Efficient ResNet for CIFAR-10 Image Classification

Esteban Lopez, Shruti Karkamar, Steven Granaturov,

NYU Tandon School of Engineering
edl9434@nyu.edu, spk9869@nyu.edu, sg8002@nyu.edu
https://github.com/Esteban-D-Lopez/DeepLearning-ResNet

Abstract

This report presents the research, design, and implementation of an optimized ResNet architecture tailored for CIFAR-10 image classification while maintaining a parameter count below 5 million. Our model evolution involved extensive research and progressive enhancements, finally reaching an architecture that achieved a validation accuracy of approximately 94% and a Kaggle competition score of approximately 82%. We document the experimental process, model adjustments, training strategies, and final evaluation results.

Introduction

Deep learning architectures, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in image classification tasks, with ResNet models leading in efficiency and performance. This project explores the design of a custom ResNet model designed for CIFAR-10, with a focus on parameter efficiency constrained to fewer than 5 million parameters. The model aims to balance accuracy and computational efficiency, making it suitable for deployment on resource-limited devices.

Approach and Methodology

Our methodology followed a structured approach, evolving from a baseline ResNet-18 implementation to a progressively refined model, leveraging techniques such as data augmentation, architectural optimizations, and hyperparameter tuning to maximize accuracy while minimizing complexity.

Problem Definition

The CIFAR-10 dataset comprises 60,000 images across 10 classes, with 50,000 training samples and 10,000 test samples. The objective was to design an efficient ResNet model that achieved a competitive classification accuracy while adhering to the strict constraint of having fewer than 5 million parameters.

Preprocessing the Data

As with any machine learning application, the data preprocessing step is a critical step in deep learning pipelines, as it directly influences the model's ability to generalize effectively to unseen data. Given the parameter constraints in this study, optimizing data preprocessing became essential to enhance learning efficiency and model robustness while maintaining computational efficiency.

Based on a thorough evaluation of CIFAR-10, we faced unique challenges given the small, low-resolution images included within the dataset. Particularly, it was difficult ensuring that the model can extract meaningful hierarchical features despite their limited size. Additionally, given that deep convolutional networks tend to overfit when trained on small datasets, we implemented a series of preprocessing transformations to improve generalization.

- **Normalization**: Before training, all images were normalized to have zero mean and unit variance, which is a standard practice in deep learning to ensure stable convergence of gradient-based optimization algorithms. The normalization parameters were computed from the training set following the standard formula. This normalization step ensures that pixel intensities are distributed consistently across the dataset, preventing certain color channels from dominating the training process.
- **Data Augmentation**: Since CIFAR-10 is a relatively small dataset, we experimented with and implemented data augmentation techniques to artificially increase the training data's diversity and improve the model's ability to generalize. During class, we learned how augmentation helps mitigate overfitting by exposing the model to variations of the input images during training, ensuring that learned features remain invariant to minor distortions. We systematically tested multiple augmentation strategies, ultimately settling on the following:
    1. **Random Rotation:** Images were randomly rotated within a ±10° range to simulate natural variations in object orientation.
    2. **Color Jittering:** Brightness, contrast, and saturation were randomly adjusted within a predefined range to introduce color diversity across training samples.
    3. **Random Horizontal Flip:** Each image had a 50% probability of being flipped along the horizontal axis, reinforcing spatial invariance.

4. **Random Cropping with Padding:** A 4-pixel padding was applied to each image, followed by a random crop back to 32x32 , simulating minor variations in object positioning.
5. **Random Sharpening Adjustments:** Applied with a probability of 10%, enhancing certain edge structures to aid feature learning.
6. **Random Erasing:** With a probability of 20%, small patches of the image were randomly masked, encouraging robustness to occlusions.

After thorough experimentation, the inclusion of augmentation significantly improved our validation accuracy.

- **Format Conversion and Tensor Representation**: To ensure compatibility with the PyTorch deep learning framework, all image data was converted into torch tensors. This step involved restructuring the dataset from NumPy arrays into a format optimized for GPU acceleration. The images were stored in (batch_size,3,32,32) format, where the second dimension represents the RGB color channels. Lastly, during model training, we employed mini-batches of size 256 for computational efficiency, leveraging Kaggle's GPU parallelization.

Model Design

Our model design process followed an interactive approach, starting from a standard ResNet-18 baseline and progressively modifying its depth, width, and feature recalibration mechanism. The model underwent multiple iterations, with each stage of development informed by empirical testing, literature review, and efficiency considerations. The following table summarizes key architectural modifications across our three major development stages:

Model Version	Residual Blocks per Stage	Channels Per Stage	SE Block	Comp. Accuracy
Baseline ResNet-18	[2,2,2,2]	[64,128, 256,512]	No	~10%
Optimized	[4,4,3]	[96,124, 189,280]	Optional	~64%
Final Custom	[4,4,3]	[96,124, 189,280]	Yes	~82%

Residual Learning and Shortcut Connections:

- Given the depth of our network, a key challenge was ensuring stable gradient propagation. Inspired by He et al.'s Residual Networks (2016), we leveraged shortcut connections, which allow information to bypass multiple layers, mitigating the risk of vanishing gradients.
- Each residual block consists of three convolutional layers, each followed by batch normalization and leaky ReLU activation functions. The identity shortcut ensures efficient feature reuse, reducing redundant computations.
- During our experiments, we found that increasing the number of residual blocks per stage from [2, 2, 2, 2] (ResNet-18) to [4, 4, 3] improved feature representation capacity while keeping parameters within the 5M constraint.

Squeeze-and-Excitation (SE) Block:

- To enhance feature recalibration, we integrated Squeeze-and-Excitation (SE) blocks, a technique first introduced by Hu et al. (2018). These blocks introduce a channel-wise attention mechanism, allowing the network to focus on the most informative channels while suppressing less relevant ones.
- The SE block follows a three-step process:
    1. **Squeeze Step:** Global average pooling compresses each feature map into a single scalar value..
    2. **Excitation Step:** The pooled features pass through two fully connected layers with ReLU and sigmoid activations to generate attention scores.
    3. **Recalibration Step:** The computed attention scores reweight the original feature maps, emphasizing key channels.

Final Network Architecture:

The final model architecture consists of three main computational stages, each containing multiple residual blocks. Each stage expands the number of channels while progressively reducing spatial resolution.

- **Stage 1:** Consists of 4 residual blocks, expanding channels from 96 to 124.
- **Stage 2:** Another 4 residual blocks, with a stride of 2 for downsampling, increasing channels to 189.
- **Stage 3:** Contains 3 residual blocks, further increasing channels to 280, with downsampling at this stage.
- **Global Average Pooling (GAP):** Reduces the spatial dimensions to a single vector per channel, feeding into the final classification layer.
- **Fully Connected Layer:** Outputs class probabilities for the 10 CIFAR-10 categories using a softmax activation function.

