Project 2 Report: Multi-Conditioned CNN trained on CIFAR-10 and VGG_BatchNorm Test
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GitHub Code Link: https://github.com/henrywch/VGG_BatchNorm

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1. Training a Network on CIFAR-10

Network Architecture

The designed CNN model includes the following components:

- **Convolutional Layers**: Three `Conv2d` layers with filter sizes (64, 128, 256).
- **Batch Normalization**: Applied after each convolutional layer.
- **Activation Function**: Leaky ReLU (slope=0.1).
- **Pooling**: MaxPool2d (2x2) after each block.
- **Fully Connected Layers**: Three linear layers (512 → 256 → 10) with dropout (rate=0.5).
- **Total Parameters**: ~2.6 million.

Optimization Strategies and Code Examples

> All model weights can be found in codes/CIFAR_CNN

1. Activations

Three Activations were tested: `LeakyReLU`, `ReLU`, and `eLU`.

```
def _get_activation(self, activation):
    if activation == 'relu':
        return nn.ReLU()
    elif activation == 'leaky_relu':
        return nn.LeakyReLU(0.1)
    elif activation == 'elu':
        return nn.ELU()
    else:
        raise ValueError("Unsupported activation")
```

Comparison Table (`LeakyReLU` vs. `ReLU` vs. `eLU`):

Activation	Test Accuracy (%)	Explanation
LeakyReLU	89.45	Revive Dying
ReLU	89.31	Popularized

Activation	Test Accuracy (%)	Explanation
eLU	87.45	Less Performant

Model Weights

- best_model_LeakyReLU_CrossEntropy_Adam_CosineAnnealingLR_8945.pth
- best_model_ReLU_CrossEntropy_Adam_CosineAnnealingLR_8931.pth
- best_model_eLU_CrossEntropy_Adam_CosineAnnealingLR_8745.pth

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2. Loss Functions

Tested `CrossEntropyLoss`, `LabelSmoothingCrossEntropy`, `Focal Loss`, `MSE Loss`:

```
# Configuration
training_config = {
    ...,
    'l1_lambda': 0.0,  # L1 regularization strength
    'grad_clip': 5.0,  # Gradient clipping
    'epochs': 50,
    'loss': 'focal',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.1,  # For label smoothing
    'focal_params': {'alpha': 1.0, 'gamma': 1.0},
    ...
}

# Custom Loss Functions
class FocalLoss(nn.Module):
    """Focal Loss for imbalanced classes"""

    def __init__(self, alpha=1, gamma=2, reduction='mean'):
        super().__init__()
        self.alpha = alpha
        self.gamma = gamma
        self.reduction = reduction

    def forward(self, inputs, targets):
        ce_loss = F.cross_entropy(inputs, targets, reduction='none')
        pt = torch.exp(-ce_loss)
        focal_loss = self.alpha * (1 - pt) ** self.gamma * ce_loss
        return focal_loss.mean() if self.reduction == 'mean' else focal_loss.sum()


class LabelSmoothingCrossEntropy(nn.Module):
    """Label smoothing cross entropy"""

    def __init__(self, smoothing=0.1):
        super().__init__()
        self.smoothing = smoothing

    def forward(self, x, target):
        confidence = 1. - self.smoothing
        logprobs = F.log_softmax(x, dim=-1)
        nll_loss = -logprobs.gather(dim=-1, index=target.unsqueeze(1))
        nll_loss = nll_loss.squeeze(1)
        smooth_loss = -logprobs.mean(dim=-1)
        loss = confidence * nll_loss + self.smoothing * smooth_loss
```

```
        return loss.mean()

# Loss function selection
if training_config['loss'] == 'cross_entropy':
    criterion = nn.CrossEntropyLoss()
elif training_config['loss'] == 'focal':
    criterion = FocalLoss(**training_config['focal_params'])
elif training_config['loss'] == 'mse':
    criterion = nn.MSELoss()
elif training_config['loss'] == 'label_smoothing':
    criterion = LabelSmoothingCrossEntropy(training_config['label_smoothing'])
else:
    raise ValueError("Invalid loss function")
```

