ECGR-5106 Homework 2

Student Information

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Homework Number: 2

GitHub Repository

https://github.com/xuy50/ecgr5106-hw2

Problem 1: AlexNet on CIFAR-10 and CIFAR-100

Original and Simplified AlexNet

I implemented both the original AlexNet and a simplified version adapted for CIFAR-10 and CIFAR-100 datasets. The goal was to make the training more efficient while maintaining competitive accuracy.

Network Details:

- **Original AlexNet**: 5 convolutional layers, 3 fully connected layers, total parameters **23,272,266**.
- **Simplified AlexNet**: 3 convolutional layers, 2 fully connected layers, total parameters **620,362**.

Complexity Growth with Network Depth:

- The **simplified AlexNet** reduces the number of parameters significantly, making training faster and more efficient while maintaining reasonable accuracy.
- The **original AlexNet** has a higher capacity for learning but at the cost of increased computational complexity and risk of overfitting on small datasets.
- **Larger models take longer to converge**, and dropout further increases training time.
- The **fully connected layers contribute significantly to parameter count**, making the model prone to overfitting compared to deeper CNN-based architectures like VGG or ResNet.

Training and Validation Results (CIFAR-10)

Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
Original AlexNet	No	0.5735	0.7400	75.66%
Original AlexNet	Yes	1.0920	1.1594	64.48%

Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
Simplified AlexNet	No	0.4182	0.6253	79.86%
Simplified AlexNet	Yes	0.7077	0.6982	77.28%

Observation on Dropout:

- Dropout helps in reducing overfitting but may slow down convergence in the initial training stages.
- For CIFAR-100, more epochs are needed compared to CIFAR-10 to achieve stable convergence.
- Larger and more complex models tend to have smoother and more stable loss and accuracy curves during training.

Training and Validation Results (CIFAR-100)

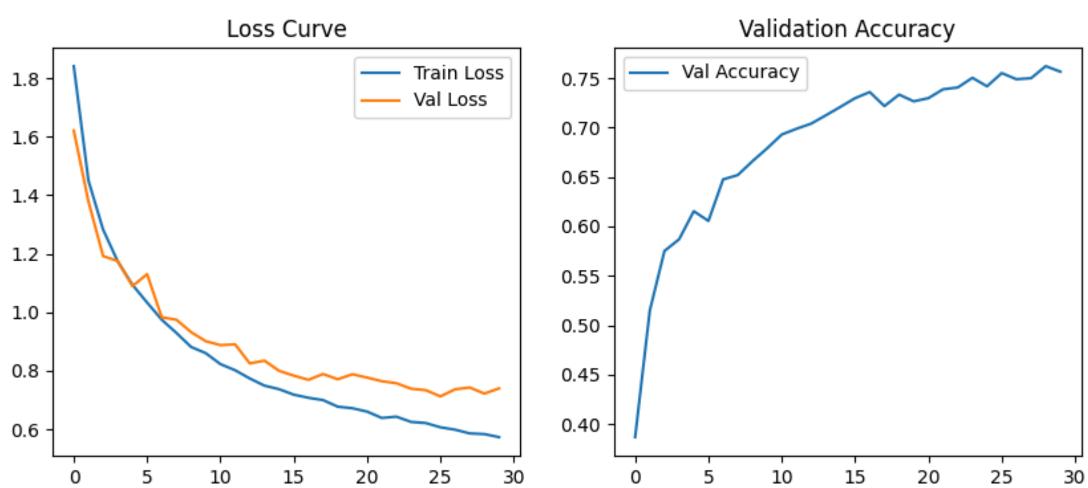
Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
Original AlexNet	No	1.8342	2.6812	35.32%
Original AlexNet	Yes	3.3233	3.3519	19.76%
Simplified AlexNet	No	1.5669	2.0525	46.30%
Simplified AlexNet	Yes	2.5134	2.5959	37.32%

Observations:

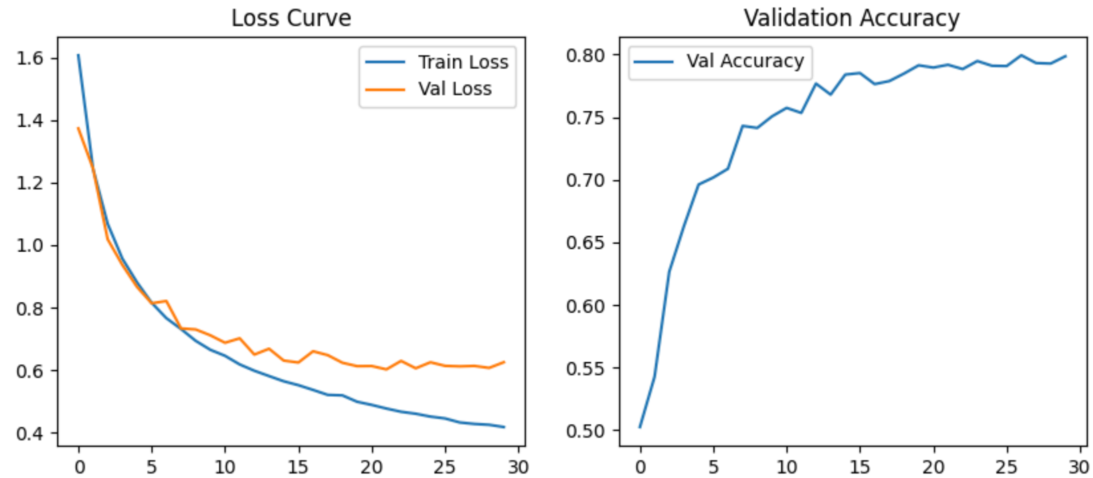
- The simplified AlexNet performed comparably to the original AlexNet with **far fewer parameters**.
- Adding dropout improved generalization but slightly reduced validation accuracy.
- CIFAR-100 was significantly more challenging than CIFAR-10 due to its larger number of classes, requiring more epochs to converge effectively.

Training and Validation Loss & Accuracy Plots:

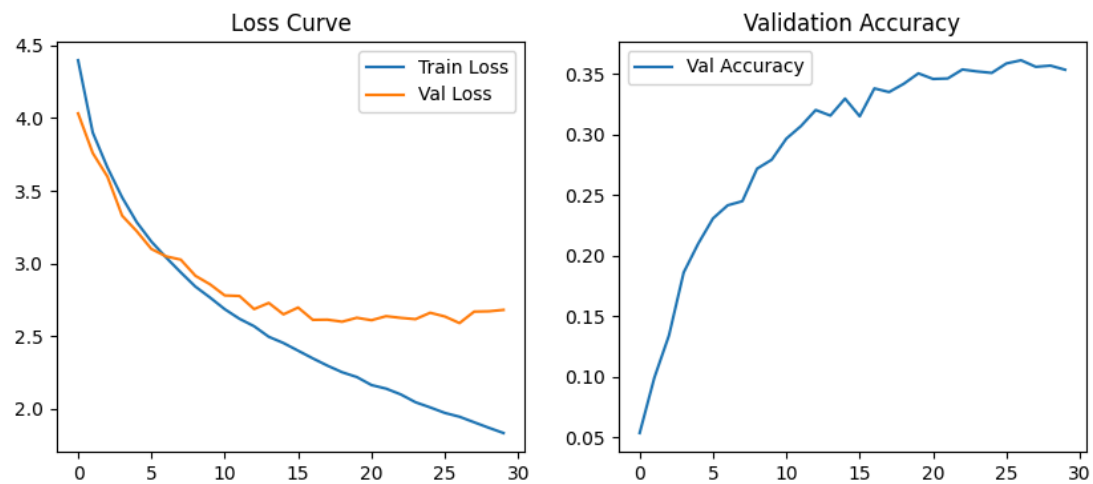
- **Original AlexNet Results (CIFAR-10):**