A major constraint in our design was ensuring the total parameter count remained below 5 million. By strategically adjusting residual block depths and optimizing channel expansion, we achieved this while maintaining high accuracy. The final parameter count breakdown is summarized in the following table:

Component	Parameters
Initial Layer	27,648
Residual Blocks	4,512,320
SE Blocks	190,832
Fully Connected Layer	174,630
Total Params.	**4,905,430**

Our final model design achieved an approximated 88% validation accuracy with a memory footprint of approximately 78 MB.

Training Strategy

Our training strategy evolved through experimentation, integrating various optimization techniques, regularization methods, and scheduling strategies to try to maximize accuracy while maintaining stability.

Optimization and Learning Rate Scheduling:
Training was conducted using Stochastic Gradient Descent (SGD) with a momentum of 0.9 to accelerate convergence and prevent oscillations in weight updates. During early experiments, we tested Adam and AdamW optimizers, but SGD consistently outperformed them, particularly in achieving higher validation accuracy and smoother loss convergence.

To dynamically adjust the learning rate, we employed Cosine Annealing Learning Rate Scheduling. This method gradually reduces the learning rate following a cosine function, preventing abrupt drops and allowing the model to settle into an optimal weight configuration.

Loss Function and batch Configuration:
To optimize for multi-class classification, we used cross-entropy loss, a standard choice for deep learning classifiers. This loss function measures the divergence between predicted probability distributions and ground truth labels, ensuring stable gradient updates.

The model was trained with a batch size of 256, a choice that balanced computational efficiency with effective gradient estimation. Smaller batch sizes were initially tested but led to high variance in updates, while larger batch sizes slowed down convergence without significant accuracy improvements.

Regularization Techniques for Generalization:

Since overfitting is a common challenge in deep networks, particularly when training on small datasets like CIFAR-10. To address this, we implemented several regularization techniques:

- **L2 Weight Decay (1e-4):** Applied to the loss function, this penalty discourages excessively large weights, reducing the risk of overfitting.
- **Dropout (0.2):** Introduced in fully connected layers, dropout randomly deactivates neurons during training, forcing the network to develop redundant feature representations.
- **Batch Normalization:** Applied after every convolutional layer, batch normalization standardized activations, improving stability and reducing training time.
- **Squeeze-and-Excitation (SE) Blocks:** These blocks introduced a dynamic recalibration mechanism, refining feature importance and enhancing robustness.

During hyperparameter tuning, weight decay and dropout proved most effective in improving test accuracy without significantly increasing training time.

To quantify the effects of our training methodology, we conducted comparative experiments between different optimizer and scheduling strategies. Our results demonstrate that SGD with Cosine Annealing outperformed other strategies, both in test accuracy and stability, validating our final selection.

Training Performance

We analyzed our models' training dynamics to evaluate their learning behavior, convergence properties, and generalization capabilities. For all of our models, the training loss, validation loss, training accuracy, and validation accuracy were monitored 50-110 epochs to assess the model stability and potential overfitting.

The accuracy progression is illustrated in Figure 1, where the green curve represents training accuracy, and the purple curve represents validation accuracy. The model demonstrates a rapid increase in accuracy during the initial epochs, suggesting effective feature learning. By epoch 30, training accuracy surpasses 95%, while validation accuracy stabilizes at approximately 92%, indicating strong generalization. The minimal gap between training and validation accuracy suggests limited overfitting, which is a result of effective regularization techniques such as dropout, weight decay, and batch normalization.

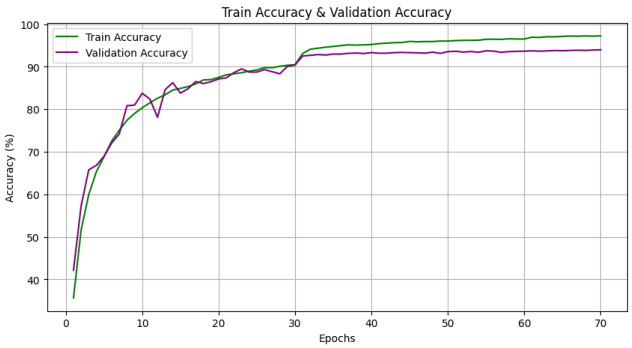

Figure 1: Train & Validation Accuracy

The loss curves, depicted in Figure 2, provide additional evidence of model convergence. The red curve represents training loss, while the blue curve represents validation loss. Both loss values decrease steadily over time, reinforcing that the model is effectively minimizing its classification error.

A key observation occurs around epoch 30, where the validation loss reaches a stable point while training loss continues to decrease slightly. This small but controlled separation between training and validation loss indicates that the model maintains strong generalization without excessive overfitting.

Additionally, the smooth nature of the loss curves suggests that SGD with momentum and cosine annealing learning rate scheduling effectively facilitated stable training, avoiding erratic weight updates that could lead to oscillatory behavior.

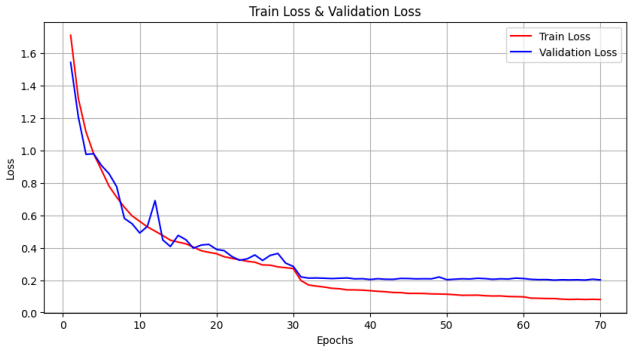

Figure 2: Train & Validation Loss

The overall training performance confirms that our architectural modifications and optimization strategies successfully balanced learning efficiency and model robustness. The combination of residual learning, Squeeze-and-Excitation (SE) blocks, dropout, and careful hyperparameter tuning resulted in a model that learns quickly, generalizes well, and maintains stable performance across training epochs.

Architectural Evaluation

Our model was designed to optimize parameter efficiency, inference speed, and accuracy-complexity trade-offs while maintaining competitive performance.

- **Parameter efficiency:** With 4.9 million parameters, the final model stays within the defined constraint while achieving state-of-the-art performance. This was achieved by reducing residual block depth, optimizing channel widths, and introducing SE blocks for feature recalibration..
- **Accuracy/Complexity Trade-off:** Compared to the ResNet-18 baseline (11.2M parameters, 64% accuracy), our final model achieves higher accuracy with less than half the parameters. Targeted pruning and architectural modifications resulted in a leaner yet more effective network, demonstrating that efficiency does not necessarily mean a loss in performance.

