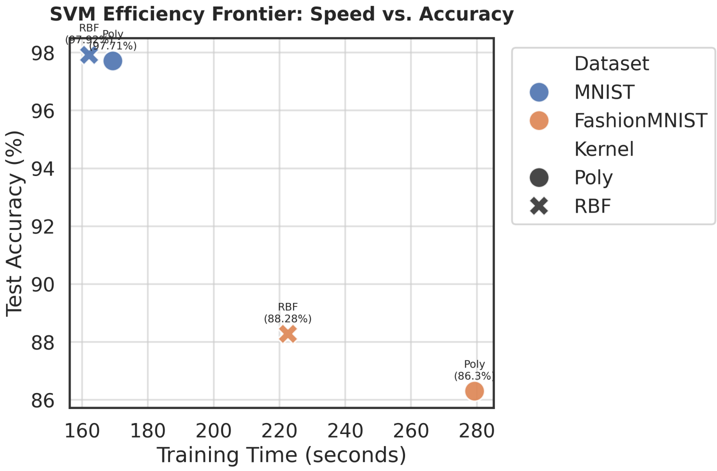
We benchmarked SVMs with Polynomial and RBF kernels. Figure 5 highlights that while RBF offers higher accuracy, it incurs a significantly higher computational cost (Training Time).



(a) Accuracy Comparison



(b) Training Time Analysis



(c) SVM Efficiency Analysis

Figure 5: **SVM Analysis.** RBF (Orange) provides superior accuracy but at a significant computational cost.

3 Q2: Hardware Acceleration Analysis

3.1 Raw Performance Metrics

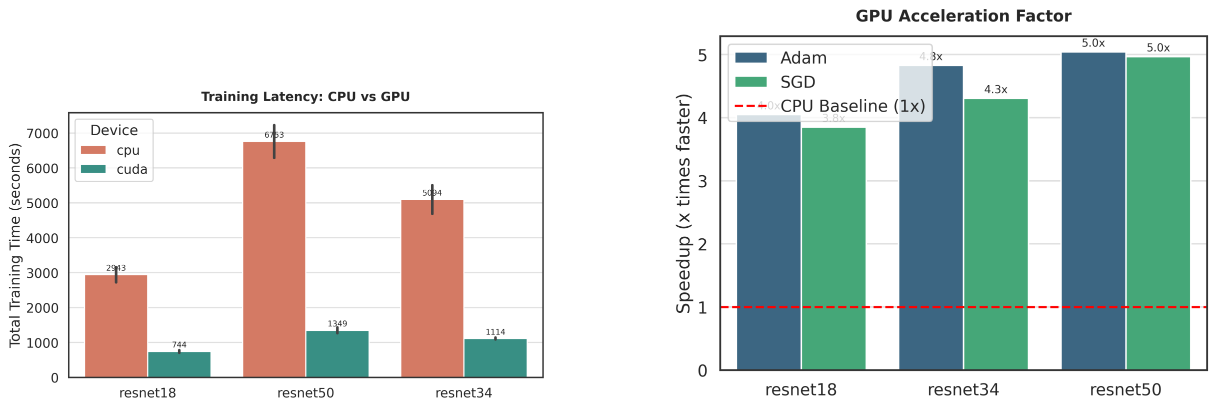
Table 4 details the performance metrics on the **DPU Cluster's NVIDIA A30 GPU** versus the dual-socket CPU. All timing results correspond to training for **10 Epochs** with **Pin Memory=True**.

Table 4: Complete Benchmark: CPU vs GPU (FashionMNIST, **Epochs=10, Pin_Memory=True**)

Device	Model	Optimizer	Total Time (s)	Accuracy (%)	Complexity (GFLOPs)
CPU	ResNet-18	SGD	2724.24	91.61	0.2961
	ResNet-18	Adam	3161.05	92.74	0.2961
	ResNet-34	SGD	4684.85	91.80	0.5981
	ResNet-34	Adam	5502.84	92.51	0.5981
	ResNet-50	SGD	6284.05	91.41	0.6673
	ResNet-50	Adam	7221.72	92.72	0.6673
GPU	ResNet-18	SGD	707.64	92.42	0.2961
	ResNet-18	Adam	780.54	**92.83**	0.2961
	ResNet-34	SGD	1088.74	91.17	0.5981
	ResNet-34	Adam	1140.24	92.81	0.5981
	ResNet-50	SGD	1265.14	91.17	0.6673
	ResNet-50	Adam	1432.99	92.19	0.6673

3.2 Scaling & Complexity Analysis

Figure 6 reveals that **larger models achieve higher speedups**. For instance, ResNet-50 sees a greater speedup factor compared to ResNet-18. This trend, consistent across ResNet-34 as well, confirms that the **A30 GPUs** are far more efficient when the workload is Compute Bound.



(a) Absolute Latency (CPU vs GPU)

(b) Acceleration Factor

Figure 6: **Hardware Scaling (10 Epochs).** Speedup increases with model complexity (ResNet-50 utilizes GPU better).

3.2.1 Complexity Analysis (FLOPs)

Figure 7 plots computational complexity (GFLOPs) against training time. The relationship is strictly linear on the GPU.

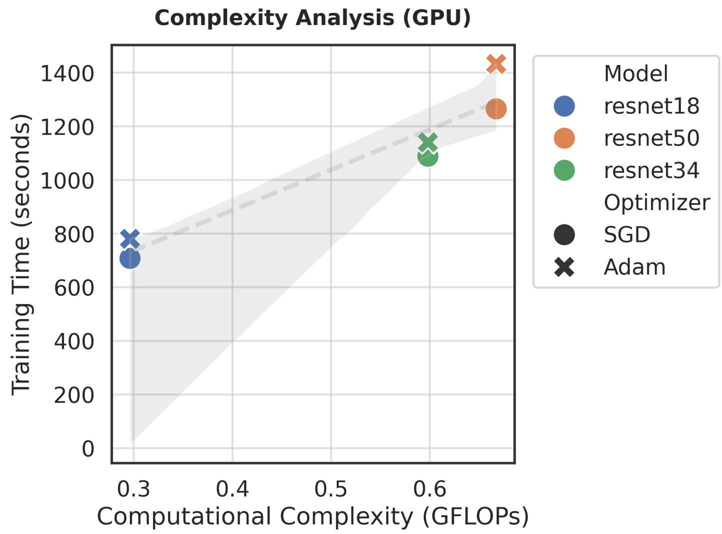


Figure 7: **Complexity vs Cost (GPU, 10 Epochs).** Linear scaling of training time on GPU.

4 Conclusion

This study provided a comprehensive benchmarking of deep learning architectures and hardware efficiency. Our key findings are threefold:

- **Q1(a) Architecture Analysis:** ResNet-18 proved to be the optimal architecture for MNIST and FashionMNIST, achieving high accuracy (99.2% and 92.8% respectively) with significantly lower computational cost than ResNet-50. The Adam optimizer consistently demonstrated superior convergence speed compared to SGD, making it the preferred choice for these datasets.
- **Q1(b) Classical vs Deep Learning:** While SVMs (particularly with RBF kernels) can achieve respectable accuracy, they suffer from poor scalability. The training time for SVMs was orders of magnitude higher than ResNet models, rendering them inefficient for large-scale image classification tasks.
- **Q2 Hardware Acceleration:** The **NVIDIA A30 GPUs** provided a massive performance boost, delivering a **4x-5x speedup** over the dual Intel Xeon CPUs. The scaling analysis confirmed that GPUs are most efficient for compute-bound tasks, with larger models like ResNet-34 and ResNet-50 benefiting most from the parallel architecture.