

COMPARATIVE ANALYSIS OF NEURAL NETWORK ARCHITECTURES FOR IMAGE CLASSIFICATION

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ABSTRACT. This report presents a comparative analysis of two primary neural network architectures—Fully Connected Networks (FCNs) and Convolutional Neural Networks (CNNs)—for image classification on the FashionMNIST dataset. Multiple model variants with varying parameter budgets are designed and trained using the AdamW optimizer and StepLR learning-rate scheduling. Comparative experiments highlight how architectural choices and model capacity influence classification accuracy, training efficiency, and generalization performance.

1. INTRODUCTION AND OVERVIEW

Deep learning methods have become integral to image recognition tasks, offering substantial gains over traditional feature engineering approaches. While standard Fully Connected Networks (FCNs) can achieve high accuracy, their dense connectivity makes them computationally inefficient for high-dimensional image data. Convolutional Neural Networks (CNNs), by contrast, exploit local spatial hierarchies and parameter sharing, enabling better scalability and feature extraction efficiency. This project aims to quantitatively evaluate how these architectural differences influence learning dynamics, accuracy, and generalization under fixed parameter budgets. Specifically, we seek to determine whether CNNs achieve higher parameter efficiency and faster convergence compared to equally sized FCNs.

2. THEORETICAL BACKGROUND

2.1. Fully Connected Neural Networks (FCNs). A **Fully Connected Neural Network (FCN)** consists of one or more hidden layers where every neuron in a given layer is connected to all neurons in the preceding layer. This dense connectivity allows for learning complex, hierarchical representations. Formally, the forward pass for layer l is given by:

$$(1) \quad h^{(l)} = f(W^{(l)} h^{(l-1)} + b^{(l)}),$$

where $W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector for layer l , and $f(\cdot)$ is a non-linear activation function. While this architecture can capture rich feature interactions, it also leads to a large number of parameters, which may be prohibitive for resource-constrained environments.

2.2. Convolutional Neural Networks (CNNs). **Convolutional Neural Networks (CNNs)** are designed for grid-like data (e.g., images), leveraging local receptive fields and parameter sharing. Instead of connecting every neuron to all input pixels, a **convolutional layer** learns small filters

(kernels) that scan across the input, extracting local features such as edges and textures. Formally, for an input X and a $k \times k$ filter W , the convolution output at (i, j) is:

$$(2) \quad Z_{ij} = \sum_{p=0}^{k-1} \sum_{q=0}^{k-1} W_{p,q} X_{i+p, j+q} + b.$$

where b is a bias term and Z_{ij} is the corresponding output feature map value. By **sharing** the same filter parameters across different spatial locations, CNNs greatly reduce the total number of parameters relative to a similarly sized Fully Connected Network (FCN).

Pooling (e.g., max pooling) then downscales feature maps, providing translational invariance. By stacking multiple convolution and pooling layers, CNNs learn increasingly abstract representations, typically requiring fewer parameters than fully connected architectures while achieving superior performance on image classification tasks such as FashionMNIST.

2.3. Activation Functions. Activation functions introduce non-linearity, preventing FCNs from being simple linear models. Common functions include:

$$(3) \quad \sigma(x) = \frac{1}{1 + e^{-x}}, \quad \text{ReLU}(x) = \max(0, x), \quad \text{LeakyReLU}(x) = \max(ax, x).$$

2.4. Loss Function. For multi-class classification, the **cross-entropy loss** is optimized during training to improve prediction accuracy, defined as:

$$(4) \quad L(y, \hat{y}) = - \sum_{i=1}^n y_i \log \hat{y}_i.$$

2.5. Optimization Algorithms. Optimization algorithms iteratively update model weights to minimize the loss function. **SGD, RMSProp, and Adam** are commonly used.

