Section 3: Architecture

Familiar Concepts:

- Convolutional Layers: The model uses multiple convolutional layers to extract features from images.
- Fully Connected Layers: The last layers of the network perform classification.
- Activation Functions: The network uses activation functions to introduce non-linearity.
- Pooling Layers: Pooling reduces the spatial size of feature maps.

New Ideas Introduced:

1.

Use of ReLU Activation Function:

2.

- ReLU (Rectified Linear Unit) speeds up training by avoiding the vanishing gradient problem.
- It performs significantly better than traditional activation functions like tanh and sigmoid.

3.

Training on Multiple GPUs:

4.

- The network is split across two GPUs to improve efficiency.
- o GPUs communicate only at specific layers, reducing overhead.

5.

Local Response Normalization (LRN):

6.

- Normalizes neuron responses within a local neighborhood.
- o Encourages competition among neurons to improve generalization.

7.

Overlapping Pooling:

8.

- Instead of standard pooling, overlapping pooling is used to reduce overfitting.
- o It decreases the error rate compared to non-overlapping pooling.

Section 4: Reducing Overfitting

Familiar Concepts:

- Overfitting: When a model memorizes training data instead of generalizing.
- Data Augmentation: A technique to artificially expand the training dataset.

New Ideas Introduced:

1.

Data Augmentation Techniques:

2.

- Image Cropping & Flipping: Random 224×224 patches are extracted from 256×256 images.
- Color Intensity Modifications: Principal Component Analysis (PCA) is used to alter brightness and color variations.

3.

Dropout Regularization:

4.

- Randomly disables neurons during training with a 50% probability.
- o Prevents co-adaptation of neurons, forcing them to learn independent features.
- At test time, all neurons are used, but their outputs are scaled by 0.5.

Section 5: Details of Learning

Familiar Concepts:

- Stochastic Gradient Descent (SGD): Optimization algorithm for training deep networks.
- Learning Rate: Controls how much weights are updated in each step.
- Momentum: Helps accelerate convergence by smoothing updates.

New Ideas Introduced:

1.

Specific Learning Parameters:

2.

- Mini-batch size: 128 images per batch.
- o **Momentum:** Set to 0.9 for stable updates.
- Weight Decay (Regularization): 0.0005 to prevent overfitting.

3.

Learning Rate Scheduling:

4.

- Starts at **0.01** and is reduced manually when validation accuracy plateaus.
- This ensures stable convergence.

5.

Weight Initialization:

6.

- O Weights are initialized from a Gaussian distribution with zero mean.
- o Biases in some layers are set to 1 instead of 0 to speed up early training.

Conclusion

AlexNet introduced several innovations, such as ReLU activation, multiple GPUs, LRN, overlapping pooling, advanced data augmentation, dropout, and learning rate scheduling. These techniques significantly improved deep learning performance and paved the way for modern CNN architectures.