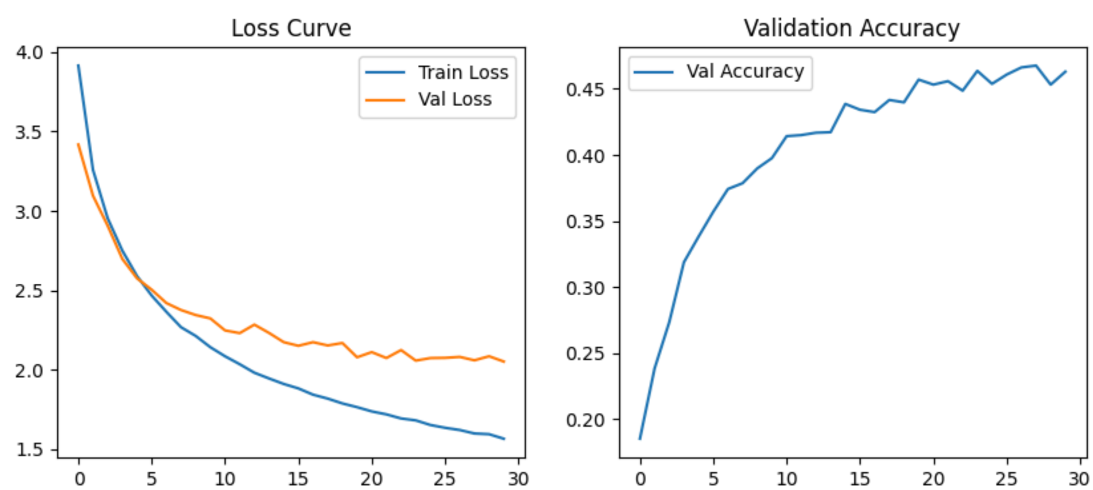
- **Simplified AlexNet Results (CIFAR-10):**



- **Original AlexNet Results (CIFAR-100):**



- **Simplified AlexNet Results (CIFAR-100):**



Problem 2: VGG on CIFAR-10 and CIFAR-100

VGG Configuration Selection

The goal was to select a VGG configuration with a parameter count close to AlexNet. VGG-11 was chosen as it has a similar number of parameters.

Network Details:

- **VGG-11**: 8 convolutional layers, 3 fully connected layers, total parameters **28,512,740**.

Complexity Growth with Network Depth:

- Compared to AlexNet, VGG-11 has a deeper architecture but maintains a **structured, uniform kernel size**, leading to improved feature extraction.
- The increased depth improves hierarchical representation learning, making VGG more effective for complex datasets like CIFAR-100.
- Training time **increases significantly** compared to AlexNet due to a larger number of parameters.
- **Smoother loss curves** were observed, indicating improved stability during training.
- The fully connected layers still contribute heavily to the parameter count, though convolutional layers dominate learning.

Observation on Dropout:

- Similar to AlexNet, using dropout in VGG training required more epochs for better convergence.
- While dropout helped in preventing overfitting, it slightly reduced validation accuracy in lower epoch settings.
- Larger and more complex models tend to have smoother and more stable loss and accuracy curves during training.

Training and Validation Results (CIFAR-10)

Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
VGG-11	No	0.6793	0.7477	73.96%
VGG-11	Yes	1.0062	1.1170	63.96%