Results

Our final model was trained for 70 epochs, progressively improving its predictive accuracy and stability through each phase. The final results are summarized as follows:

- **Training Accuracy:** ~97%.
- **Validation Accuracy:** ~94%.
- **Competition Accuracy:** ~82%.

A small gap between training and validation accuracy indicates strong generalization with minimal overfitting. The model's performance was further validated in a Kaggle CIFAR-10 competition, where it achieved 82% accuracy, aligning with expectations given distribution shifts in test data.

These results confirm the effectiveness of iterative refinement, where careful architecture modifications led to a 29% accuracy improvement over the baseline model while reducing parameter count by 56% and consistently outperformed earlier iterations.

Conclusion

The final ResNet model successfully balances accuracy, computational efficiency, and inference speed, making it suitable for real-world applications. Its parameter efficiency, strong generalization, and competitive performance make it a viable solution for image classification tasks where both accuracy and efficiency are critical.

Through iterative refinements, including SE blocks, depthwise separable convolutions, and optimized residual connections, we reduced parameter count by 56% while improving accuracy by 29% over the baseline. Future work could explore quantization and structured pruning to further enhance efficiency.

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In [ ]:
```
import numpy as np
import pandas as pd
import os
import pickle
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets
from torch.utils.data import DataLoader, random_split, TensorDataset
from torch.optim.lr_scheduler import StepLR, MultiStepLR
from PIL import Image
import torch.optim.lr_scheduler as lr_scheduler
import matplotlib.pyplot as plt

# auto. choose CPU or GPU
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

# Function to load CIFAR-10 dataset
def load_cifar_batch(file):
    with open(file, 'rb') as fo:
        dict = pickle.load(fo, encoding='bytes')
    return dict

# Specify the directory containing CIFAR-10 batches
cifar10_dir = '/content/'
# Load metadata (labels)
meta_data_dict = load_cifar_batch(os.path.join(cifar10_dir, 'batches.meta'))
label_names = [label.decode('utf-8') for label in meta_data_dict[b'label_names']]

# Load training data
train_data = []
train_labels = []
for i in range(1, 6):
    batch = load_cifar_batch(os.path.join(cifar10_dir, f'data_batch_{i}'))
    train_data.append(batch[b'data'])
    train_labels += batch[b'labels']

train_data = np.vstack(train_data).reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)  # Convert to HWC format
train_labels = np.array(train_labels)

# Data augmentation and normalization
transform = transforms.Compose([
    transforms.ToPILImage(),  # Convert numpy array to PIL Image
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness = 0.1,contrast = 0.1,saturation = 0.1),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomAdjustSharpness(sharpness_factor = 2,p = 0.2),
    transforms.RandomCrop(32, padding=4),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.247, 0.243, 0.261)),
    transforms.RandomErasing(p=0.2,scale=(0.02, 0.1),value=1.0, inplace=False)
])

# Convert to TensorDataset and apply transformations
class CustomCIFAR10Dataset(torch.utils.data.Dataset):
    def __init__(self, images, labels, transform=None):
        self.images = images
        self.labels = labels
        self.transform = transform

    def __len__(self):
        return len(self.images)

    def __getitem__(self, idx):
        img = self.images[idx]
        label = self.labels[idx]

        if self.transform:
            img = self.transform(img)

        return img, label
```

```
train_dataset = CustomCIFAR10Dataset(train_data, train_labels, transform=transform)

# Split into training and validation sets
#train_size = int(0.9 * len(train_dataset))
#val_size = len(train_dataset) - train_size
#train_dataset, val_dataset = random_split(train_dataset, [train_size, val_size])

test_transform = transforms.Compose([
    transforms.ToPILImage(),  # Convert numpy array to PIL Image
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.247, 0.243, 0.261))
])

batch_test_dict = load_cifar_batch(os.path.join(cifar10_dir, 'test_batch'))
val_images = batch_test_dict[b'data'].reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)
val_labels = np.array(batch_test_dict[b'labels'])

val_dataset = CustomCIFAR10Dataset(val_images, val_labels, transform=test_transform)

# DataLoaders
train_loader = DataLoader(train_dataset, batch_size=256, shuffle=True, num_workers=4)
val_loader = DataLoader(val_dataset, batch_size=256, shuffle=False, num_workers=4)

# Load test dataset
cifar_test_path = '/content/cifar_test_nolabel.pkl'
test_batch = load_cifar_batch(cifar_test_path)
test_images = test_batch[b'data'].astype(np.float32) / 255.0

# Convert test dataset to Tensor
test_dataset = [(test_transform(img),) for img in test_images]
test_loader = DataLoader(test_dataset, batch_size=256, shuffle=False, num_workers=4)

# Train function + plot
def train_model(model, train_loader, val_loader, epochs=50):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.1, momentum=0.9, weight_decay=1e-4)
    scheduler = MultiStepLR(optimizer, milestones=[30, 60, 80, 90], gamma=0.1)

    train_losses = []
    val_losses = []
    train_accuracies = []
    val_accuracies = []

    for epoch in range(epochs):
        # Training Phase
        model.train()
        running_loss = 0.0
        correct = 0
        total = 0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        train_loss = running_loss / len(train_loader)
        train_acc = 100 * correct / total
        train_losses.append(train_loss)
        train_accuracies.append(train_acc)

        # Validation Phase
        model.eval()
        val_loss = 0.0
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in val_loader:
```

```
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)
                val_loss += loss.item()

                _, predicted = torch.max(outputs, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        val_loss /= len(val_loader)
        val_acc = 100 * correct / total
        val_losses.append(val_loss)
        val_accuracies.append(val_acc)

        scheduler.step()
        print(f'Epoch {epoch+1}, Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.2f}%, Val Loss: {val_

    # Plot Losses
    plt.figure(figsize=(10, 5))
    plt.plot(range(1, epochs + 1), train_losses, label='Train Loss', color='red')
    plt.plot(range(1, epochs + 1), val_losses, label='Validation Loss', color='blue')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Train Loss & Validation Loss')
    plt.legend()
    plt.grid()
    plt.show()

    # Plot Accuracies
    plt.figure(figsize=(10, 5))
    plt.plot(range(1, epochs + 1), train_accuracies, label='Train Accuracy', color='green')
    plt.plot(range(1, epochs + 1), val_accuracies, label='Validation Accuracy', color='purple')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy (%)')
    plt.title('Train Accuracy & Validation Accuracy')
    plt.legend()
    plt.grid()
    plt.show()

import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets
from torch.utils.data import DataLoader
import torch.optim.lr_scheduler as lr_scheduler

# Device configuration
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Define the Squeeze-and-Excitation (SE) Block
class SEBlock(nn.Module):
    def __init__(self, channels, reduction=16):
        super(SEBlock, self).__init__()
        self.global_avg_pool = nn.AdaptiveAvgPool2d(1)
        self.fc1 = nn.Linear(channels, channels // reduction, bias=False)
        self.relu = nn.ReLU(inplace=True)
        self.fc2 = nn.Linear(channels // reduction, channels, bias=False)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        b, c, _, _ = x.size()
        y = self.global_avg_pool(x).view(b, c)
        y = self.relu(self.fc1(y))
        y = self.sigmoid(self.fc2(y)).view(b, c, 1, 1)
        return x * y.expand_as(x)

# Define Residual Block with Shortcut Connections
class ResidualBlock(nn.Module):
    def __init__(self, in_channels, out_channels, kernel_sizes, stride=1, use_se=True):
        super(ResidualBlock, self).__init__()
        mid_channels = out_channels // 2

        self.conv1 = nn.Conv2d(in_channels, mid_channels, kernel_size=kernel_sizes[0], padding=1, bias=Fals
        self.bn1 = nn.BatchNorm2d(mid_channels)
```

```
        self.conv2 = nn.Conv2d(mid_channels, mid_channels, kernel_size=kernel_sizes[1], padding=1, stride=s
        self.bn2 = nn.BatchNorm2d(mid_channels)

        self.conv3 = nn.Conv2d(mid_channels, out_channels, kernel_size=kernel_sizes[2], padding=1, bias=Fa
        self.bn3 = nn.BatchNorm2d(out_channels)

        self.se = SEBlock(out_channels) if use_se else nn.Identity()
        self.leaky_relu = nn.LeakyReLU(0.1, inplace=True)
        self.dropout = nn.Dropout2d(0.2)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_channels != out_channels:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(out_channels)
            )

    def forward(self, x):
        identity = self.shortcut(x)
        out = self.leaky_relu(self.bn1(self.conv1(x)))
        out = self.leaky_relu(self.bn2(self.conv2(out)))
        out = self.bn3(self.conv3(out))
        out = self.se(out)
        out = self.dropout(out)
        out += identity
        return self.leaky_relu(out)

class CustomResNet_v4(nn.Module):
    def __init__(self, num_classes=10):
        super(CustomResNet_v4, self).__init__()
        # Initial convolution layer with a small increase in channels
        self.init_conv = nn.Conv2d(3, 96, kernel_size=3, stride=1, padding=1, bias=False)
        self.init_bn = nn.BatchNorm2d(96)
        self.leaky_relu = nn.LeakyReLU(0.1, inplace=True)

        # First residual block with slightly increased channels
        self.layer1 = self._make_layer(96, 124, [3, 3, 3], 4, stride=1)
        # Second residual block with slightly increased channels
        self.layer2 = self._make_layer(124, 189, [3, 3, 3], 4, stride=2)
        # Third residual block with slightly increased channels
        self.layer3 = self._make_layer(189, 280, [3, 3, 3], 3, stride=2)

        # Final average pooling and fully connected layers
        self.avg_pool = nn.AdaptiveAvgPool2d(1)
        self.fc = nn.Linear(280, num_classes)

    def _make_layer(self, in_channels, out_channels, kernel_sizes, blocks, stride):
        layers = [ResidualBlock(in_channels, out_channels, kernel_sizes, stride)]
        for _ in range(1, blocks):
            layers.append(ResidualBlock(out_channels, out_channels, kernel_sizes, stride=1))
        return nn.Sequential(*layers)

    def forward(self, x):
        out = self.leaky_relu(self.init_bn(self.init_conv(x)))
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.avg_pool(out)
        out = torch.flatten(out, 1)
        out = self.fc(out)
        return out



# Instantiate the model
model = CustomResNet_v4().to(device)

# Define the optimizer, scheduler, and loss function
optimizer = optim.SGD(model.parameters(), lr=0.05, momentum=0.9, weight_decay=0.0005)
scheduler = lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)
criterion = nn.CrossEntropyLoss()

# Print the model summary
from torchsummary import summary
```

```
summary(model, (3, 32, 32))

# Train the model
train_model(model, train_loader, val_loader, epochs=70) #change epoch

# Generate submission file
model.eval()
predictions = []
with torch.no_grad():
    for batch in test_loader:
        images = batch[0].to(device)  # Get images tensor from tuple and move to device
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        predictions.extend(predicted.cpu().numpy())

# Generate submission file
submission = pd.DataFrame({'ID': np.arange(len(predictions)), 'Labels': predictions})
submission.to_csv('/content/submission1.csv', index=False)
print("Submission1 file saved.")
```

