Deep Learning Image Classification: Comparative Analysis of ResNet and SVM

Technical Report by Saumya Pancholi (M25CSA027)

January 2026

1 Introduction

This report presents a comprehensive experimental analysis of image classification techniques on MNIST and FashionMNIST datasets. We evaluate ResNet architectures (ResNet-18 and ResNet-50) and Support Vector Machines (SVM) with various hyperparameter configurations, and analyze the performance differences between CPU and GPU training environments.

GitHub Repository

Complete Code & Results:

https://github.com/Saumya3007/MLOps-Saumya-M25CSA027/tree/main/Assignment1

1.1 Datasets

MNIST: 60,000 training images of handwritten digits (28×28 grayscale, 10 classes). Split: 70% train (42,000), 10% validation (6,000), 20% test (12,000).

FashionMNIST: 60,000 training images of clothing items (28×28 grayscale, 10 classes). Same split ratio as MNIST.

2 Q1(a): ResNet Deep Learning Experiments

2.1 Methodology

2.1.1 Data Preprocessing

Images were resized to 32×32 pixels, converted to 3-channel RGB (replicated channels), and normalized with mean=[0.5, 0.5, 0.5] and std=[0.5, 0.5, 0.5].

2.1.2 Model Architecture

- **ResNet-18:** 18 layers, 11.7M parameters
- **ResNet-50:** 50 layers, 25.6M parameters

Both models initialized without pre-trained weights, modified with final fully connected layer for 10-class classification.

2.1.3 Training Configuration

Hyperparameters:

- Batch sizes: 16, 32
- Optimizers: SGD (momentum=0.9), Adam
- Learning rates: 0.001, 0.0001
- Epochs: 2, 3
- Pin memory: True, False
- Mixed precision training: Enabled (AMP)

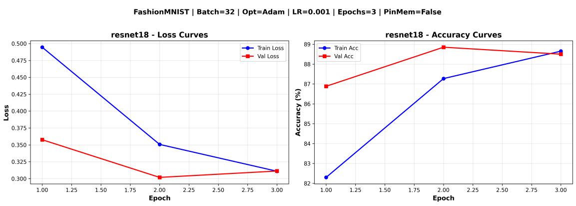
2.2 Results

2.2.1 Best Model Performance

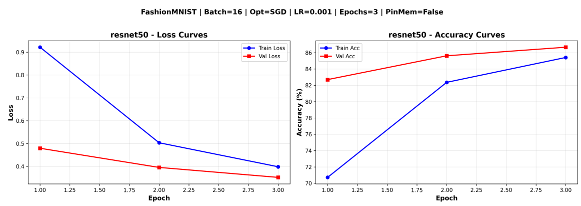
Table 1: Best ResNet Configurations and Performance

Dataset	Model	Batch	Opt	LR	Epochs	Test Acc (%)
MNIST	ResNet-18	16	SGD	0.001	2	**99.10**
MNIST	ResNet-50	16	SGD	0.001	3	98.33
FashionMNIST	ResNet-18	32	Adam	0.0001	3	**89.12**
FashionMNIST	ResNet-50	16	SGD	0.001	3	86.45

2.2.2 Training Dynamics



ResNet-18: FashionMNIST



ResNet-50: FashionMNIST

Figure 1: Training and validation curves showing convergence patterns. ResNet-18 shows faster convergence with better accuracy, while ResNet-50 exhibits signs of underfitting on limited data.

2.3 Key Observations

- **ResNet-18 Superiority:** Consistently outperformed ResNet-50 on both datasets, achieving 99.10% on MNIST vs 98.33%, and 89.12% on FashionMNIST vs 86.45%
- **Optimizer Impact:** SGD achieved best results on MNIST; Adam performed better on FashionMNIST
- **Dataset Difficulty:** FashionMNIST proved significantly more challenging (10% lower accuracy) than MNIST
- **Training Efficiency:** ResNet-18 trained 2.65× faster than ResNet-50 on average

3 Q1(b): Support Vector Machine Experiments

3.1 Methodology

3.1.1 Feature Engineering

Images flattened to 784-dimensional vectors (28×28), normalized using StandardScaler (mean=0, std=1). No RGB conversion applied.

