Background:

Transfer learning leverages representations learned from large-scale pretrained neural networks to reduce computational cost and data requirements when training on new tasks. By reusing hierarchical feature representations—commonly learned from datasets such as ImageNet—models can achieve faster convergence and improved performance, particularly in low-data regimes. However, the effectiveness of transfer learning depends strongly on the similarity between source and target domains, as representational alignment determines how well pretrained features generalize. Additionally, recent work suggests that compact architectures can achieve performance comparable to more complex models under transfer settings, highlighting important trade-offs between model capacity, efficiency, and generalization.

Research questions:

1) How does the level of similarity between source and target dataset affect performance for transfer learning?
2) How are the number of epochs affected for transfer learning?
3) Can compact models achieve the same level of performance as complex models during transfer learning?

Methodology:

Transfer learning was evaluated using three convolutional neural network architectures: ImageNet-pretrained AlexNet and ShuffleNet, and ResNet-50 (trained from scratch on CIFAR-100 for specific experiments). Target datasets included CIFAR-10 and MNIST (image classification tasks) as well as GTZAN (audio genre classification). Training employed regularization and optimization strategies including dropout, data augmentation, and learning rate scheduling. Model performance was assessed using classification accuracy.

To analyze the effect of domain similarity, ImageNet-pretrained AlexNet was evaluated across CIFAR-10, MNIST, and GTZAN. Convergence efficiency was examined by measuring the number of epochs required for ResNet-50 trained on CIFAR-100 from scratch, to reach a predefined accuracy threshold on CIFAR-10. Additionally, compact model performance was investigated by comparing pretrained ShuffleNet against larger architectures on CIFAR-10, assessing trade-offs between model complexity and transfer effectiveness.

Results:

Transfer learning performance varied strongly with domain similarity. ImageNet-pretrained AlexNet achieved high test accuracy on image-based datasets, reaching 95.9% on MNIST and strong performance on CIFAR-10 after 100 epochs, but performance dropped markedly on the GTZAN audio dataset (45.0% test accuracy), indicating limited cross-domain generalization. On CIFAR-10, ResNet-50 trained from scratch and via transfer learning achieved comparable final test accuracies (~89–90%) after 40 epochs; however, transfer learning reached a baseline accuracy of 86% substantially earlier (epoch 9 vs. epoch 14), requiring only 9/14 of the training epochs and achieving baseline performance with 60% of the training data, demonstrating improved efficiency in low-data regimes. Additionally, the compact ShuffleNet V2 architecture achieved performance comparable to larger models (~91% test accuracy), suggesting that reduced model complexity does not significantly compromise transfer effectiveness in image classification tasks.