(A)

```
# Configuration
model_config = {
    'filters': (64, 128, 256),
    'activation': 'leaky_relu',
    'use_batchnorm': True,
    'dropout_rate': 0.5,
}

training_config = {
    'optimizer': 'adam',
    'lr': 0.001,
    'weight_decay': 1e-4,  # L2 regularization
    'l1_lambda': 0.001,  # L1 regularization strength
    'grad_clip': 1.0,  # Gradient clipping
    'epochs': 50,
    'loss': 'cross_entropy',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.1,  # For label smoothing
    'focal_params': {'alpha': 0.25, 'gamma': 2},
    'scheduler': {
        'name': 'step',
        'step_size': 20,
        'gamma': 0.1,
        'patience': 5,
        'factor': 0.5,
        'min_lr': 1e-5
    }
}
```

(B)

```
# Configuration
model_config = {
    'filters': (64, 128, 256),
    'activation': 'leaky_relu',
    'use_batchnorm': True,
    'dropout_rate': 0.3,
}

training_config = {
    'optimizer': 'adam',
    'lr': 0.0005,
    'weight_decay': 1e-5,  # L2 regularization
    'momentum': 0.9,
```

```
    'l1_lambda': 0.0,  # L1 regularization strength
    'grad_clip': 1.0,  # Gradient clipping
    'epochs': 75,
    'loss': 'label_smoothing',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.2,  # For label smoothing
    'focal_params': {'alpha': 0.25, 'gamma': 2},
    'scheduler': {
        'name': 'cosine',
        'step_size': 20,
        'gamma': 0.1,
        'patience': 5,
        'factor': 0.5,
        'min_lr': 1e-5
    }
}
```

(C)

```
# Configuration
model_config = {
    'filters': (64, 128, 256),
    'activation': 'leaky_relu',
    'use_batchnorm': True,
    'dropout_rate': 0.5,
}

training_config = {
    'optimizer': 'adam',
    'lr': 0.005,
    'weight_decay': 1e-5,  # L2 regularization
    'l1_lambda': 0.0,  # L1 regularization strength
    'grad_clip': 5.0,  # Gradient clipping
    'epochs': 50,
    'loss': 'focal',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.1,  # For label smoothing
    'focal_params': {'alpha': 1.0, 'gamma': 1.0},
    'scheduler': {
        'name': 'cosine',
        'step_size': 20,
        'gamma': 0.1,
        'patience': 5,
        'factor': 0.5,
        'min_lr': 1e-6
    }
}
```

(D)

```
# Configuration
model_config = {
    'filters': (128, 256, 512),
    'activation': 'relu',
    'use_batchnorm': True,
    'dropout_rate': 0.3,
}

training_config = {
    'optimizer': 'adam',
    'lr': 0.001,
```

```
    'weight_decay': 1e-5,  # L2 regularization
    'momentum': 0.9,
    'l1_lambda': 0.0,  # L1 regularization strength
    'grad_clip': 5.0,  # Gradient clipping
    'epochs': 100,
    'loss': 'mse',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.1,  # For label smoothing
    'focal_params': {'alpha': 0.25, 'gamma': 2},
    'scheduler': {
        'name': 'cosine',
        'step_size': 20,
        'gamma': 0.1,
        'patience': 5,
        'factor': 0.5,
        'min_lr': 1e-6
    }
}
```

Comparison Table (`CrossEntropyLoss` vs. `LabelSmoothingCrossEntropy` vs. `Focal Loss` vs. `MSE Loss`):

Loss Function	Test Accuracy (%)	Training Args	Explanation
CrossEntropy	88.42	See (A)	Robust and High Stability
Label Smoothing	89.61	See (B), 75 epoches	Of Median Stability, High Performance
Focal Loss (γ=2)	87.61	See (C)	Fast but less Stable, Balanced Config
MSE Loss	90.03	See (D), 100 epoches	Stable, Of Normal Performance