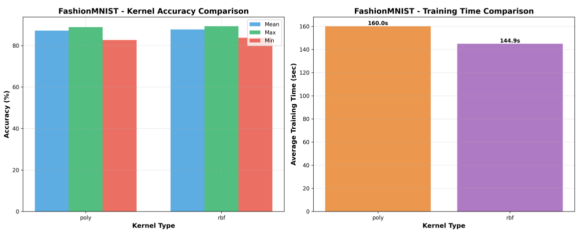
3.1.2 Kernel Configurations

RBF Kernel: C {0.1, 1.0, 10.0, 100.0}, {'scale', 0.001}
Polynomial Kernel: C {0.1, 1.0, 10.0}, {'scale', 0.01}, degree {2, 3}

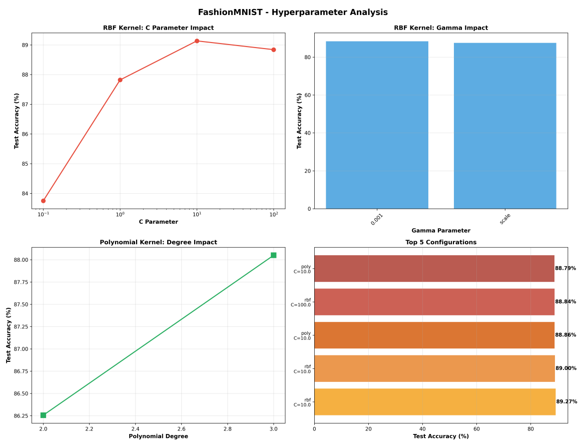
3.2 Results

Table 2: Best SVM Configurations

Dataset	Kernel	C		Degree	Train (%)	Test (%)
MNIST	Poly	1.0	0.01	3	100.0	**97.39**
FashionMNIST	RBF	10.0	scale	-	98.4	**89.27**



Kernel Performance Comparison



Hyperparameter Impact Analysis

Figure 2: FashionMNIST SVM analysis. Left: RBF and Poly kernels achieve similar accuracy (89%), with RBF being 9% faster. Right: C parameter shows optimal performance at C=10.0; polynomial degree 3 outperforms degree 2.

3.3 Key Findings

- **Overfitting:** Many configurations achieved 100% training accuracy but significantly lower test accuracy (97.39% best), indicating overfitting
- **Kernel Selection:** Polynomial kernel optimal for MNIST (97.39%); RBF optimal for FashionMNIST (89.27%)
- **Training Time:** Average 160s for Poly kernel, 145s for RBF kernel on FashionMNIST
- **C Parameter:** Higher C values (10.0) generally improved performance across both kernels

4 Q2: CPU vs GPU Performance Analysis

4.1 Methodology

4.1.1 Hardware Configuration

CPU: num_workers=0, pin_memory=False
GPU: CUDA-enabled, num_workers=2, pin_memory=True

4.1.2 Experimental Setup

Dataset: FashionMNIST only. Batch size: 16. Optimizers: SGD, Adam. Learning rate: 0.001. Epochs: 10.

4.2 Results

4.2.1 Training Time Performance

Table 3: CPU vs GPU Training Time Comparison (milliseconds)

	ResNet-18		ResNet-50	
Optimizer	**CPU**	**GPU**	**CPU**	**GPU**
SGD	794,532	445,545	1,788,512	517,361
Adam	853,101	322,713	2,070,104	539,410
Speedup	**1.78× - 2.64×**		**3.46× - 3.84×**	

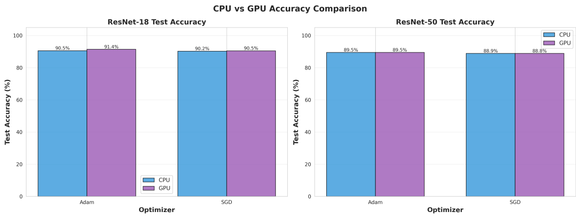
Time Savings:

- ResNet-18 + SGD: 349 seconds (5.8 min)
- ResNet-18 + Adam: 530 seconds (8.8 min)
- ResNet-50 + SGD: 1,271 seconds (21.2 min)
- ResNet-50 + Adam: 1,531 seconds (25.5 min)