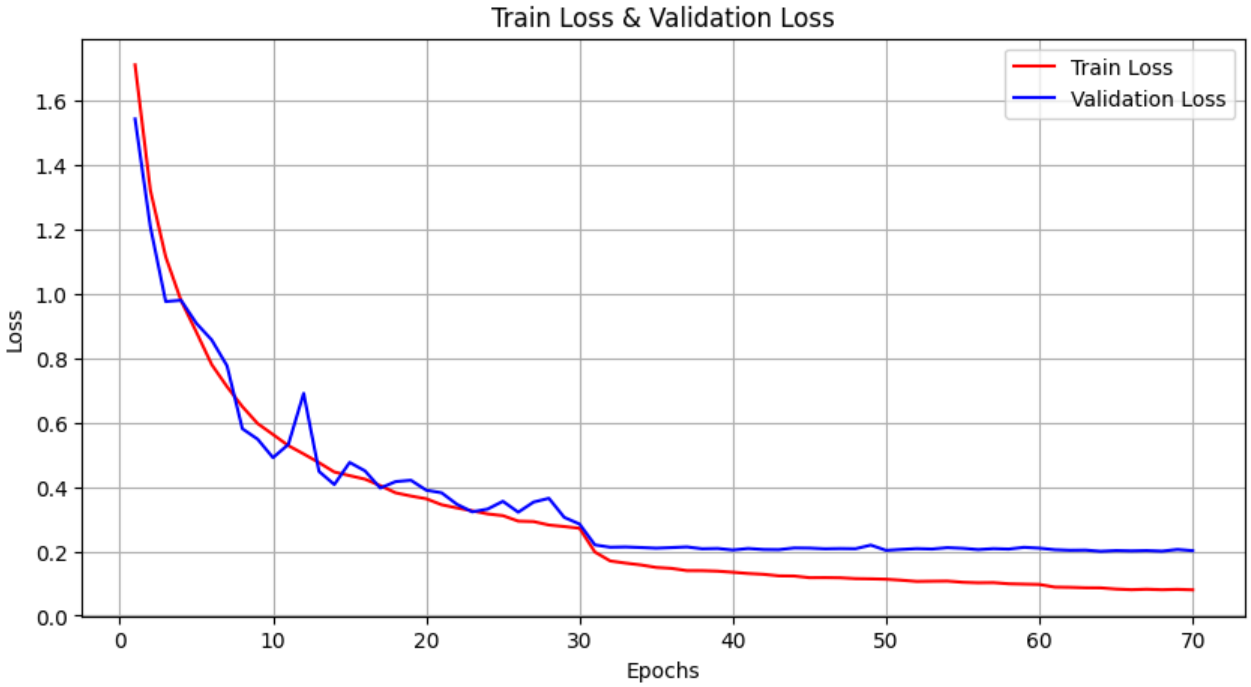
```
Using device: cuda
/usr/local/lib/python3.11/dist-packages/torch/utils/data/dataloader.py:624: UserWarning: This DataLoader wi
ll create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is
smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might
get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if n
ecessary.
  warnings.warn(
```