Model Weights

- best_model_LeakyReLU_CrossEntropy_Adam_StepLR_8842.pth
- best_model_LeakyReLU_LabelSmoothingCrossEntropy_Adam_CosineAnnealingLR_8961.pth
- best_model_LeakyReLU_FocalLoss_Adam_CosineAnnealingLR_8761.pth
- best_model_ReLU_MSELoss_Adam_CosineAnnealingLR_9003.pth

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3. Optimizers

The code supports `Adam`, `SGD` and `CustomSignSGD` with configurable hyperparameters:

```
# Configuration
training_config = {
    'optimizer': 'adam',
    'lr': 0.005,
    'weight_decay': 1e-5,  # L2 regularization
    ...
}

# Optimizer
if training_config['optimizer'] == 'adam':
    optimizer = optim.Adam(model.parameters(), lr=training_config['lr'],
                           weight_decay=training_config['weight_decay'])
elif training_config['optimizer'] == 'sgd':
    optimizer = optim.SGD(model.parameters(), lr=training_config['lr'], momentum=0.9,
                          weight_decay=training_config['weight_decay'])
```

> For Optimizers the Configurations are almost the same.
>
> ```
> # Configuration
> model_config = {
>  'filters': (64, 128, 256),
>  'activation': 'leaky_relu',
>  'use_batchnorm': True,
>  'dropout_rate': 0.5,
> }
>
> training_config = {
>  'optimizer': 'adam', # The Only Difference of the Three Optimizing Methods
>  'lr': 0.001,
>  'weight_decay': 1e-4,  # L2 regularization
>  'momentum': 0.9,
>  'l1_lambda': 0.0,  # L1 regularization strength
>  'grad_clip': 1.0,  # Gradient clipping
>  'epochs': 50,
>  'loss': 'cross_entropy',  # Options: cross_entropy, focal, mse, label_smoothing
>  'label_smoothing': 0.1,  # For label smoothing
>  'focal_params': {'alpha': 0.25, 'gamma': 2},
>  'scheduler': {
>      'name': 'step',
>      'step_size': 20,
>      'gamma': 0.1,
>      'patience': 5,
>      'factor': 0.5,
>      'min_lr': 1e-5
>  }
> }
> ```

Comparison Table (`Adam` vs. `SGD` vs. `CustomSignSGD`):

Optimizer	Test Accuracy (%)	Explanation
Adam	88.42	First and Second Order Refinement
SGD	78.58	Partial Adam
CustomSignSGD	82.64	Signed SGD

Model Weights

- best_model_LeakyReLU_CrossEntropy_Adam_StepLR_8842.pth
- best_model_LeakyReLU_CrossEntropy_SGD_StepLR_7858.pth
- best_model_LeakyReLU_CrossEntropy_CustomSignSGD_StepLR_8264.pth

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4. Learning Rate Schedulers

Three schedulers were tested: `StepLR`, `ReduceLROnPlateau`, and `CosineAnnealingLR`.

```
# Configuration
training_config = {
    ...,
    'scheduler': {
        'name': 'cosine',
        'step_size': 20,
```

```
        'gamma': 0.1,
        'patience': 5,
        'factor': 0.5,
        'min_lr': 1e-6
    }
}

# Scheduler
scheduler_config = training_config['scheduler']
scheduler = None
if scheduler_config['name'] == 'step':
    scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=scheduler_config['step_size'],
                                          gamma=scheduler_config['gamma'])
elif scheduler_config['name'] == 'plateau':
    scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min',
                                                     patience=scheduler_config['patience'],
                                                     factor=scheduler_config['factor'])
elif scheduler_config['name'] == 'cosine':
    scheduler = optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=training_config['epochs'],
                                                     eta_min=scheduler_config['min_lr'])
```

