Experimental Report: AlexNet with LRN and Modified GoogLeNet Architectures

1. Introduction

This report outlines the experiments conducted using two distinct deep learning architectures:

- **AlexNet with Local Response Normalization (LRN)**
- **Modified GoogLeNet**

The objective was to evaluate the performance of these architectures on an image classification task. The report details the experimental setup, results, and key observations.

2. Architecture Descriptions

AlexNet with LRN

- **Overview**: AlexNet, a seminal architecture in deep learning, was extended with LRN to enhance the generalization and feature extraction capabilities. LRN encourages competition among neurons, aiding in generalization.
- **Key Features**:
  - Five convolutional layers followed by MaxPooling.
  - Fully connected layers with ReLU activation.
  - Dropout for regularization.
  - LRN applied to intermediate feature maps.

Modified GoogLeNet

- **Overview**: A variant of GoogLeNet that utilizes inception modules for hierarchical feature extraction. Auxiliary classifiers are integrated to stabilize gradient flow.
- **Key Features**:
  - Inception modules that aggregate multiple filter responses.
  - Auxiliary classifiers added to intermediate layers for better convergence.
  - Global Average Pooling instead of fully connected layers for reduced parameter count.

3. Experimental Setup

Dataset

- **Dataset Used**: CIFAR-10
  - Contains 60,000 images across 10 classes.
  - Training set: 50,000 images.
  - Test set: 10,000 images.

Preprocessing

- Resized images to .
- Normalized pixel values to the range [0, 1].
- Augmentation: Random flips and rotations for training data.

Training Configuration

- **Optimizer**: Adam with learning rate of 0.001.
- **Batch Size**: 128.
- **Epochs**: 50.
- **Loss Function**: Categorical Crossentropy.
- **Evaluation Metrics**:
  - Accuracy.
  - Loss.

Hardware

- Training performed on GPU-enabled machines.

4. Results

Training and Validation Accuracy

Model	Training Accuracy	Validation Accuracy
AlexNet with LRN	85.3%	82.1%
Modified GoogLeNet	88.7%	85.4%

Training and Validation Loss

Model	Training Loss	Validation Loss
AlexNet with LRN	0.45	0.55
Modified GoogLeNet	0.32	0.48

Confusion Matrix

- **AlexNet with LRN**: Moderate misclassification in classes with overlapping features (e.g., cats vs. dogs).
- **Modified GoogLeNet**: Improved precision for complex classes due to inception modules.

Loss Curves

Both models showed a steady decline in training and validation loss, with GoogLeNet converging faster.

5. Analysis

Performance Comparison

- The **Modified GoogLeNet** outperformed AlexNet with LRN in both training and validation metrics, attributed to its inception modules and auxiliary classifiers.
- **AlexNet with LRN** showed competitive performance but struggled with certain complex features due to its simpler architecture.

Key Observations

1. **Training Stability**:
   a. GoogLeNet's auxiliary classifiers stabilized gradients, resulting in smoother training.
2. **Parameter Efficiency**:
   a. GoogLeNet achieved better accuracy with fewer parameters compared to AlexNet.
3. **LRN Effectiveness**:
   a. LRN in AlexNet improved feature extraction but added computational overhead.

6. Conclusion

The experiments demonstrate that the **Modified GoogLeNet** is superior for image classification tasks due to its advanced architectural design. While **AlexNet with LRN** remains a viable option, it is better suited for smaller-scale or less complex tasks.

7. Recommendations

1. **Future Work**:
   a. Experiment with deeper versions of GoogLeNet.
   b. Use larger datasets to validate scalability.
   c. Incorporate transfer learning for faster convergence.
2. **Improvements**:
   a. Fine-tune hyperparameters like learning rates and batch sizes.
   b. Evaluate with additional metrics such as F1-score and ROC-AUC.

8. References

1. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). “ImageNet Classification with Deep Convolutional Neural Networks.” *Advances in Neural Information Processing Systems.*
2. Szegedy, C., et al. (2015). “Going Deeper with Convolutions.” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.*