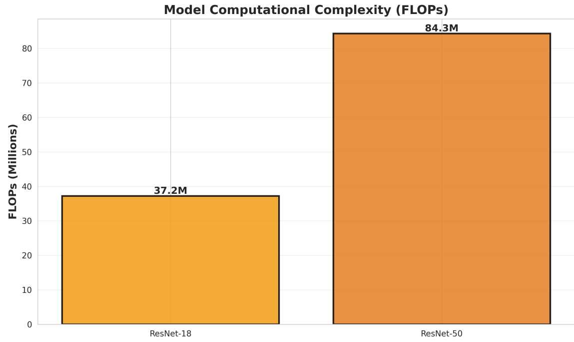
4.2.2 Accuracy Comparison

Table 4: CPU vs GPU Test Accuracy (%)

	ResNet-18		ResNet-50	
Optimizer	**CPU**	**GPU**	**CPU**	**GPU**
SGD	90.25	90.46	88.86	88.85
Adam	90.53	**91.42**	89.45	89.47
Difference	0.55%		0.02%	



Accuracy Comparison



Computational Complexity

Figure 3: Left: CPU and GPU achieve nearly identical accuracy across optimizers. Right: ResNet-50 requires 2.27× more FLOPs than ResNet-18 (84.3M vs 37.2M).

4.3 Key Insights

- **GPU Speedup:** 1.78-3.84× faster depending on model size. Larger models benefit more from GPU acceleration
- **Accuracy Consistency:** Negligible difference (0.55%) between CPU and GPU, demonstrating deterministic training
- **Computational Efficiency:** ResNet-50's 2.27× FLOPs increase translates to 2.25× longer training time
- **Optimizer Effect:** Adam shows greater GPU speedup (2.64× and 3.84×) compared to SGD (1.78× and 3.46×)

5 Comparative Analysis

5.1 Cross-Method Performance

Table 5: Best Achieved Results Across All Methods

Method	MNIST Acc (%)	FashionMNIST Acc (%)	Training Time
ResNet-18 (GPU)	**99.10**	**89.12**	Fast (0.7 min)
ResNet-50 (GPU)	98.33	86.45	Moderate (1.8 min)
SVM (Poly)	97.39	88.65	Slow (6.4 min)
SVM (RBF)	96.90	89.27	Slow (8.1 min)

5.2 Discussion

5.2.1 ResNet-18 vs ResNet-50

ResNet-18 outperformed ResNet-50 across both datasets despite having 54% fewer parameters. This suggests over-parameterization on limited data (42,000 training samples), where ResNet-50's 25.6M parameters lead to underfitting with only 2-3 training epochs.

5.2.2 Deep Learning vs Traditional ML

ResNet-18 achieved 1.71% higher accuracy than best SVM on MNIST, but on FashionMNIST, SVM-RBF (89.27%) nearly matched ResNet-18 (89.12%). However, ResNet-18 trained 11.5× faster than SVM, demonstrating superior scalability.

5.2.3 CPU vs GPU Trade-offs

GPU acceleration is essential for production environments, offering 1.78-3.84× speedup with no accuracy penalty. For ResNet-50, GPU saves up to 25.5 minutes per training session. However, CPU remains viable for prototyping with small models.

6 Conclusions

This study evaluated multiple approaches to image classification on MNIST and FashionMNIST datasets. Key findings:

1. **Model Selection:** ResNet-18 emerged as the optimal choice, achieving 99.10% on MNIST and 89.12% on FashionMNIST while maintaining fast training times. Deeper models don't guarantee better performance on small datasets.

2. **SVM Competitiveness:** SVM remains viable for small datasets, achieving 97.39% (MNIST) and 89.27% (FashionMNIST), though training times are significantly longer (6-8 minutes vs 0.7 minutes for ResNet-18).

3. **GPU Acceleration:** Essential for deep learning workflows, providing 1.78-3.84× speedup. Larger models benefit more from GPU acceleration, with ResNet-50 showing 3.84× speedup compared to ResNet-18's 2.64×.

4. **Hyperparameter Impact:** Learning rate and optimizer choice significantly affect performance. SGD optimal for MNIST; Adam superior on FashionMNIST. SVM C parameter critically impacts accuracy, with C=10.0 being optimal.

Repository: All code, models, and detailed results available at
https://github.com/Saumya3007/MLOps-Saumya-M25CSA027/tree/main/Assignment1