Changes made in codes can be seen here:

```
# Configuration
model_config = {
    'filters': (128, 256, 512),
    'activation': 'leaky_relu',
    'use_batchnorm': True,
    'dropout_rate': 0.3,
}

training_config = {
    'optimizer': 'adam',
    'lr': 0.001,
    'weight_decay': 1e-4,  # L2 regularization
    'momentum': 0.9,
    'l1_lambda': 1e-5,  # L1 regularization strength
    'grad_clip': 5.0,  # Gradient clipping
    'epochs': 50,
    'loss': 'label_smoothing',  # Options: cross_entropy, focal, mse, label_smoothing
    'label_smoothing': 0.1,  # For label smoothing
    'focal_params': {'alpha': 0.25, 'gamma': 2},
    'scheduler': {
        'name': 'step',
        'step_size': 20,
        'gamma': 0.1,
        'patience': 3,
        'factor': 0.2,
        'min_lr': 1e-5
    }
}

# Scheduler
scheduler_config = training_config['scheduler']
scheduler = None
if scheduler_config['name'] == 'step':
    scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=scheduler_config['step_size'],
     gamma=scheduler_config['gamma'])
elif scheduler_config['name'] == 'plateau':
```

```
    scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', threshold=0.001,
threshold_mode='rel', cooldown=2, patience=scheduler_config['patience'],
     factor=scheduler_config['factor'])
elif scheduler_config['name'] == 'cosine':
    scheduler = optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=training_config['epochs'],
     eta_min=scheduler_config['min_lr'])
```

Comparison Table (`StepLR` vs. `ReduceLROnPlateau`, vs. `CosineAnnealingLR`):

Scheduler	Test Accuracy (%)	Explanation
StepLR (step=20)	88.53	The logic is reducing lr alongside steps
ReduceLROnPlateau	88.44	- or gradients to avoid step over, and
CosineAnnealingLR	88.98	- the performances almost tied

Model Weights

- best_model_LeakyReLU_CrossEntropy_Adam_StepLR_8853.pth
- best_model_LeakyReLU_CrossEntropy_Adam_ReduceLROnPlateau_8844.pth
- best_model_LeakyReLU_CrossEntropy_Adam_CosineAnnealingLR_8898.pth

---

Results and Insights

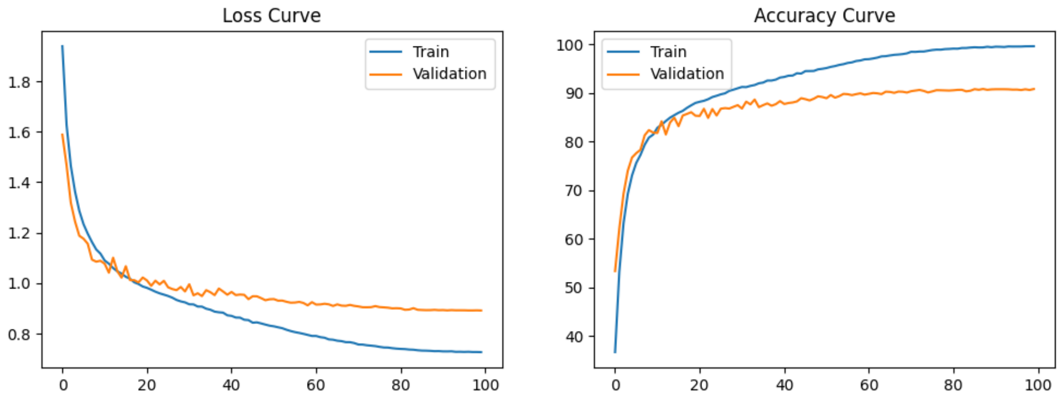
Codes for Best Configuration for now

```
elif activation == 'leaky_relu':
 return nn.LeakyReLU(0.05)

...

# Configuration
model_config = {
 'filters': (128, 256, 512),
 'activation': 'leaky_relu',
 'use_batchnorm': True,
 'dropout_rate': 0.4,
}

training_config = {
 'optimizer': 'adam',
 'lr': 0.002,
 'weight_decay': 1e-5,  # L2 regularization
 'momentum': 0.9,
 'l1_lambda': 0.0,  # L1 regularization strength
 'grad_clip': 5.0,  # Gradient clipping
 'epochs': 100,
 'loss': 'label_smoothing',  # Options: cross_entropy, focal, mse, label_smoothing
 'label_smoothing': 0.15,  # For label smoothing
 'focal_params': {'alpha': 0.25, 'gamma': 2},
 'scheduler': {
     'name': 'cosine',
     'step_size': 20,
```

```
        'gamma': 0.1,
        'patience': 3,
        'factor': 0.2,
        'min_lr': 1e-6
    }
  }
```