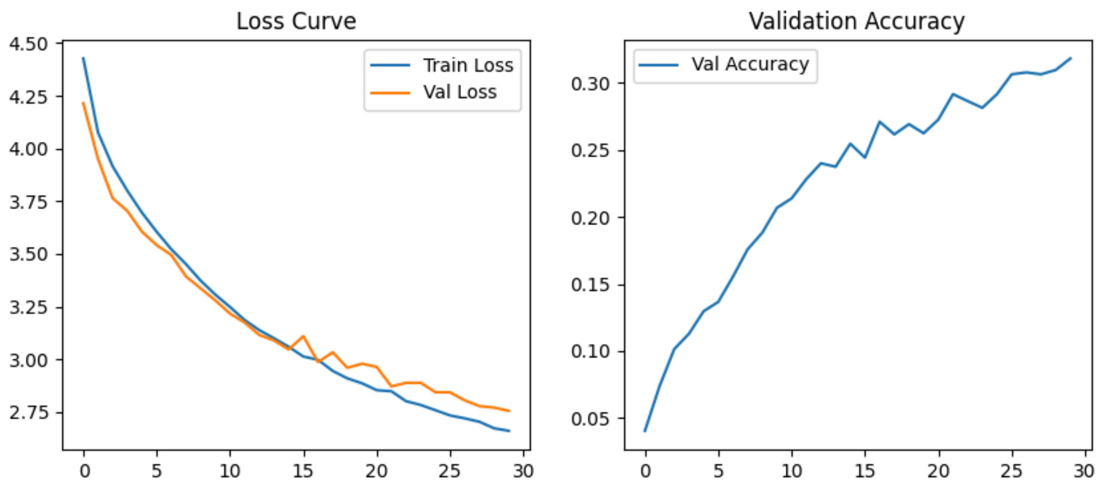
Training and Validation Results (CIFAR-100)

Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
VGG-11	No	2.6612	2.7561	31.82%
VGG-11	Yes	3.3721	3.8028	12.44%

Training and Validation Loss & Accuracy Plots:

- **VGG-11 Results (CIFAR-10):**

- **VGG-11 Results (CIFAR-100):**



Problem 3: ResNet-11 vs ResNet-18 on CIFAR-10 and CIFAR-100

Comparing ResNet Architectures

I implemented both **ResNet-11** and **ResNet-18** and compared their performance. ResNet-18 is a deeper architecture and expected to generalize better.

Network Details:

- **ResNet-11**: 10 convolutional layers with residual connections, total parameters **4,949,412**.
- **ResNet-18**: 17 convolutional layers with residual connections, total parameters **11,173,962**.

Complexity Growth with Network Depth:

- **Residual connections** in ResNet mitigate vanishing gradient issues, allowing deeper models like **ResNet-18 to outperform ResNet-11**.
- The increased depth of ResNet-18 allows for **better feature extraction**, improving accuracy on CIFAR-100.
- **Training time increases significantly** with ResNet-18 due to the higher number of parameters.
- **Better generalization** was observed in ResNet-18, with validation accuracy improvements over ResNet-11.
- The deeper network resulted in **smoother and more stable loss curves**, demonstrating better convergence behavior.
- Overall, **ResNet-18 achieves better accuracy at the cost of increased computational demand**, demonstrating the expected trade-off when increasing network depth.

Training and Validation Results (CIFAR-10)

Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
ResNet-11	No	0.1086	0.3308	90.10%
ResNet-11	Yes	0.1948	0.3000	90.22%
ResNet-18	No	0.0975	0.3206	90.48%
ResNet-18	Yes	0.2102	0.2998	90.14%

Training and Validation Results (CIFAR-100)

