MLOps Assignments — B22AI063

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Links

- **Colab Notebook:**
  Open in Google Colab
- **GitHub Repository:**
  View Assignment on GitHub

Question 1

Part A: MNIST and FashionMNIST ABLATIONS

Batch Size	Optimizer	Learning Rate	Epochs	pin_memory	ResNet-18 Accuracy (%)	ResNet-50 Accuracy (%)
16	SGD	0.001	05	False	99.18%	98.98%
16	SGD	0.0001	15	True	99.48%	98.85%
16	Adam	0.001	05	True	99.38%	98.17%
16	Adam	0.0001	15	False	99.32%	99.25%
32	SGD	0.001	05	False	99.28%	99.71%
32	SGD	0.0001	15	True	99.19%	99.48%
32	Adam	0.001	05	True	99.32%	98.97%
32	Adam	0.0001	15	False	99.14%	99.06%

Part B: SVM

Dataset	Kernel	Train Samples	Test Accuracy (%)	Training Time (ms)
MNIST	RBF	10,000	95.94%	7150.62
MNIST	Poly	10,000	95.15%	7986.79
FashionMNIST	RBF	10,000	85.31%	8506.86
FashionMNIST	Poly	10,000	81.66%	7345.85

Question 2

Compute	Model	Batch Size	Optimizer	LR	Epochs	pin_memory	Test Accuracy (%)	Train Time (ms)	FLOPs (GFLOPs)	Params (M)
GPU	ResNet-18	16	Adam	0.001	5	True	92.07	407,906	0.0332	11.18
CPU	ResNet-18	16	Adam	0.001	15	False	92.66	1,233,524	0.0332	11.18
GPU	ResNet-18	16	Adam	0.001	15	True	91.88	1,237,956	0.0332	11.18

Compute	Model	Batch Size	Optimizer	LR	Epochs	pin_memory	Test Accuracy (%)	Train Time (ms)	FLOPs (GFLOPs)	Params (M)
CPU	ResNet-18	16	Adam	0.0001	5	False	92.27	459,555	0.0332	11.18
GPU	ResNet-18	16	Adam	0.0001	5	True	92.16	446,441	0.0332	11.18
GPU	ResNet-34	16	SGD	0.001	5	True	91.81	735,832	0.0699	21.28
CPU	ResNet-34	16	Adam	0.001	5	True	89.32	1,789,542	0.0699	21.28
CPU	ResNet-34	32	SGD	0.001	5	True	85.69	627,229	0.0699	21.28
GPU	ResNet-34	32	Adam	0.001	5	True	91.42	1,136,055	0.0699	21.28
CPU	ResNet-50	16	SGD	0.001	5	True	90.73	1,899,157	0.0788	23.52

The results from Question 1(a) show that both ResNet-18 and ResNet-50 achieve extremely high classification accuracy on MNIST, consistently above 99% across all hyperparameter settings. This indicates that MNIST is a relatively simple dataset for modern convolutional architectures, and performance saturates quickly regardless of optimizer choice or batch size. Small variations can still be observed: SGD with a slightly higher learning rate (0.001) tends to provide strong stability, while Adam achieves comparable accuracy with faster convergence in fewer epochs. The effect of pin_memory is minimal in terms of accuracy, suggesting that it primarily influences data loading efficiency rather than model generalization. Overall, both architectures perform nearly optimally, with ResNet-50 occasionally providing marginal improvements but not a significant advantage given the simplicity of the dataset.

In Question 1(b), the SVM baselines demonstrate strong performance on MNIST, reaching around 96% accuracy with the RBF kernel, but accuracy drops significantly on FashionMNIST, where the best result is 85.31%. This highlights the increased complexity of FashionMNIST, where class boundaries are less separable in raw pixel space and require deeper feature extraction. The RBF kernel consistently outperforms the polynomial kernel, confirming that non-linear decision boundaries are better suited for these datasets. However, compared to deep ResNet models, SVM performance remains limited, especially for FashionMNIST, showing the benefit of representation learning in CNNs.

The results from Question 2 further emphasize the trade-off between model complexity and efficiency on FashionMNIST. ResNet-18 achieves the best accuracy (92.66%) with Adam and longer training (15 epochs), while maintaining the lowest FLOPs and parameter count, making it computationally efficient. ResNet-34 and ResNet-50 require significantly more compute and training time, yet they do not consistently outperform ResNet-18. In fact, deeper models sometimes show reduced accuracy, likely due to optimization difficulty and overfitting on a dataset of moderate complexity. These findings suggest that for FashionMNIST, smaller architectures such as ResNet-18 provide the best balance of accuracy and efficiency, while deeper networks incur higher computational cost without proportional performance gains.