**Part 4: Experimentation and Reporting**

**Objective:**

To analyze how different hyperparameters affect model performance and compare ANN and CNN models.

**1. Hyperparameter Tuning**

Experiments were done by changing:

* **Batch Sizes:** 32, 64, 128
* **Learning Rates:** 0.001, 0.01, 0.1
* **Architectures:** Added or reduced layers and filters

**Findings:**

| **Parameter** | **Best Value** | **Effect** |
| --- | --- | --- |
| Batch Size | 64 | Balanced speed and accuracy |
| Learning Rate | 0.001 | Stable and accurate |
| ANN Neurons | (256,128) | Slightly improved accuracy |
| CNN Filters | (32,64,128) | Best performance on CIFAR-10 |

**2. Model Comparison**

| **Model** | **Dataset** | **Accuracy** | **Training Time** | **Comments** |
| --- | --- | --- | --- | --- |
| ANN | MNIST | 97–98% | Fast | Good for simple images |
| ANN | CIFAR-10 | 55–60% | Fast | Poor on complex images |
| CNN | MNIST | 99% | Moderate | Excellent accuracy |
| CNN | CIFAR-10 | 85% | Longer | Performs best |
| Transfer Learning (VGG16) | CIFAR-10 | 88–90% | Medium | Best generalization |

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**3. Detailed Report Summary**

**ANN (Artificial Neural Network) – Strengths and Performance**

The Artificial Neural Network (ANN) is a simple and fast model that performs well on small and low-dimensional datasets like **MNIST**, where each image is grayscale and contains simple handwritten digits.  
Since ANN consists of fully connected layers, it can easily learn basic patterns when the number of input features is small. It trains quickly, requires less computational power, and is easy to implement and modify.

However, ANN has some limitations — it does not capture spatial relationships in images (for example, it treats all pixels independently). This means that when the data becomes more complex, such as colored images or objects with shapes and textures (like those in CIFAR-10), ANN struggles to achieve good accuracy because it cannot automatically learn features like edges or corners.

In summary, **ANN is simple, efficient, and works well for basic image classification tasks, but it is not suitable for high-dimensional, complex image data.**

**CNN (Convolutional Neural Network) – Strengths and Performance**

Convolutional Neural Networks (CNNs) are specially designed for image data. They automatically learn **spatial and visual features** such as edges, colors, textures, and shapes from images without any manual feature extraction.  
In this project, the CNN model performed significantly better than ANN, especially on the **CIFAR-10 dataset**, which contains colored images of different objects. CNN was able to generalize well, achieving higher accuracy and better classification results for each class.

The model used multiple convolutional and pooling layers that helped it focus on important features while reducing noise. Dropout and data augmentation were also used to reduce overfitting and improve generalization.

Although CNNs require **more training time and computational resources**, they provide a **major improvement in accuracy and performance** for complex image tasks.

In summary, **CNNs are ideal for image recognition problems because they automatically extract meaningful features and can handle large and complex datasets effectively.**

**Transfer Learning (VGG16) – Strengths and Performance**

Transfer Learning allows us to use pre-trained models like **VGG16**, which have already learned useful image features from massive datasets such as ImageNet.  
In this project, the pre-trained model was fine-tuned for the CIFAR-10 dataset. The earlier layers of VGG16 were kept frozen (to retain previously learned features like edges and colors), while new layers were added on top to adapt the model for the CIFAR-10 classes.

This approach **reduced training time** significantly because most of the network weights were already optimized. Despite fewer training epochs, the model achieved very high accuracy and strong generalization.  
It also performed better than the CNN built from scratch, especially when the training data was limited, because the pre-trained model already had a rich understanding of image features.

In summary, **Transfer Learning with VGG16 provided the highest accuracy with less training time and proved to be the most efficient approach overall.**

**Conclusion**

* **ANN** worked best for simple and small datasets like MNIST. It trained quickly but was not powerful enough for complex colored images.
* **CNN** provided much better accuracy on complex datasets like CIFAR-10 because of its ability to automatically learn and extract image features.
* **Transfer Learning (VGG16)** gave the best results overall. It combined accuracy and efficiency, achieving high performance with less training effort.
* The **optimal hyperparameters** found during experimentation were a **batch size of 64** and a **learning rate of 0.001**, which gave stable and consistent results across all models.

Overall, this project shows that as image data becomes more complex, more advanced models like CNNs and Transfer Learning perform far better than simple ANNs. Transfer Learning, in particular, offers an excellent balance between accuracy, speed, and generalization, making it the most effective approach for modern image classification tasks.

**Final Summary**

* **ANN Accuracy (MNIST):** ~98%
* **CNN Accuracy (CIFAR-10):** ~85%
* **Transfer Learning (CIFAR-10):** ~90%
* **Best Overall Model:** Transfer Learning with VGG16