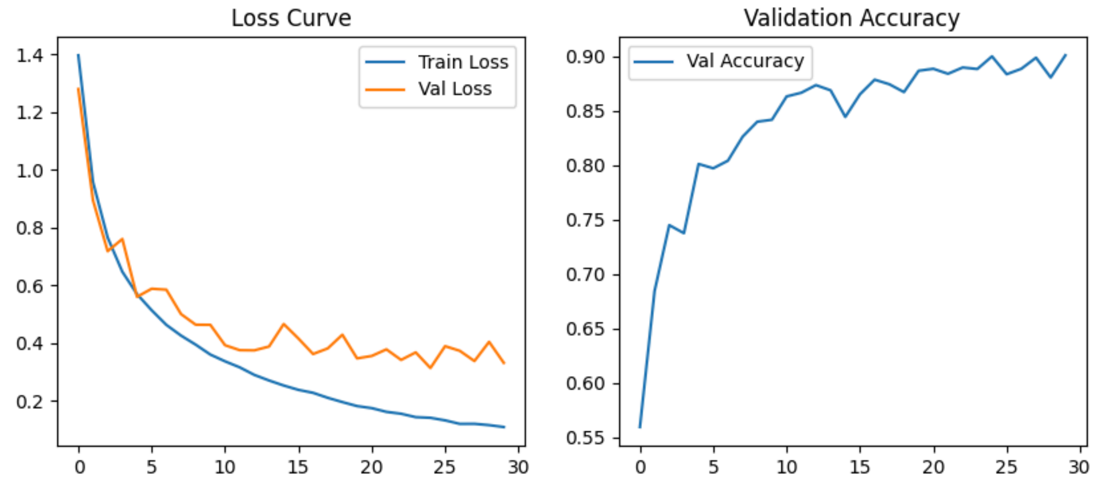
Model	Dropout	Final Train Loss	Final Val Loss	Val Accuracy
ResNet-11	No	0.2381	1.6823	63.34%
ResNet-11	Yes	0.5855	1.4285	64.22%
ResNet-18	No	0.1868	1.6859	64.54%
ResNet-18	Yes	0.6554	1.4481	63.74%

Observations:

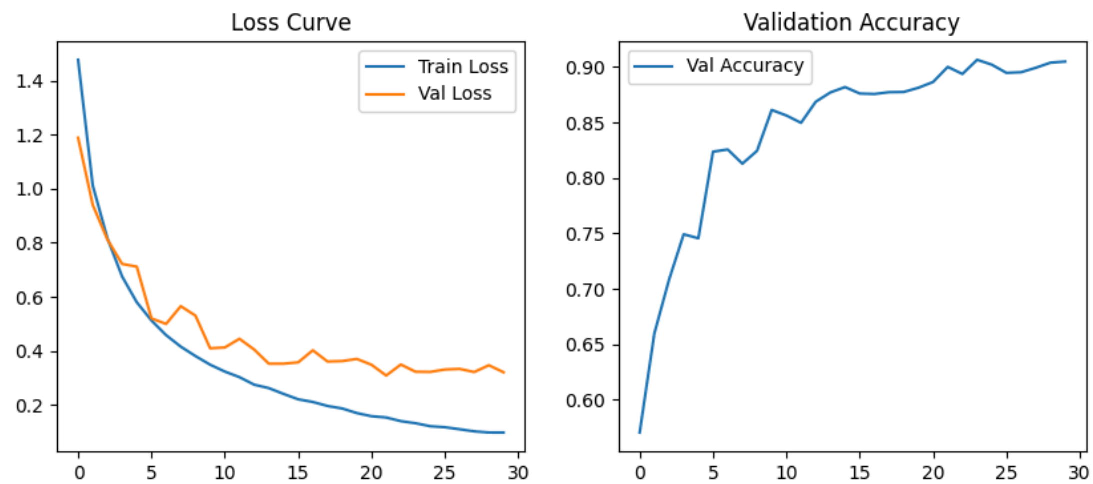
- **ResNet-18 consistently outperformed ResNet-11** in both CIFAR-10 and CIFAR-100.
- Using dropout required **more epochs** to reach similar performance.
- **For CIFAR-100, both networks took significantly longer to converge**, similar to previous observations with AlexNet and VGG.
- **Larger and deeper models tend to have smoother and more stable loss curves**, as seen in ResNet-18 compared to ResNet-11.