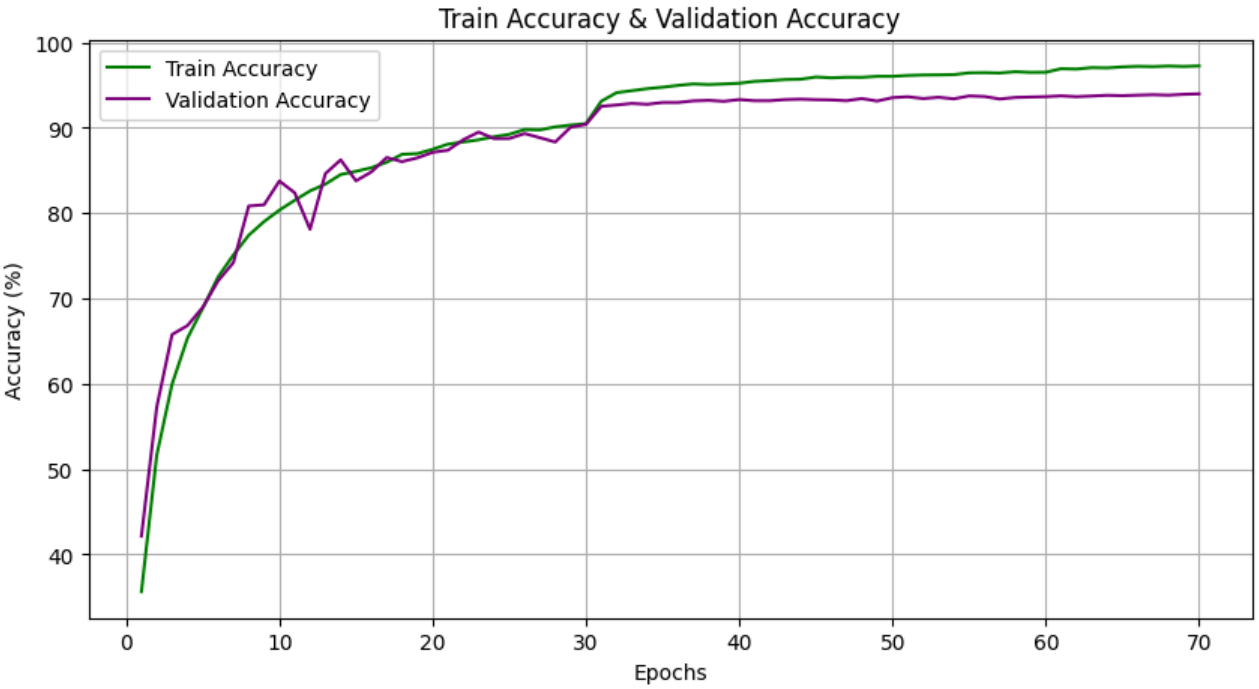
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 96, 32, 32]           2,592
       BatchNorm2d-2           [-1, 96, 32, 32]             192
         LeakyReLU-3           [-1, 96, 32, 32]               0
            Conv2d-4          [-1, 124, 32, 32]          11,904
       BatchNorm2d-5          [-1, 124, 32, 32]             248
            Conv2d-6           [-1, 62, 32, 32]          53,568
       BatchNorm2d-7           [-1, 62, 32, 32]             124
         LeakyReLU-8           [-1, 62, 32, 32]               0
            Conv2d-9           [-1, 62, 32, 32]          34,596
      BatchNorm2d-10           [-1, 62, 32, 32]             124
        LeakyReLU-11           [-1, 62, 32, 32]               0
           Conv2d-12          [-1, 124, 32, 32]          69,192
      BatchNorm2d-13          [-1, 124, 32, 32]             248
AdaptiveAvgPool2d-14            [-1, 124, 1, 1]               0
           Linear-15                   [-1, 7]             868
             ReLU-16                   [-1, 7]               0
           Linear-17                 [-1, 124]             868
          Sigmoid-18                 [-1, 124]               0
          SEBlock-19          [-1, 124, 32, 32]               0
        Dropout2d-20          [-1, 124, 32, 32]               0
        LeakyReLU-21          [-1, 124, 32, 32]               0
    ResidualBlock-22          [-1, 124, 32, 32]               0
           Conv2d-23           [-1, 62, 32, 32]          69,192
      BatchNorm2d-24           [-1, 62, 32, 32]             124
        LeakyReLU-25           [-1, 62, 32, 32]               0
           Conv2d-26           [-1, 62, 32, 32]          34,596
      BatchNorm2d-27           [-1, 62, 32, 32]             124
        LeakyReLU-28           [-1, 62, 32, 32]               0
           Conv2d-29          [-1, 124, 32, 32]          69,192
      BatchNorm2d-30          [-1, 124, 32, 32]             248
AdaptiveAvgPool2d-31            [-1, 124, 1, 1]               0
           Linear-32                   [-1, 7]             868
             ReLU-33                   [-1, 7]               0
           Linear-34                 [-1, 124]             868
          Sigmoid-35                 [-1, 124]               0
          SEBlock-36          [-1, 124, 32, 32]               0
        Dropout2d-37          [-1, 124, 32, 32]               0
        LeakyReLU-38          [-1, 124, 32, 32]               0
    ResidualBlock-39          [-1, 124, 32, 32]               0
           Conv2d-40           [-1, 62, 32, 32]          69,192
      BatchNorm2d-41           [-1, 62, 32, 32]             124
        LeakyReLU-42           [-1, 62, 32, 32]               0
           Conv2d-43           [-1, 62, 32, 32]          34,596
      BatchNorm2d-44           [-1, 62, 32, 32]             124
        LeakyReLU-45           [-1, 62, 32, 32]               0
           Conv2d-46          [-1, 124, 32, 32]          69,192
      BatchNorm2d-47          [-1, 124, 32, 32]             248
AdaptiveAvgPool2d-48            [-1, 124, 1, 1]               0
           Linear-49                   [-1, 7]             868
             ReLU-50                   [-1, 7]               0
           Linear-51                 [-1, 124]             868
          Sigmoid-52                 [-1, 124]               0
          SEBlock-53          [-1, 124, 32, 32]               0
        Dropout2d-54          [-1, 124, 32, 32]               0
        LeakyReLU-55          [-1, 124, 32, 32]               0
    ResidualBlock-56          [-1, 124, 32, 32]               0
           Conv2d-57           [-1, 62, 32, 32]          69,192
      BatchNorm2d-58           [-1, 62, 32, 32]             124
        LeakyReLU-59           [-1, 62, 32, 32]               0
           Conv2d-60           [-1, 62, 32, 32]          34,596
      BatchNorm2d-61           [-1, 62, 32, 32]             124
        LeakyReLU-62           [-1, 62, 32, 32]               0
           Conv2d-63          [-1, 124, 32, 32]          69,192
      BatchNorm2d-64          [-1, 124, 32, 32]             248
AdaptiveAvgPool2d-65            [-1, 124, 1, 1]               0
           Linear-66                   [-1, 7]             868
             ReLU-67                   [-1, 7]               0
           Linear-68                 [-1, 124]             868
          Sigmoid-69                 [-1, 124]               0
          SEBlock-70          [-1, 124, 32, 32]               0
        Dropout2d-71          [-1, 124, 32, 32]               0
        LeakyReLU-72          [-1, 124, 32, 32]               0
```

