

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
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

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 ($\gamma=2$)	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
-

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

4. Learning Rate Schedulers

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

[illegible]

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)

...

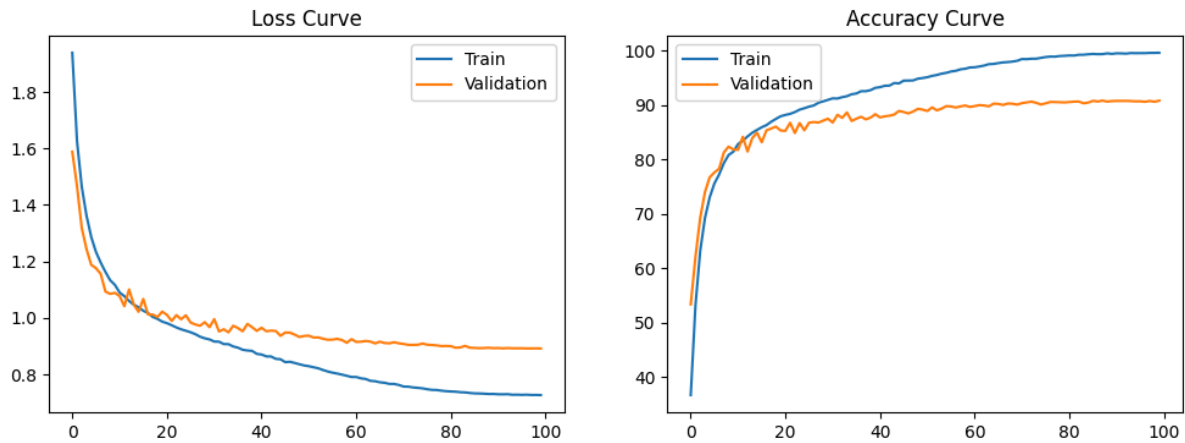
# Configuration
model_config = {
    'filters': (128, 256, 512),
    'activation': 'leaky_relu',
    'use_batchnorm': True,
    'dropout_rate': 0.4,
}

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 LabelSmoothingCrossEntropy and MSE Loss show great potential after high epoches.
- LeakyReLU and ReLU have similar performance, while eLU is significantly weaker

Training Curves:



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.

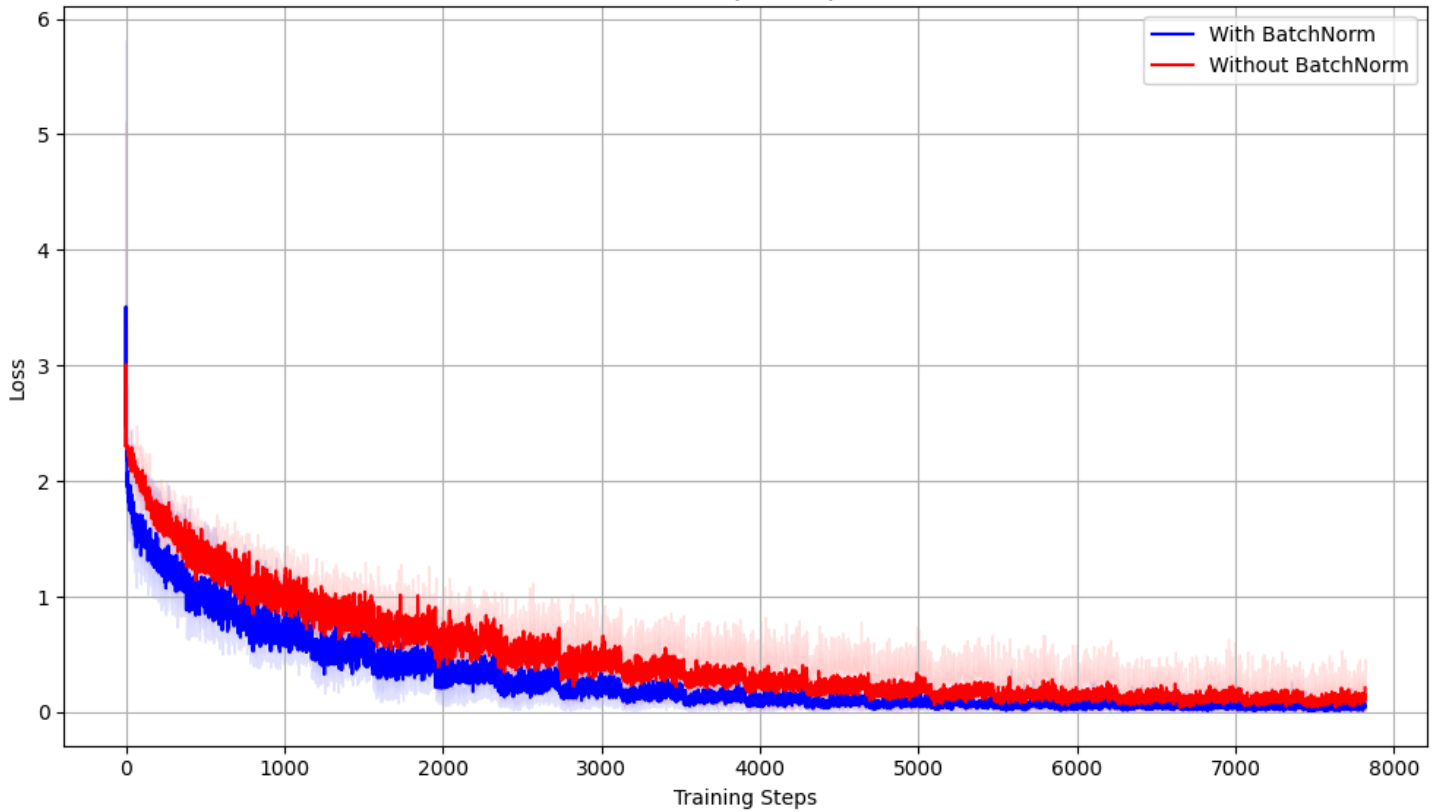
Performance Comparison

- **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:

Loss Landscape Comparison



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?

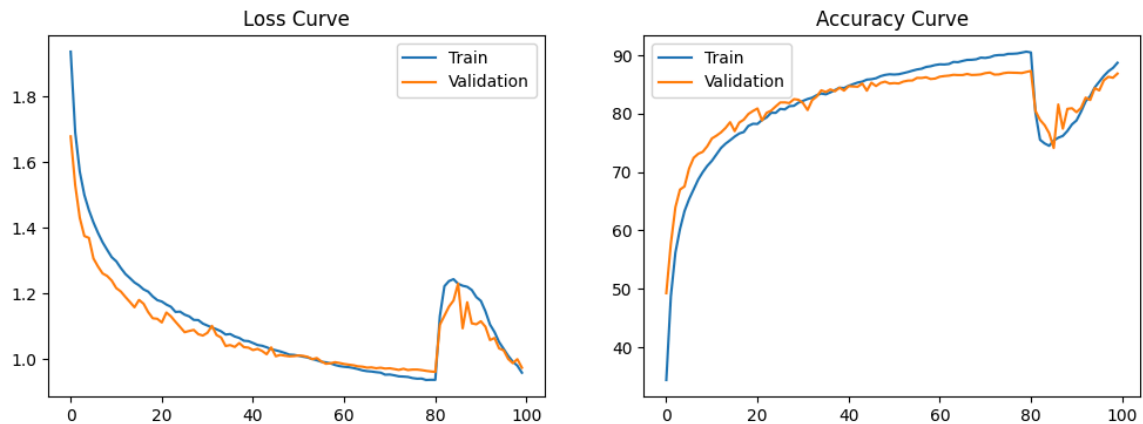
1. **Internal Covariate Shift Reduction:** BN stabilizes layer input distributions.
2. **Smoother Loss Landscape:** BN reparametrizes the optimization problem, making gradients more reliable.
3. **Faster Convergence:** Enabled by stable gradients and higher learning rates.

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])

```