Stochastic Gradient Descent (SGD) updates weights using:

$$(5) \quad w^{(t+1)} = w^{(t)} - \alpha \frac{\partial J}{\partial w},$$

where α is the learning rate. Adding **momentum** improves convergence:

$$(6) \quad v^{(t)} = \beta v^{(t-1)} + (1 - \beta) \frac{\partial J}{\partial w}, \quad w^{(t+1)} = w^{(t)} - \alpha v^{(t)}.$$

RMSProp adapts learning rates per parameter:

$$(7) \quad s^{(t)} = \gamma s^{(t-1)} + (1 - \gamma) \left(\frac{\partial J}{\partial w} \right)^2, \quad w^{(t+1)} = w^{(t)} - \frac{\alpha}{\sqrt{s^{(t)} + \epsilon}} \frac{\partial J}{\partial w}.$$

Adam (Adaptive Moment Estimation) combines momentum and adaptive learning rates:

$$(8) \quad m^{(t)} = \beta_1 m^{(t-1)} + (1 - \beta_1) \frac{\partial J}{\partial w}, \quad v^{(t)} = \beta_2 v^{(t-1)} + (1 - \beta_2) \left(\frac{\partial J}{\partial w} \right)^2,$$

with bias-corrected estimates $\hat{m}^{(t)}$ and $\hat{v}^{(t)}$. The update then is:

$$(9) \quad w^{(t+1)} = w^{(t)} - \alpha \frac{\hat{m}^{(t)}}{\sqrt{\hat{v}^{(t)} + \epsilon}} - \lambda w^{(t)},$$

where λ is the weight decay coefficient and α is the learning rate. A **StepLR** scheduler may also be used to periodically reduce α and stabilize convergence.

Learning Rate: The learning rate (α) determines the step size of parameter updates during optimization. A decay schedule can be applied to reduce α over epochs:

$$(10) \quad \alpha = d^{\text{epoch}} \cdot \alpha_0$$

where d is the decay factor and α_0 is the initial learning rate.

2.6. Overfitting/Underfitting and Regularization. **Overfitting** occurs when a model memorizes noise instead of patterns, leading to poor generalization. It is indicated by **high training accuracy but stagnant or declining validation accuracy**, along with **increasing validation loss despite decreasing training loss**. **Underfitting** happens when a model is too simple to capture patterns, resulting in **low accuracy and persistently high loss** on both training and validation sets. **Dropout Regularization** mitigates overfitting by randomly deactivating neurons during training, preventing reliance on specific features:

$$(11) \quad \tilde{a}_i = a_i \times \tilde{d}_i / (1 - p_d)$$

2.7. Weight Initialization. Proper initialization prevents vanishing or exploding gradients. Common methods include:

Random Normal: Weights are sampled from a standard normal distribution:

$$(12) \quad w \sim \mathcal{N}(0, \sigma^2),$$

where a small standard deviation σ (e.g., 0.01) is used to prevent large initial activations.

Xavier Initialization: Used with Sigmoid, Tanh, and linear activations. Designed for activation functions with zero-centered outputs, it maintains variance across layers:

$$(13) \quad w \sim \mathcal{N}\left(0, \frac{2}{n_{\text{in}} + n_{\text{out}}}\right) \quad (\text{Normal}), \quad w \sim \mathcal{U}\left(-\frac{\sqrt{6}}{\sqrt{n_{\text{in}} + n_{\text{out}}}}, \frac{\sqrt{6}}{\sqrt{n_{\text{in}} + n_{\text{out}}}}\right) \quad (\text{Uniform}).$$

Kaiming (He) Initialization: Optimized for ReLU-based activations to preserve variance:

$$(14) \quad w \sim \mathcal{N}\left(0, \frac{2}{n_{\text{in}}}\right) \quad (\text{Normal}), \quad w \sim \mathcal{U}\left(-\frac{\sqrt{6}}{\sqrt{n_{\text{in}}}}, \frac{\sqrt{6}}{\sqrt{n_{\text{in}}}}\right) \quad (\text{Uniform}).$$