- **Best Result for now**: LeakyReLU + LabelSmoothingCrossEntropy + Adam + CosineAnnealingLR achieved **91.53%** test accuracy *(codes/CIFAR_CNN/best_model_9153.pth)*.
- **Key Observations**:
  - Adam outperformed SGD due to adaptive learning rates, while CustomSignSGD only display small improvement.
  - StepLR provided controlled decay, while ReduceLROnPlateau, CosineAnnealingLR offered smoother transitions.
  - CrossEntropyLoss was more stable than Focal Loss for CIFAR-10, while LabelSmoothingCrossEntrophy and MSE Loss show great potential after high epoches.
  - LeakyReLU and ReLU have similar performance, while eLU is significantly weaker

Training Curves:



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2. Batch Normalization Analysis

VGG-A with vs. Without Batch Normalization

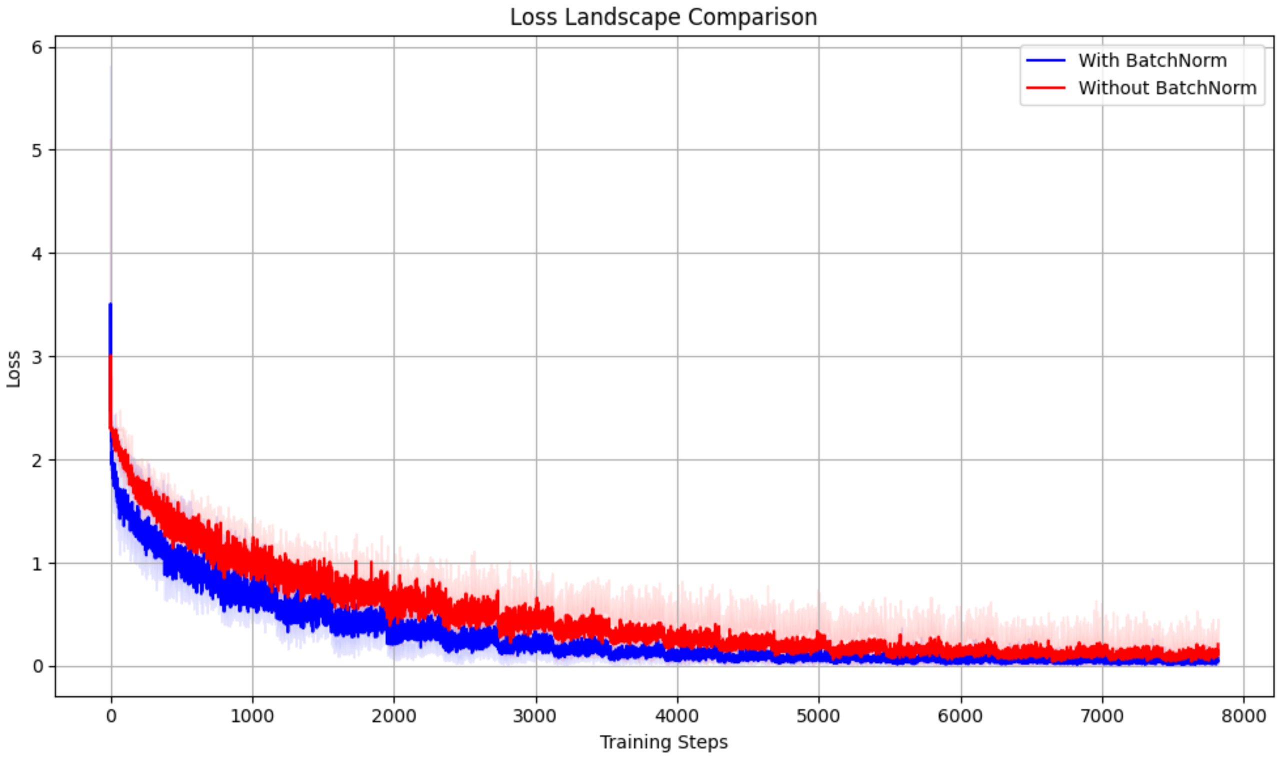
We trained two variants of VGG-A (with and without BN) using the same hyperparameters.