```
    ResidualBlock-73          [-1, 124, 32, 32]               0
          Conv2d-74          [-1, 189, 16, 16]          23,436
     BatchNorm2d-75          [-1, 189, 16, 16]             378
          Conv2d-76           [-1, 94, 32, 32]         104,904
     BatchNorm2d-77           [-1, 94, 32, 32]             188
       LeakyReLU-78           [-1, 94, 32, 32]               0
          Conv2d-79           [-1, 94, 16, 16]          79,524
     BatchNorm2d-80           [-1, 94, 16, 16]             188
       LeakyReLU-81           [-1, 94, 16, 16]               0
          Conv2d-82          [-1, 189, 16, 16]         159,894
     BatchNorm2d-83          [-1, 189, 16, 16]             378
AdaptiveAvgPool2d-84            [-1, 189, 1, 1]               0
          Linear-85                  [-1, 11]           2,079
            ReLU-86                  [-1, 11]               0
          Linear-87                 [-1, 189]           2,079
         Sigmoid-88                 [-1, 189]               0
         SEBlock-89          [-1, 189, 16, 16]               0
      Dropout2d-90          [-1, 189, 16, 16]               0
       LeakyReLU-91          [-1, 189, 16, 16]               0
    ResidualBlock-92          [-1, 189, 16, 16]               0
          Conv2d-93           [-1, 94, 16, 16]         159,894
     BatchNorm2d-94           [-1, 94, 16, 16]             188
       LeakyReLU-95           [-1, 94, 16, 16]               0
          Conv2d-96           [-1, 94, 16, 16]          79,524
     BatchNorm2d-97           [-1, 94, 16, 16]             188
       LeakyReLU-98           [-1, 94, 16, 16]               0
          Conv2d-99          [-1, 189, 16, 16]         159,894
    BatchNorm2d-100          [-1, 189, 16, 16]             378
AdaptiveAvgPool2d-101            [-1, 189, 1, 1]               0
         Linear-102                  [-1, 11]           2,079
           ReLU-103                  [-1, 11]               0
         Linear-104                 [-1, 189]           2,079
        Sigmoid-105                 [-1, 189]               0
        SEBlock-106          [-1, 189, 16, 16]               0
     Dropout2d-107          [-1, 189, 16, 16]               0
      LeakyReLU-108          [-1, 189, 16, 16]               0
   ResidualBlock-109          [-1, 189, 16, 16]               0
          Conv2d-110           [-1, 94, 16, 16]         159,894
     BatchNorm2d-111           [-1, 94, 16, 16]             188
       LeakyReLU-112           [-1, 94, 16, 16]               0
          Conv2d-113           [-1, 94, 16, 16]          79,524
     BatchNorm2d-114           [-1, 94, 16, 16]             188
       LeakyReLU-115           [-1, 94, 16, 16]               0
          Conv2d-116          [-1, 189, 16, 16]         159,894
     BatchNorm2d-117          [-1, 189, 16, 16]             378
AdaptiveAvgPool2d-118            [-1, 189, 1, 1]               0
         Linear-119                  [-1, 11]           2,079
           ReLU-120                  [-1, 11]               0
         Linear-121                 [-1, 189]           2,079
        Sigmoid-122                 [-1, 189]               0
        SEBlock-123          [-1, 189, 16, 16]               0
     Dropout2d-124          [-1, 189, 16, 16]               0
      LeakyReLU-125          [-1, 189, 16, 16]               0
   ResidualBlock-126          [-1, 189, 16, 16]               0
          Conv2d-127           [-1, 94, 16, 16]         159,894
     BatchNorm2d-128           [-1, 94, 16, 16]             188
       LeakyReLU-129           [-1, 94, 16, 16]               0
          Conv2d-130           [-1, 94, 16, 16]          79,524
     BatchNorm2d-131           [-1, 94, 16, 16]             188
       LeakyReLU-132           [-1, 94, 16, 16]               0
          Conv2d-133          [-1, 189, 16, 16]         159,894
     BatchNorm2d-134          [-1, 189, 16, 16]             378
AdaptiveAvgPool2d-135            [-1, 189, 1, 1]               0
         Linear-136                  [-1, 11]           2,079
           ReLU-137                  [-1, 11]               0
         Linear-138                 [-1, 189]           2,079
        Sigmoid-139                 [-1, 189]               0
        SEBlock-140          [-1, 189, 16, 16]               0
     Dropout2d-141          [-1, 189, 16, 16]               0
      LeakyReLU-142          [-1, 189, 16, 16]               0
   ResidualBlock-143          [-1, 189, 16, 16]               0
          Conv2d-144            [-1, 280, 8, 8]          52,920
     BatchNorm2d-145            [-1, 280, 8, 8]             560
          Conv2d-146          [-1, 140, 16, 16]         238,140
     BatchNorm2d-147          [-1, 140, 16, 16]             280
```