Training and Validation Loss & Accuracy Plots:

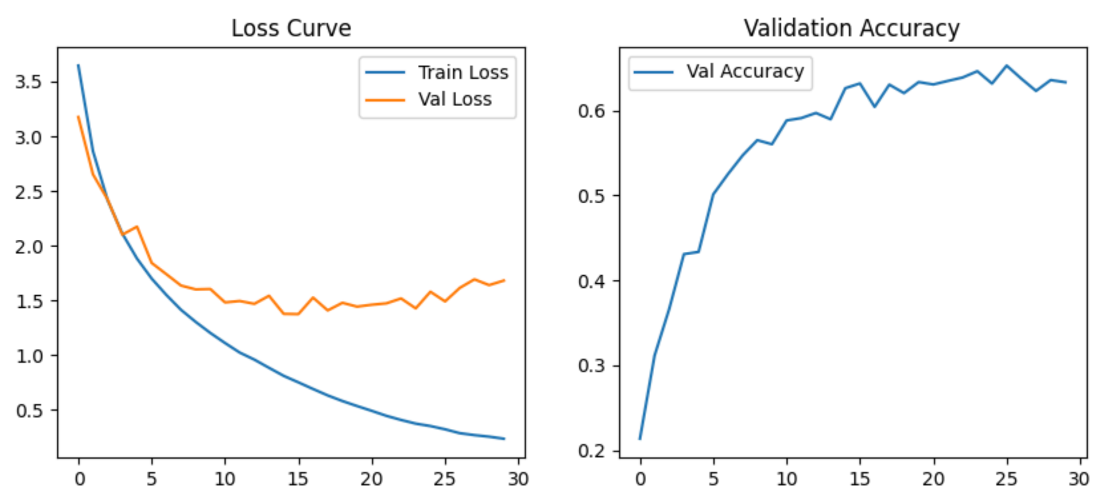
- **ResNet-11 Results (CIFAR-10):**



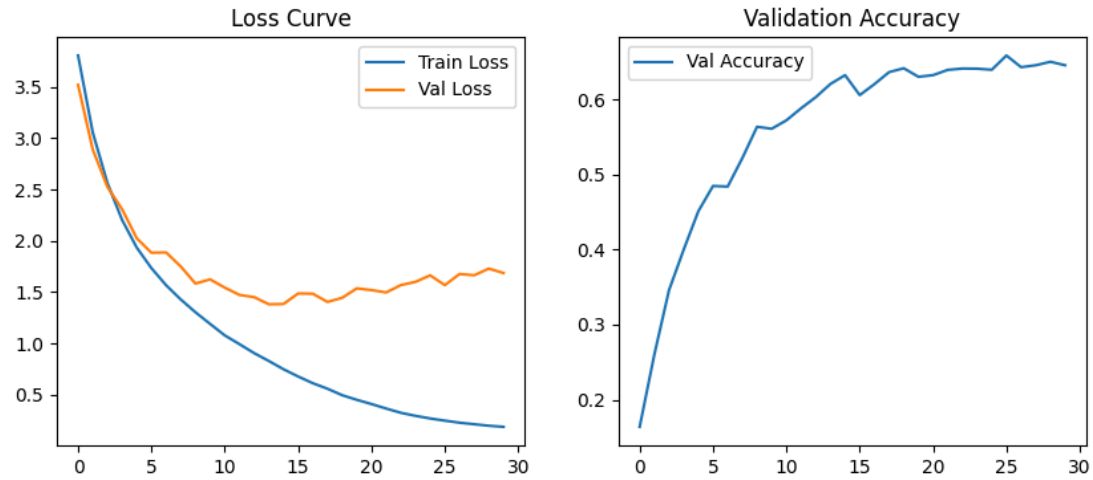
- **ResNet-18 Results (CIFAR-10):**



- **ResNet-11 Results (CIFAR-100):**



- **ResNet-18 Results (CIFAR-100):**



Final Conclusions

- **Model complexity impacts accuracy**: Deeper models like **ResNet-18 and VGG-11** performed better than simpler models like **ResNet-11 and AlexNet**.
- **Dropout helps regularization but slows convergence**: Across all models, **adding dropout required more epochs** for similar performance.
- **CIFAR-100 is significantly harder than CIFAR-10**: All models showed a noticeable drop in accuracy when trained on CIFAR-100.
- **Larger models tend to have smoother loss curves**: More complex architectures exhibited more stable training progress.
- **ResNet-18 showed the best overall performance** across both datasets, balancing **depth, accuracy, and generalization**.