Performance Comparison

- **With BN**:
  - Faster convergence (50% validation accuracy by epoch 10).
  - Smoother loss landscape (lower variance).
- **Without BN**:
  - Slower convergence (50% validation accuracy by epoch 25).
  - Unstable training with higher loss fluctuations.

Loss Landscape Visualization

The loss landscape was analyzed by training models with different learning rates and plotting the min/max loss bounds:



Observations:

- BN reduces the Lipschitz constant of the loss landscape, enabling smoother optimization.
- The gradient predictiveness improved with BN, allowing larger learning rates without divergence.

How Does BN Help Optimization?

1. **Internal Covariate Shift Reduction**: BN stabilizes layer input distributions.
2. **Smoother Loss Landscape**: BN reparametrizes the optimization problem, making gradients more reliable.
3. **Faster Convergence**: Enabled by stable gradients and higher learning rates.

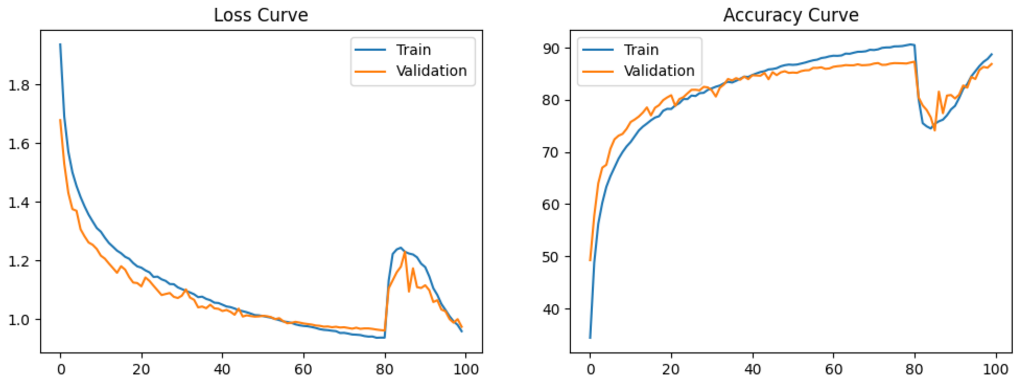
---

3. Conclusion

This project demonstrates the effectiveness of modern CNN architectures on CIFAR-10 and the critical role of Batch Normalization in stabilizing training. The best model achieved **91.53%** test accuracy using a compact 2.6M-parameter network. BN significantly improved training stability and convergence speed, as validated by loss landscape analysis.

Future Work: Explore advanced architectures (e.g., ResNet) and optimization techniques like SWA or AdamW.