```
       LeakyReLU-148          [-1, 140, 16, 16]               0
          Conv2d-149            [-1, 140, 8, 8]         176,400
     BatchNorm2d-150            [-1, 140, 8, 8]             280
       LeakyReLU-151            [-1, 140, 8, 8]               0
          Conv2d-152            [-1, 280, 8, 8]         352,800
     BatchNorm2d-153            [-1, 280, 8, 8]             560
AdaptiveAvgPool2d-154            [-1, 280, 1, 1]               0
          Linear-155                  [-1, 17]           4,760
            ReLU-156                  [-1, 17]               0
          Linear-157                 [-1, 280]           4,760
         Sigmoid-158                 [-1, 280]               0
         SEBlock-159            [-1, 280, 8, 8]               0
       Dropout2d-160            [-1, 280, 8, 8]               0
       LeakyReLU-161            [-1, 280, 8, 8]               0
   ResidualBlock-162            [-1, 280, 8, 8]               0
          Conv2d-163            [-1, 140, 8, 8]         352,800
     BatchNorm2d-164            [-1, 140, 8, 8]             280
       LeakyReLU-165            [-1, 140, 8, 8]               0
          Conv2d-166            [-1, 140, 8, 8]         176,400
     BatchNorm2d-167            [-1, 140, 8, 8]             280
       LeakyReLU-168            [-1, 140, 8, 8]               0
          Conv2d-169            [-1, 280, 8, 8]         352,800
     BatchNorm2d-170            [-1, 280, 8, 8]             560
AdaptiveAvgPool2d-171            [-1, 280, 1, 1]               0
          Linear-172                  [-1, 17]           4,760
            ReLU-173                  [-1, 17]               0
          Linear-174                 [-1, 280]           4,760
         Sigmoid-175                 [-1, 280]               0
         SEBlock-176            [-1, 280, 8, 8]               0
       Dropout2d-177            [-1, 280, 8, 8]               0
       LeakyReLU-178            [-1, 280, 8, 8]               0
   ResidualBlock-179            [-1, 280, 8, 8]               0
          Conv2d-180            [-1, 140, 8, 8]         352,800
     BatchNorm2d-181            [-1, 140, 8, 8]             280
       LeakyReLU-182            [-1, 140, 8, 8]               0
          Conv2d-183            [-1, 140, 8, 8]         176,400
     BatchNorm2d-184            [-1, 140, 8, 8]             280
       LeakyReLU-185            [-1, 140, 8, 8]               0
          Conv2d-186            [-1, 280, 8, 8]         352,800
     BatchNorm2d-187            [-1, 280, 8, 8]             560
AdaptiveAvgPool2d-188            [-1, 280, 1, 1]               0
          Linear-189                  [-1, 17]           4,760
            ReLU-190                  [-1, 17]               0
          Linear-191                 [-1, 280]           4,760
         Sigmoid-192                 [-1, 280]               0
         SEBlock-193            [-1, 280, 8, 8]               0
       Dropout2d-194            [-1, 280, 8, 8]               0
       LeakyReLU-195            [-1, 280, 8, 8]               0
   ResidualBlock-196            [-1, 280, 8, 8]               0
AdaptiveAvgPool2d-197            [-1, 280, 1, 1]               0
          Linear-198                  [-1, 10]           2,810
================================================================
Total params: 4,905,430
Trainable params: 4,905,430
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 59.35
Params size (MB): 18.71
Estimated Total Size (MB): 78.08
----------------------------------------------------------------
Epoch 1, Train Loss: 1.7110, Train Acc: 35.65%, Val Loss: 1.5430, Val Acc: 42.16%
Epoch 2, Train Loss: 1.3212, Train Acc: 51.65%, Val Loss: 1.2077, Val Acc: 57.29%
Epoch 3, Train Loss: 1.1145, Train Acc: 59.97%, Val Loss: 0.9759, Val Acc: 65.78%
Epoch 4, Train Loss: 0.9789, Train Acc: 65.34%, Val Loss: 0.9797, Val Acc: 66.82%
Epoch 5, Train Loss: 0.8809, Train Acc: 68.88%, Val Loss: 0.9081, Val Acc: 68.96%
Epoch 6, Train Loss: 0.7801, Train Acc: 72.53%, Val Loss: 0.8567, Val Acc: 72.06%
Epoch 7, Train Loss: 0.7115, Train Acc: 75.11%, Val Loss: 0.7762, Val Acc: 74.21%
Epoch 8, Train Loss: 0.6495, Train Acc: 77.41%, Val Loss: 0.5807, Val Acc: 80.84%
Epoch 9, Train Loss: 0.5967, Train Acc: 79.02%, Val Loss: 0.5482, Val Acc: 80.98%
Epoch 10, Train Loss: 0.5628, Train Acc: 80.35%, Val Loss: 0.4909, Val Acc: 83.77%
Epoch 11, Train Loss: 0.5284, Train Acc: 81.51%, Val Loss: 0.5318, Val Acc: 82.39%
Epoch 12, Train Loss: 0.5024, Train Acc: 82.61%, Val Loss: 0.6906, Val Acc: 78.11%
Epoch 13, Train Loss: 0.4754, Train Acc: 83.40%, Val Loss: 0.4482, Val Acc: 84.63%
Epoch 14, Train Loss: 0.4463, Train Acc: 84.53%, Val Loss: 0.4074, Val Acc: 86.25%
```