2.8. Batch Normalization. **Batch Normalization** stabilizes training by normalizing activations within each mini-batch:

$$(15) \quad \hat{x} = \frac{x - \mu}{\sigma}, \quad y = \gamma \hat{x} + \beta,$$

where μ and σ are batch statistics, and γ, β are learnable parameters. This allows for higher learning rates and faster convergence. **Batch Size** defines the number of samples per iteration, influencing model convergence and generalization. A common batch size is:

$$(16) \quad J = \frac{1}{m} \sum_{i=1}^m L(\tilde{y}^{(i)}, y^{(i)}).$$

2.9. Evaluation Metrics. Model performance is evaluated using:

$$(17) \quad \text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}.$$

This measures both training progress and validation/test performance.

3. ALGORITHM IMPLEMENTATION AND DEVELOPMENT

3.0. Implementation Overview. This project is implemented in **Python** using the **PyTorch** framework for model construction and automatic differentiation. **Torchvision** is used for dataset handling and preprocessing, while **scikit-learn** supports data partitioning and validation. Training dynamics and performance metrics are visualized using **Matplotlib**. All computations are performed on GPU-accelerated hardware for efficient model training and evaluation.

3.1. Data Processing and Model Architecture. The implementation begins by loading and preprocessing the FashionMNIST dataset using **Torchvision**. Images are transformed into tensors and normalized, after which the dataset is partitioned into training, validation, and test sets using **scikit-learn**’s `train_test_split`. Data is then efficiently handled through **DataLoader** objects from **torch.utils.data**, which enable mini-batch processing for faster training.

Two main types of models are implemented using **PyTorch**’s `nn.Module`: **Fully Connected Neural Networks (FCNs)** and **Convolutional Neural Networks (CNNs)**. The FCNs are constructed with two hidden layers incorporating **ReLU activations**, **batch normalization**, and a fixed **dropout rate** to reduce overfitting. The network weights are initialized via **Xavier Normal** initialization, ensuring stable gradients during training.

In contrast, the CNN architectures exploit the spatial structure of images. They consist of two convolutional layers with small 3×3 kernels to extract local features, followed by **max pooling** layers that downsample the feature maps, and finally a fully connected layer for classification. This design, which leverages parameter sharing and local receptive fields, results in a significantly lower parameter count compared to an equivalent FCN, while still capturing essential image features.

3.2. Training and Evaluation. Models are trained using the **AdamW** optimizer with decoupled weight decay and a **StepLR** scheduler to progressively reduce the learning rate and stabilize convergence. During training, both loss and accuracy metrics are logged across epochs and visualized using **Matplotlib** to monitor learning behavior and generalization trends. Hyperparameter configurations are tuned empirically, with the best-performing settings selected based on validation accuracy.

3.3. Hyperparameter Tuning and Model Improvements.

3.3.1. Learning Rate and Optimizer Selection. To achieve stable convergence and high accuracy, multiple learning rates (0.001, 0.0005, 0.0001) are tested for both FCN and CNN models. The optimization algorithm is fixed as **AdamW**, which combines adaptive moment estimation with decoupled weight decay to enhance generalization. A **StepLR** scheduler periodically decreases the learning rate to maintain stability during later epochs. Validation accuracy and loss trends across different learning rates are analyzed to identify the most effective configuration for each model variant.

3.3.2. Regularization and Overfitting Control. **Dropout Regularization** is employed to prevent overfitting by randomly deactivating neurons during training. A fixed dropout rate of 0.3 is used for all architectures, as earlier experiments demonstrated this value offers the best balance between accuracy and generalization. This method helps reduce co-adaptation among neurons and stabilizes validation accuracy across epochs, particularly in higher-capacity models.

3.3.3. Weight Initialization Strategies. The model weights are initialized using **Xavier Normal Initialization**, which maintains variance across layers and prevents gradient vanishing or explosion. This initialization method is chosen for both FCNs and CNNs after comparative evaluation in prior experiments showed it leads to consistent and stable training performance.

3.3.4. Normalization and Convergence Stability. **Batch Normalization** is incorporated after each hidden or convolutional layer to reduce internal covariate shift and accelerate training. It enables the use of higher learning rates and improves convergence speed. Validation accuracy is monitored with and without batch normalization to assess its impact on training smoothness and final test performance.

3.3.5. Model Comparison and Performance Evaluation. Following hyperparameter tuning, the best-performing configurations for all FCN and CNN variants are selected based on validation accuracy. Key performance metrics—including training time, parameter count, and test accuracy—are summarized in comparative tables and visualized through training and validation curves. These analyses highlight the trade-offs between model complexity and generalization, as well as the efficiency advantages of convolutional architectures over fully connected ones.

4. COMPUTATIONAL RESULTS

4.1. FCN Models Comparison. The **Fully Connected Network (FCN)** baseline was designed with fewer than **100K weights**, featuring two hidden layers with **ReLU activation**, **batch normalization**, and a **dropout rate** for regularization. The model was initialized using **Xavier Normal** and optimized with **AdamW** under a **StepLR scheduler**, with a fixed batch size. As model **FCN 100K** shown in **Figure 1**, the training loss steadily decreased while accuracy improved, reaching peak validation performance before stabilizing. The **final test accuracy of 88.25%** > 88% confirms the model satisfied the target constraint while maintaining strong generalization.

To analyze the effect of model capacity, we trained **FCN 50K** and **FCN 200K** under the same procedure, comparing them to the baseline **FCN 100K**. Each model was trained with three learning rates {0.001, 0.0005, 0.0001}, as shown in **Table 1**, which lists the best validation accuracies and corresponding epochs. Overall, the largest model **FCN 200K** achieved the highest validation accuracy of **90.15%** and a final test accuracy of **89.59%**, while the smallest model **FCN 50K** reached **88.67%** on validation and **87.94%** on test. Table 2 presents the optimal hyperparameter configuration and the final metrics for each variant.

Results indicate that increasing model capacity enhances accuracy, with the largest model achieving the highest validation and test performance. However, while the smallest model underperformed due to limited capacity, the largest model exhibited early signs of overfitting, with validation accuracy plateauing earlier than the baseline. As illustrated in Figure 1, **FCN 50K** model had steady but lower accuracy, **FCN 200K** model reached peak performance but required stronger regularization, and the baseline provided a balance between accuracy and generalization. Thus, **FCN 100K offers the best trade-off between complexity and accuracy**, making it the most optimal configuration.

FCN Variant	LR = 0.001	LR = 0.0005	LR = 0.0001
FCN_200K	90.15%(Epoch 19)	89.92%(Epoch 20)	88.63%(Epoch 19)
FCN_100K	89.33%(Epoch 18)	89.27%(Epoch 20)	87.08%(Epoch 18)
FCN_50K	88.67%(Epoch 20)	88.02%(Epoch 20)	86.22%(Epoch 20)

TABLE 1. Learning Rates Comparison for Different FCN Variants

Parameter	FCN_200K	FCN_100K	FCN_50K
Dropout Rate	0.3	0.3	0.3
Hidden Dimensions	224-112	96-48	64-32
Learning Rate	0.001	0.001	0.001
Epochs	19	18	20
Total Parameters (k)	202.17	80.51	52.65
Best Validation Accuracy	90.15%	89.33%	88.67%
Test Accuracy	89.59%	88.25%	87.94%

TABLE 2. Optimal Configurations and Performance Metrics for FCN Variants

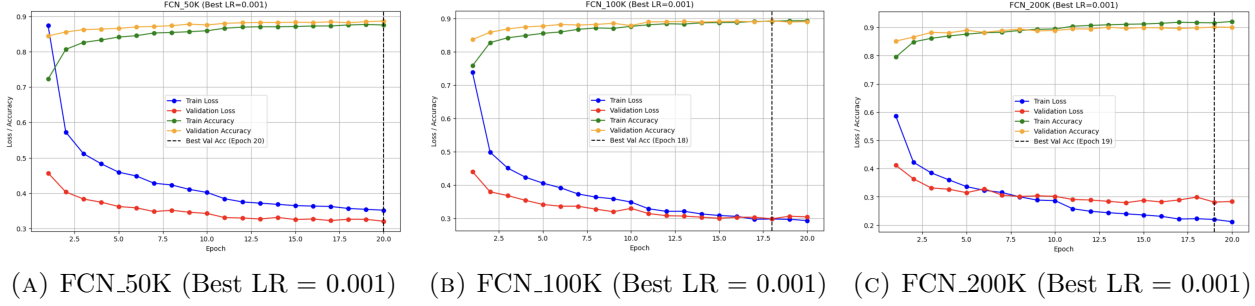


FIGURE 1. Training and Validation Loss and Accuracy Curves for FCN Variants

4.2. CNN Models Comparison. We next investigated **Convolutional Neural Networks (CNNs)** of different capacities: **CNN_100K**, **CNN_50K**, **CNN_20K**, and **CNN_10K**. Each architecture featured two convolutional layers (with 3×3 kernels, max pooling, and **ReLU activations**) followed by a fully connected layer. Similar to the FCN experiments, we trained each variant with three learning rates $\{0.001, 0.0005, 0.0001\}$, recording the best validation accuracies and epochs, as shown in **Table 3**.

Overall, as shown in **Table 4**, the larger CNNs achieved higher performance: **CNN_100K** attained a best validation accuracy of **91.62%** and a test accuracy of **91.04%**, surpassing the smaller models. The intermediate **CNN_50K** reached **90.68%** on validation and **90.23%** on test, striking a balance between accuracy and complexity. By contrast, the smallest model **CNN_10K** peaked at **88.27%** validation accuracy and **87.36%** on test. **Table 4** presents the final configurations and key metrics for each variant, while **Figure 2** illustrates the training and validation curves. Notably, the deeper models converge more rapidly and to higher accuracies, whereas the smaller ones plateau earlier. Despite slight overfitting tendencies in the larger networks, careful regularization (e.g., dropout) preserved robust generalization. Thus, **CNN_100K** delivers the highest overall accuracy, smaller CNNs more suitable for resource-constrained scenarios and the larger ones ideal when maximum performance is the priority. This highlights a clear trade-off between model size and final accuracy.

CNN Variant	LR = 0.001	LR = 0.0005	LR = 0.0001
CNN_100K	91.62%(Epoch 20)	91.05%(Epoch 20)	88.45%(Epoch 20)
CNN_50K	90.68%(Epoch 18)	89.80%(Epoch 19)	86.77%(Epoch 20)
CNN_20K	89.43%(Epoch 19)	88.57%(Epoch 20)	84.60%(Epoch 20)
CNN_10K	88.27%(Epoch 20)	86.28%(Epoch 17)	81.70%(Epoch 19)

TABLE 3. Learning Rates Comparison for Different CNN Variants

Parameter	CNN_100K	CNN_50K	CNN_20K	CNN_10K
Convolution Channels	[16, 32]	[8, 16]	[6, 12]	[4, 8]
Learning Rate	0.001	0.001	0.001	0.001
Epochs	20	18	19	20
FC Units	120	120	60	45
Total Parameters (k)	102.13	50.58	19.39	9.84
Best Validation Accuracy (%)	91.62	90.68	89.43	88.27
Test Accuracy (%)	91.04	90.23	88.62	87.36

TABLE 4. Optimal Configurations and Performance Metrics for the CNN Variants

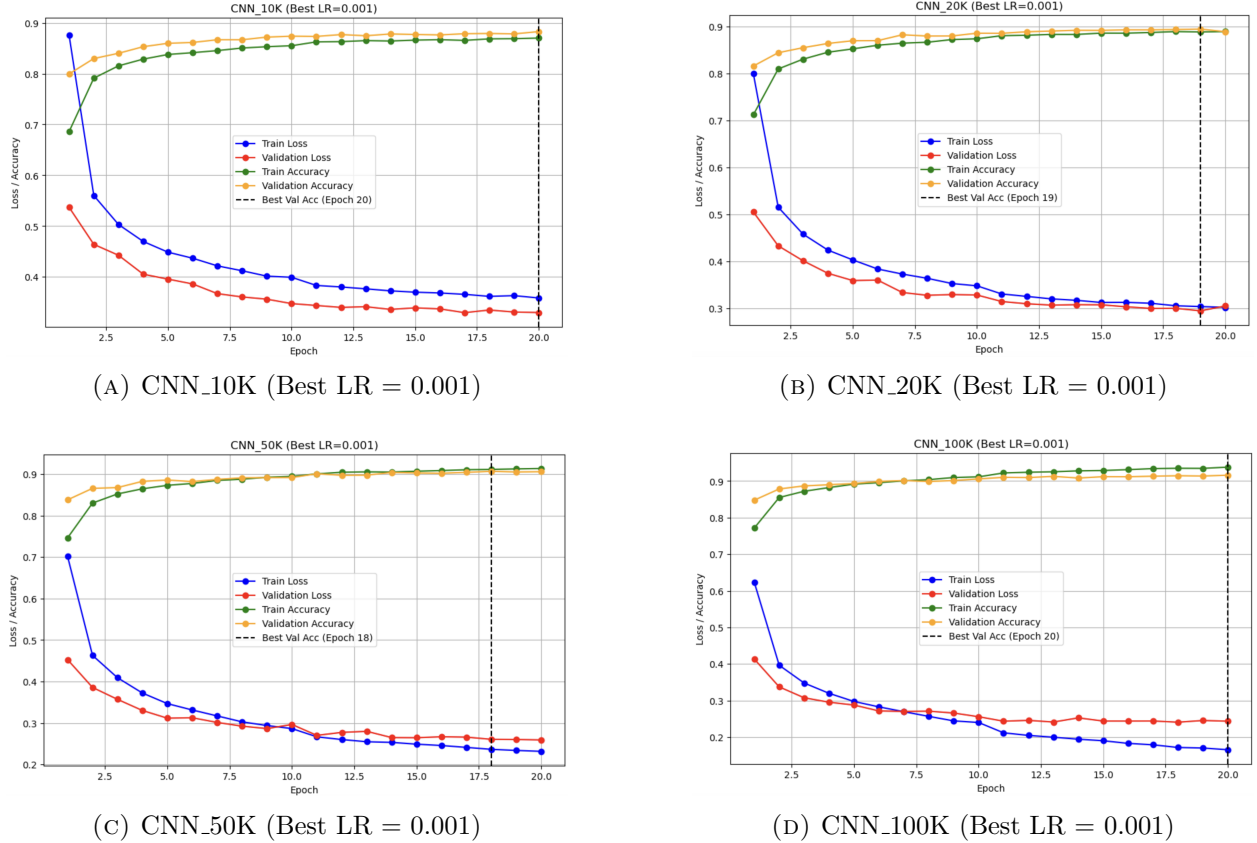


FIGURE 2. Training and Validation Loss and Accuracy Curves for CNN Variants

4.3. FCN and CNN Models Comparison. Finally, we compare the **FCN** and **CNN** variants side by side in terms of validation/test accuracies, number of parameters, and estimated training times. Table 5 consolidates the best-performing configuration for each model. Overall, we observe that **CNN_100K** achieves the highest test accuracy (91.04%), surpassing even the largest fully-connected model **FCN_200K** (89.59%). The CNN variants generally benefit from localized feature extraction in convolution layers, leading to higher accuracy with fewer parameters than an equally large FCN. However, **CNN_100K** also incurs the longest training time (about 305.7s), reflecting the computational overhead of deeper convolutional architectures.

On the other hand, smaller models such as **FCN_50K** and **CNN_10K** train faster (150.4s and 178.8s, respectively) but exhibit lower accuracy (87–88%), highlighting the trade-off between capacity and performance. Among the moderate-sized configurations, **CNN_50K** stands out with 90.23% test accuracy in just 50.58k parameters, providing an excellent balance of speed, model size, and generalization. Hence, from an efficiency standpoint, smaller networks require less computation time and memory, though at the cost of reduced accuracy, while larger models (especially **CNN_100K**) achieve superior results but demand more training time and computational resources.

From Table 5, we conclude that **CNN_100K** is the most accurate model overall, while **FCN_200K** is the largest fully-connected variant. The **CNN** architectures leverage fewer parameters to achieve competitive or superior accuracies relative to the FCNs, though they typically require more complex operations (convolutions). Ultimately, the choice depends on one’s resource constraints and accuracy goals: larger models deliver higher accuracy but at increased computational cost, whereas smaller networks train faster and consume fewer resources at the expense of lower accuracy.

Model	Weights (k)	Best Val Acc (%)	Test Acc (%)	Train Time (s)
FCN_50K	52.65	88.67	87.94	150.4
FCN_100K	80.51	89.33	88.25	180.2
FCN_200K	202.17	90.15	89.59	220.6
CNN_10K	9.84	88.27	87.36	178.8
CNN_20K	19.39	89.43	88.62	222.2
CNN_50K	50.58	90.68	90.23	184.6
CNN_100K	102.13	91.62	91.04	305.7

TABLE 5. Comparison of FCN and CNN Variants

4.4. Statistical Analysis of Model Scaling Trends. Across all experiments, validation accuracy improved by approximately 0.7–1.5% for each doubling of parameter count, whereas training time increased superlinearly with model size. CNNs demonstrated roughly $1.4\times$ higher accuracy per 100K parameters compared to FCNs, confirming their superior parameter efficiency. Moreover, models exceeding 100K parameters tended to show diminishing returns in accuracy gain relative to computational cost, suggesting an optimal capacity range between 50K and 100K parameters for balanced performance and efficiency. These quantitative observations highlight the importance of architectural design when scaling model size for practical deployment.

5. SUMMARY AND CONCLUSIONS

In this report, we compared various **FCN** and **CNN** configurations for FashionMNIST classification, emphasizing how architecture and parameter budgets influence performance. Each model was trained using an identical procedure but with distinct hyperparameter settings, including different hidden dimensions or convolutional channels. Our findings underscore the effectiveness of CNNs in exploiting spatial information, with the best **CNN** variant (**CNN_100K**) reaching a **91.04%** test accuracy—surpassing the best **FCN** variant (**FCN_200K**), which achieved **89.59%**. Furthermore, our experiments demonstrate that a higher weight count consistently yields higher accuracy, although it comes with increased computational overhead. Nevertheless, smaller FCNs and CNNs remain attractive when memory and training speed are prioritized. Overall, the choice of network depends on resource constraints and accuracy goals, with high weights CNNs typically offering superior efficiency and representational power.

Our future work could extend this comparative framework to modern architectures such as ResNets and Vision Transformers, examining how skip connections and self-attention mechanisms further improve feature extraction and generalization. Additional studies could explore model compression techniques such as pruning and quantization to enhance deployment efficiency, or investigate transfer learning performance on larger, more complex datasets such as CIFAR-10 and ImageNet. Integrating interpretability analyses, such as Grad-CAM or feature attribution, would also provide deeper insight into learned representations and model decision processes.

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