If Utilizing SWA (Stochastic Weight Averaging, Optimizer and LR_scheduler codes see `codes/CIFAR_CNN/main_swa.py`), the best test accuracy is **85.17%** ("codes/CIFAR_CNN/best_model_swa.pth")

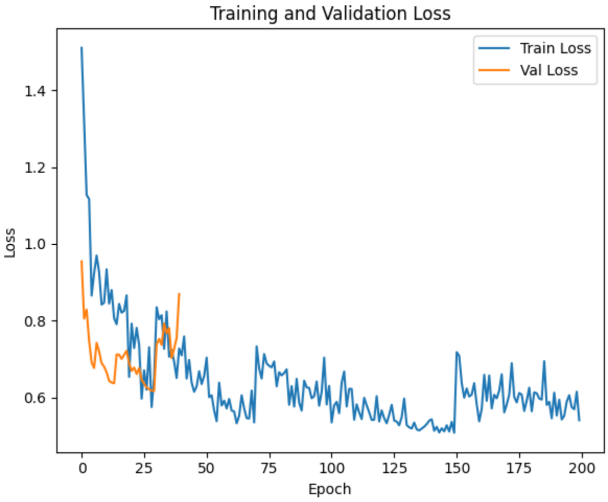


If Utilizing ResNet and AdamW (CNN and Optimizer, codes see `codes/CIFAR_CNN/main_resnet_adamw.py`), the best test accuracy is **95.22%** ("codes/CIFAR_CNN/best_model_resnet_adamw.pth")

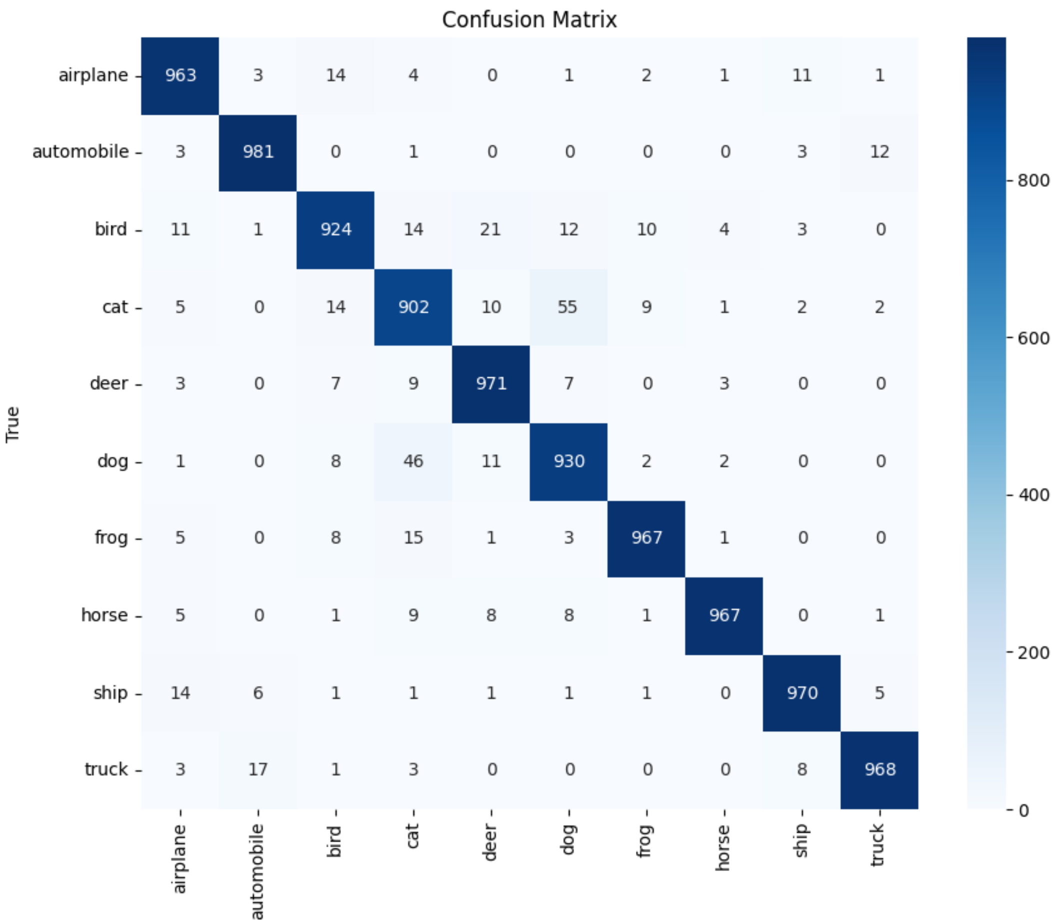
ResNet Implementation

```
class BasicBlock(nn.Module):
expansion = 1

def __init__(self, in_planes, planes, stride=1):
  super(BasicBlock, self).__init__()
  self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride, padding=1,
bias=False)
  self.bn1 = nn.BatchNorm2d(planes)
  self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1, bias=False)
  self.bn2 = nn.BatchNorm2d(planes)
  self.shortcut = nn.Sequential()
  if stride != 1 or in_planes != self.expansion * planes:
      self.shortcut = nn.Sequential(
          nn.Conv2d(in_planes, self.expansion * planes, kernel_size=1, stride=stride,
bias=False),
          nn.BatchNorm2d(self.expansion * planes)
      )

  # Select activation
  if activation_type == "Swish":
      self.activation = Swish()
  elif activation_type == "GELU":
      self.activation = nn.GELU()
  elif activation_type == "Mish":
      self.activation = Mish()
  else:
      self.activation = nn.ReLU()

def forward(self, x):
  out = self.activation(self.bn1(self.conv1(x)))
  out = self.bn2(self.conv2(out))
  out += self.shortcut(x)
  out = self.activation(out)
  return out

class ResNet(nn.Module):
def __init__(self, block, num_blocks, num_classes=10):
  super(ResNet, self).__init__()
```

```
    self.in_planes = 64
    self.conv1 = nn.Conv2d(3, 64, kernel_size=3, stride=1, padding=1, bias=False)
    self.bn1 = nn.BatchNorm2d(64)
    self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
    self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
    self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
    self.linear = nn.Linear(256 * block.expansion, num_classes)
    self.activation = Swish() if activation_type == "Swish" else nn.GELU()

  def _make_layer(self, block, planes, num_blocks, stride):
    strides = [stride] + [1] * (num_blocks - 1)
    layers = []
    for stride in strides:
        layers.append(block(self.in_planes, planes, stride))
        self.in_planes = planes * block.expansion
    return nn.Sequential(*layers)

  def forward(self, x):
    out = self.activation(self.bn1(self.conv1(x)))
    out = self.layer1(out)
    out = self.layer2(out)
    out = self.layer3(out)
    out = nn.AdaptiveAvgPool2d((1, 1))(out)
    out = torch.flatten(out, 1)
    out = self.linear(out)
    return out

  def ResNet18():
  return ResNet(BasicBlock, [2, 2, 2, 2])
```


Training and Validation Loss
Train Loss
Val Loss
Loss
Epoch
0 25 50 75 100 125 150 175 200
0.6 0.8 1.0 1.2 1.4


Training and Validation Accuracy
Train Accuracy
Val Accuracy
Accuracy (%)
Epoch
0 25 50 75 100 125 150 175 200
40 50 60 70 80 90 100


Confusion Matrix
True
airplane 963 3 14 4 0 1 2 1 11 1
automobile 3 981 0 1 0 0 0 0 3 12
bird 11 1 924 14 21 12 10 4 3 0
cat 5 0 14 902 10 55 9 1 2 2
deer 3 0 7 9 971 7 0 3 0 0
dog 1 0 8 46 11 930 2 2 0 0
frog 5 0 8 15 1 3 967 1 0 0
horse 5 0 1 9 8 8 1 967 0 1
ship 14 6 1 1 1 1 1 0 970 5
truck 3 17 1 3 0 0 0 0 8 968
airplane automobile bird cat deer dog frog horse ship truck
0 200 400 600 800