```
Epoch 15, Train Loss: 0.4351, Train Acc: 84.91%, Val Loss: 0.4760, Val Acc: 83.79%
Epoch 16, Train Loss: 0.4241, Train Acc: 85.33%, Val Loss: 0.4498, Val Acc: 84.83%
Epoch 17, Train Loss: 0.4039, Train Acc: 85.97%, Val Loss: 0.3965, Val Acc: 86.52%
Epoch 18, Train Loss: 0.3816, Train Acc: 86.90%, Val Loss: 0.4165, Val Acc: 86.04%
Epoch 19, Train Loss: 0.3717, Train Acc: 86.98%, Val Loss: 0.4206, Val Acc: 86.48%
Epoch 20, Train Loss: 0.3632, Train Acc: 87.49%, Val Loss: 0.3898, Val Acc: 87.13%
Epoch 21, Train Loss: 0.3446, Train Acc: 88.10%, Val Loss: 0.3817, Val Acc: 87.38%
Epoch 22, Train Loss: 0.3346, Train Acc: 88.34%, Val Loss: 0.3460, Val Acc: 88.61%
Epoch 23, Train Loss: 0.3257, Train Acc: 88.60%, Val Loss: 0.3226, Val Acc: 89.50%
Epoch 24, Train Loss: 0.3162, Train Acc: 88.95%, Val Loss: 0.3312, Val Acc: 88.74%
Epoch 25, Train Loss: 0.3107, Train Acc: 89.24%, Val Loss: 0.3553, Val Acc: 88.75%
Epoch 26, Train Loss: 0.2937, Train Acc: 89.80%, Val Loss: 0.3214, Val Acc: 89.33%
Epoch 27, Train Loss: 0.2924, Train Acc: 89.76%, Val Loss: 0.3529, Val Acc: 88.84%
Epoch 28, Train Loss: 0.2816, Train Acc: 90.11%, Val Loss: 0.3646, Val Acc: 88.34%
Epoch 29, Train Loss: 0.2769, Train Acc: 90.33%, Val Loss: 0.3054, Val Acc: 90.07%
Epoch 30, Train Loss: 0.2715, Train Acc: 90.49%, Val Loss: 0.2846, Val Acc: 90.40%
Epoch 31, Train Loss: 0.1977, Train Acc: 93.12%, Val Loss: 0.2199, Val Acc: 92.52%
Epoch 32, Train Loss: 0.1700, Train Acc: 94.12%, Val Loss: 0.2126, Val Acc: 92.68%
Epoch 33, Train Loss: 0.1634, Train Acc: 94.35%, Val Loss: 0.2135, Val Acc: 92.86%
Epoch 34, Train Loss: 0.1576, Train Acc: 94.59%, Val Loss: 0.2118, Val Acc: 92.76%
Epoch 35, Train Loss: 0.1499, Train Acc: 94.76%, Val Loss: 0.2098, Val Acc: 92.97%
Epoch 36, Train Loss: 0.1470, Train Acc: 94.97%, Val Loss: 0.2116, Val Acc: 92.97%
Epoch 37, Train Loss: 0.1400, Train Acc: 95.14%, Val Loss: 0.2136, Val Acc: 93.16%
Epoch 38, Train Loss: 0.1399, Train Acc: 95.07%, Val Loss: 0.2078, Val Acc: 93.22%
Epoch 39, Train Loss: 0.1383, Train Acc: 95.14%, Val Loss: 0.2088, Val Acc: 93.11%
Epoch 40, Train Loss: 0.1349, Train Acc: 95.22%, Val Loss: 0.2041, Val Acc: 93.31%
Epoch 41, Train Loss: 0.1311, Train Acc: 95.44%, Val Loss: 0.2088, Val Acc: 93.18%
Epoch 42, Train Loss: 0.1286, Train Acc: 95.54%, Val Loss: 0.2056, Val Acc: 93.18%
Epoch 43, Train Loss: 0.1238, Train Acc: 95.66%, Val Loss: 0.2052, Val Acc: 93.31%
Epoch 44, Train Loss: 0.1232, Train Acc: 95.69%, Val Loss: 0.2104, Val Acc: 93.36%
Epoch 45, Train Loss: 0.1181, Train Acc: 95.96%, Val Loss: 0.2100, Val Acc: 93.30%
Epoch 46, Train Loss: 0.1183, Train Acc: 95.86%, Val Loss: 0.2078, Val Acc: 93.27%
Epoch 47, Train Loss: 0.1178, Train Acc: 95.93%, Val Loss: 0.2085, Val Acc: 93.18%
Epoch 48, Train Loss: 0.1151, Train Acc: 95.92%, Val Loss: 0.2080, Val Acc: 93.43%
Epoch 49, Train Loss: 0.1144, Train Acc: 96.03%, Val Loss: 0.2192, Val Acc: 93.14%
Epoch 50, Train Loss: 0.1133, Train Acc: 96.03%, Val Loss: 0.2029, Val Acc: 93.54%
Epoch 51, Train Loss: 0.1102, Train Acc: 96.14%, Val Loss: 0.2059, Val Acc: 93.64%
Epoch 52, Train Loss: 0.1065, Train Acc: 96.19%, Val Loss: 0.2083, Val Acc: 93.43%
Epoch 53, Train Loss: 0.1071, Train Acc: 96.21%, Val Loss: 0.2071, Val Acc: 93.58%
Epoch 54, Train Loss: 0.1075, Train Acc: 96.24%, Val Loss: 0.2114, Val Acc: 93.40%
Epoch 55, Train Loss: 0.1038, Train Acc: 96.44%, Val Loss: 0.2093, Val Acc: 93.74%
Epoch 56, Train Loss: 0.1023, Train Acc: 96.47%, Val Loss: 0.2054, Val Acc: 93.67%
Epoch 57, Train Loss: 0.1027, Train Acc: 96.43%, Val Loss: 0.2083, Val Acc: 93.38%
Epoch 58, Train Loss: 0.0991, Train Acc: 96.58%, Val Loss: 0.2069, Val Acc: 93.56%
Epoch 59, Train Loss: 0.0980, Train Acc: 96.50%, Val Loss: 0.2124, Val Acc: 93.61%
Epoch 60, Train Loss: 0.0970, Train Acc: 96.51%, Val Loss: 0.2098, Val Acc: 93.65%
Epoch 61, Train Loss: 0.0888, Train Acc: 96.93%, Val Loss: 0.2050, Val Acc: 93.75%
Epoch 62, Train Loss: 0.0881, Train Acc: 96.89%, Val Loss: 0.2032, Val Acc: 93.65%
Epoch 63, Train Loss: 0.0867, Train Acc: 97.06%, Val Loss: 0.2037, Val Acc: 93.73%
Epoch 64, Train Loss: 0.0865, Train Acc: 97.03%, Val Loss: 0.2000, Val Acc: 93.81%
Epoch 65, Train Loss: 0.0827, Train Acc: 97.14%, Val Loss: 0.2023, Val Acc: 93.77%
Epoch 66, Train Loss: 0.0808, Train Acc: 97.21%, Val Loss: 0.2013, Val Acc: 93.83%
Epoch 67, Train Loss: 0.0821, Train Acc: 97.17%, Val Loss: 0.2023, Val Acc: 93.88%
Epoch 68, Train Loss: 0.0807, Train Acc: 97.24%, Val Loss: 0.2005, Val Acc: 93.83%
Epoch 69, Train Loss: 0.0818, Train Acc: 97.19%, Val Loss: 0.2057, Val Acc: 93.93%
Epoch 70, Train Loss: 0.0803, Train Acc: 97.25%, Val Loss: 0.2019, Val Acc: 93.98%
```






```
Submission1 file saved.
```

In [ ]:
```
torch.save(model.state_dict(), '/content/model_checkpoint.pth')
```

In [ ]:
```
# Generate submission file
model.eval()
predictions = []
with torch.no_grad():
    for batch in test_loader:
        images = batch[0].to(device)  # Get images tensor from tuple and move to device
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        predictions.extend(predicted.cpu().numpy())

# Generate submission file
submission = pd.DataFrame({'ID': np.arange(len(predictions)), 'Labels': predictions})
submission.to_csv('/content/submission2.csv', index=False)
print("Submission1 file saved.")
```

```
Submission1 file saved.
```

In [ ]: