Reflective Journal: CNN and MNIST Classification

Learning Insights

Engaging with this lab deepened my comprehension of Convolutional Neural Networks (CNNs) and their role in image classification. I developed a clearer understanding of how convolutional layers extract meaningful patterns from images, transforming raw pixel data into high-level features. The role of pooling layers in reducing computational complexity while preserving essential spatial characteristics was another important takeaway. Additionally, the introduction of activation functions like ReLU provided insight into how non-linearity is incorporated into deep learning models to enhance performance.

This experience built upon my foundational knowledge of neural networks, particularly reinforcing the shortcomings of Multi-Layer Perceptrons (MLPs) for image-related tasks. CNNs' ability to capture spatial hierarchies in images provided an eye-opening contrast to traditional fully connected networks, which struggle with large-scale image datasets. By observing how each layer processes images through feature extraction and transformation, I gained a deeper appreciation for hierarchical pattern recognition in CNNs.

A particularly intriguing aspect of this lab was how efficiently CNNs handled the MNIST dataset. The model's ability to achieve high accuracy using relatively few parameters highlighted the power of convolutional operations in extracting robust features. It also underscored the significance of structured architectures over simply increasing the number of neurons or layers. Through various training sessions, I also learned the importance of data augmentation techniques, which can help improve generalization by artificially expanding the dataset with transformations like rotation and shifting.

Challenges and Growth

One of the most significant challenges I encountered was tuning the hyperparameters effectively. Adjusting parameters such as kernel size, filter count, and learning rates influenced the model's performance in ways that were not always intuitive. I had to iteratively experiment with different values and analyze their impact to develop a more intuitive grasp of hyperparameter tuning. Additionally, understanding the role of batch size and epochs was a key learning point, as these parameters influenced both convergence speed and model accuracy.

Another challenge was addressing overfitting, which initially led to a strong training performance but weaker validation results. Implementing dropout layers and experimenting with regularization techniques helped mitigate this issue, enhancing the model's ability to generalize to unseen data. I also explored early stopping techniques, which prevent excessive training and ensure that the model does not memorize training data excessively.

To overcome these challenges, I leveraged various resources, including research papers, online courses, and documentation from TensorFlow and Keras. Additionally, visualizing feature maps and activation outputs provided deeper insights into how different layers process image data, making the theoretical concepts more tangible. Debugging tools such as learning rate schedulers and gradient visualizations also helped fine-tune the training process, allowing me to optimize my approach systematically.

Personal Development

This lab experience significantly enhanced my understanding of deep learning and CNNs, offering valuable hands-on practice in building, optimizing, and evaluating neural networks. More importantly, it fostered a mindset of critical analysis and experimentation, pushing me to look beyond surface-level accuracy metrics and assess the deeper workings of model performance. Additionally, understanding the role of transfer learning and pre-trained networks has sparked my interest in leveraging existing models for more complex tasks.

Moving forward, I am eager to explore more complex CNN architectures, such as ResNets and EfficientNets, to understand how deeper networks refine performance. Additionally, applying CNNs to diverse datasets beyond MNIST—such as CIFAR-10 or real-world medical imaging datasets—would provide a broader perspective on the practical applications of deep learning. I am particularly interested in how CNNs can be used in object detection and segmentation, which would open new doors in various industries, including healthcare and autonomous vehicles.

In summary, this lab was a transformative learning experience that reinforced both my technical and analytical skills. It not only deepened my understanding of neural networks but also nurtured a problem-solving mindset that will be invaluable in future machine-learning projects. The ability to iteratively improve models, debug issues, and experiment with various architectures has given me a newfound confidence in tackling more complex deep-learning challenges.