Modified ResNet
A comparison between three proposed ResNet model

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Abstract

In this project, we introduce three modified versions of the ResNet model with the primary goal of achieving high accuracy while adhering to a constraint of less than 5 million trainable parameters. To achieve this objective, we conducted extensive experiments, leveraging different parameters and techniques, including active learning rate, efficient optimizer, layer augmentation, and dropouts. We meticulously analyzed the results of our experiments, presenting the findings in this paper. The outcomes of our work may have implications for various applications where model size and computational resources are critical factors.

Introduction

ResNets, or residual neural networks, are a type of deep learning architecture that have been widely used in computer vision tasks such as image classification, object detection, and segmentation. They introduce residual connections that allow information to bypass layers and flow directly to the next layer, which has shown to improve the performance of deep networks. In this project, we developed and trained a ResNet architecture on the CIFAR 10 dataset (Krizhevsky 2009) with the goal of achieving high accuracy while adhering to a constraint of less than 5 million trainable parameters. To understand the effect of parameter scaling, we experimented with three different architectures, ranging from a small ResNet with 78 thousand parameters to a larger architecture with 4.9 million parameters. We utilized data visualization techniques to analyze the results of scaling. Batch normalization was integrated to improve the training of deep networks. Various optimizers were compared, and it was determined that Stochastic Gradient Descent with momentum, including Nesterov acceleration to regulate the momentum, was the most effective approach, as reported by (Liu, Gao, and Yin 2020). Additionally, we investigated the impact of dropout layers. The final model met the constraint and demonstrated computational efficiency.

ResNet Model

ResNet is a deep convolutional neural network (CNN) architecture proposed by Kaiming He et al. in 2015 (He et al. 2015) to address the challenge of training very deep neural networks. It introduces residual blocks with skip connections, allowing gradients to bypass layers and learn residual mappings, making optimization easier. ResNet typically consists of convolutional, batch normalization, activation, and pooling layers, followed by global average pooling and fully connected output layers. It has multiple variants with increasing depth and capacity, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. ResNet has achieved state-of-the-art performance in various computer vision tasks and is widely used in deep learning applications.

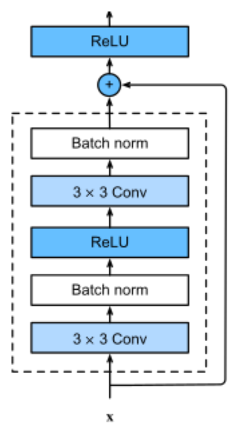


Figure 1: ResNet Block

Network Architecture

The three models, ResNetSmall, ResNetMedium, and ResNetLarge, are variations of the ResNet architecture. The main differences between these three models are the number of layers, the number of filters (or channels) in each layer, and the size of the final fully connected layer.

Small Network Layer Summary and Total Parameters

This model has 3 layers (referred to as ”layer1”, ”layer2”, and ”layer3”) and a final fully connected layer with 64 units (or neurons). The number of filters in the convolutional layers gradually increases from 16 to 64 as we go deeper into the network.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 16, 32, 32]             432
       BatchNorm2d-2           [-1, 16, 32, 32]              32
            Conv2d-3           [-1, 16, 32, 32]           2,304
       BatchNorm2d-4           [-1, 16, 32, 32]              32
            Conv2d-5           [-1, 16, 32, 32]           2,304
       BatchNorm2d-6           [-1, 16, 32, 32]              32
        BasicBlock-7           [-1, 16, 32, 32]               0
            Conv2d-8           [-1, 32, 16, 16]           4,608
       BatchNorm2d-9           [-1, 32, 16, 16]              64
           Conv2d-10           [-1, 32, 16, 16]           9,216
      BatchNorm2d-11           [-1, 32, 16, 16]              64
           Conv2d-12           [-1, 32, 16, 16]             512
      BatchNorm2d-13           [-1, 32, 16, 16]              64
       BasicBlock-14           [-1, 32, 16, 16]               0
           Conv2d-15             [-1, 64, 8, 8]          18,432
      BatchNorm2d-16             [-1, 64, 8, 8]             128
           Conv2d-17             [-1, 64, 8, 8]          36,864
      BatchNorm2d-18             [-1, 64, 8, 8]             128
           Conv2d-19             [-1, 64, 8, 8]           2,048
      BatchNorm2d-20             [-1, 64, 8, 8]             128
       BasicBlock-21             [-1, 64, 8, 8]               0
AdaptiveAvgPool2d-22             [-1, 64, 1, 1]               0
           Linear-23                   [-1, 10]             650
================================================================
Total params: 78,042
Trainable params: 78,042
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 1.53
Params size (MB): 0.30
Estimated Total Size (MB): 1.84
----------------------------------------------------------------
```

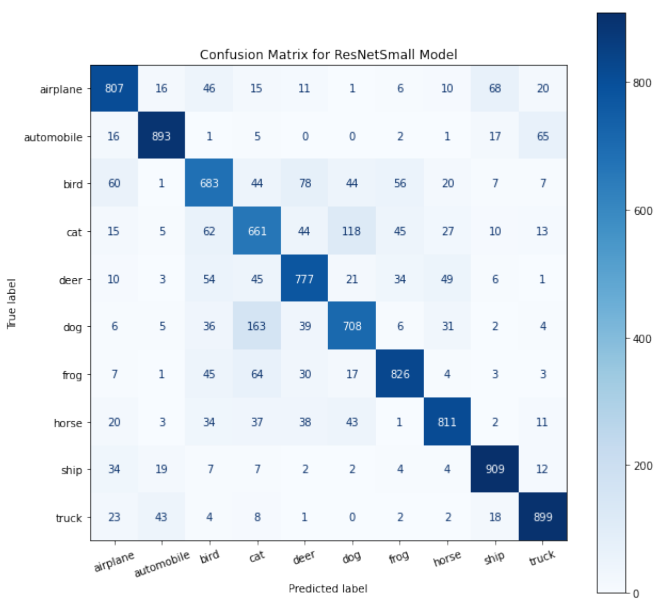


Figure 2: Confusion Matrix SmallModel

Medium Network Layer Summary and Total Parameters

This model has 4 layers (referred to as ”layer1”, ”layer2”, ”layer3”, and ”layer4”) and a final fully connected layer with 256 units. The number of filters in the convolutional layers gradually increases from 32 to 512 as we go deeper into the network.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 32, 32]             864
       BatchNorm2d-2           [-1, 32, 32, 32]              64
            Conv2d-3           [-1, 32, 32, 32]           9,216
       BatchNorm2d-4           [-1, 32, 32, 32]              64
            Conv2d-5           [-1, 32, 32, 32]           9,216
       BatchNorm2d-6           [-1, 32, 32, 32]              64
        BasicBlock-7           [-1, 32, 32, 32]               0
            Conv2d-8           [-1, 64, 16, 16]          18,432
       BatchNorm2d-9           [-1, 64, 16, 16]             128
           Conv2d-10           [-1, 64, 16, 16]          36,864
      BatchNorm2d-11           [-1, 64, 16, 16]             128
           Conv2d-12           [-1, 64, 16, 16]           2,048
      BatchNorm2d-13           [-1, 64, 16, 16]             128
       BasicBlock-14           [-1, 64, 16, 16]               0
           Conv2d-15            [-1, 128, 8, 8]          73,728
      BatchNorm2d-16            [-1, 128, 8, 8]             256
           Conv2d-17            [-1, 128, 8, 8]         147,456
      BatchNorm2d-18            [-1, 128, 8, 8]             256
           Conv2d-19            [-1, 128, 8, 8]           8,192
      BatchNorm2d-20            [-1, 128, 8, 8]             256
       BasicBlock-21            [-1, 128, 8, 8]               0
           Conv2d-22            [-1, 256, 4, 4]         294,912
      BatchNorm2d-23            [-1, 256, 4, 4]             512
           Conv2d-24            [-1, 256, 4, 4]         589,824
      BatchNorm2d-25            [-1, 256, 4, 4]             512
           Conv2d-26            [-1, 256, 4, 4]          32,768
      BatchNorm2d-27            [-1, 256, 4, 4]             512
       BasicBlock-28            [-1, 256, 4, 4]               0
AdaptiveAvgPool2d-29            [-1, 256, 1, 1]               0
           Linear-30                   [-1, 10]           2,570
================================================================
Total params: 1,228,970
Trainable params: 1,228,970
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 3.28
Params size (MB): 4.69
Estimated Total Size (MB): 7.98
----------------------------------------------------------------
```

Large Network Layer Summary and Total Parameters

This model has 4 layers (referred to as ”layer1”, ”layer2”, ”layer3”, and ”layer4”) and a final fully connected layer with 512 units. The number of filters in the convolutional layers gradually increases from 64 to 512 as we go deeper into the network.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
```

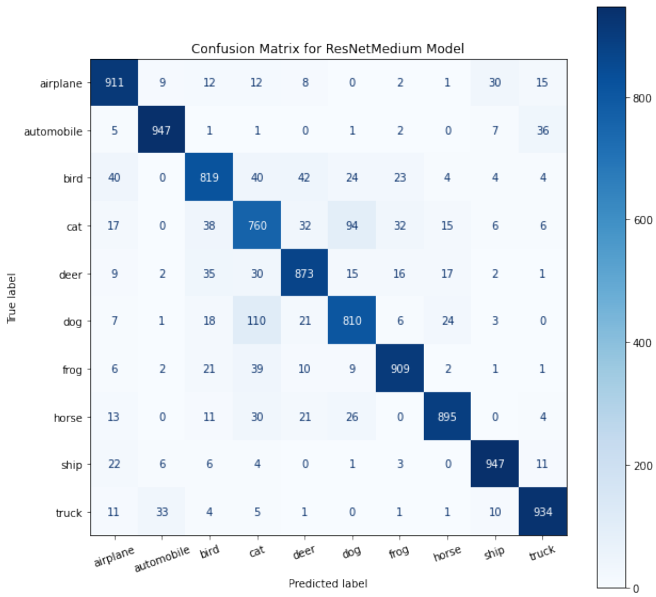


Figure 3: Confusion Matrix Medium Model

```
           Conv2d-1         [-1, 64, 32, 32]         1,728
      BatchNorm2d-2         [-1, 64, 32, 32]           128
           Conv2d-3         [-1, 64, 32, 32]        36,864
      BatchNorm2d-4         [-1, 64, 32, 32]           128
           Conv2d-5         [-1, 64, 32, 32]        36,864
      BatchNorm2d-6         [-1, 64, 32, 32]           128
       BasicBlock-7         [-1, 64, 32, 32]             0
           Conv2d-8        [-1, 128, 16, 16]        73,728
      BatchNorm2d-9        [-1, 128, 16, 16]           256
          Conv2d-10        [-1, 128, 16, 16]       147,456
     BatchNorm2d-11        [-1, 128, 16, 16]           256
          Conv2d-12        [-1, 128, 16, 16]         8,192
     BatchNorm2d-13        [-1, 128, 16, 16]           256
      BasicBlock-14        [-1, 128, 16, 16]             0
          Conv2d-15          [-1, 256, 8, 8]       294,912
     BatchNorm2d-16          [-1, 256, 8, 8]           512
          Conv2d-17          [-1, 256, 8, 8]       589,824
     BatchNorm2d-18          [-1, 256, 8, 8]           512
          Conv2d-19          [-1, 256, 8, 8]        32,768
     BatchNorm2d-20          [-1, 256, 8, 8]           512
      BasicBlock-21          [-1, 256, 8, 8]             0
          Conv2d-22          [-1, 512, 4, 4]     1,179,648
     BatchNorm2d-23          [-1, 512, 4, 4]         1,024
          Conv2d-24          [-1, 512, 4, 4]     2,359,296
     BatchNorm2d-25          [-1, 512, 4, 4]         1,024
          Conv2d-26          [-1, 512, 4, 4]       131,072
     BatchNorm2d-27          [-1, 512, 4, 4]         1,024
      BasicBlock-28          [-1, 512, 4, 4]             0
AdaptiveAvgPool2d-29          [-1, 512, 1, 1]             0
          Linear-30                 [-1, 10]         5,130
================================================================
Total params: 4,903,242
Trainable params: 4,903,242
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 6.57
Params size (MB): 18.70
Estimated Total Size (MB): 25.28
----------------------------------------------------------------
```

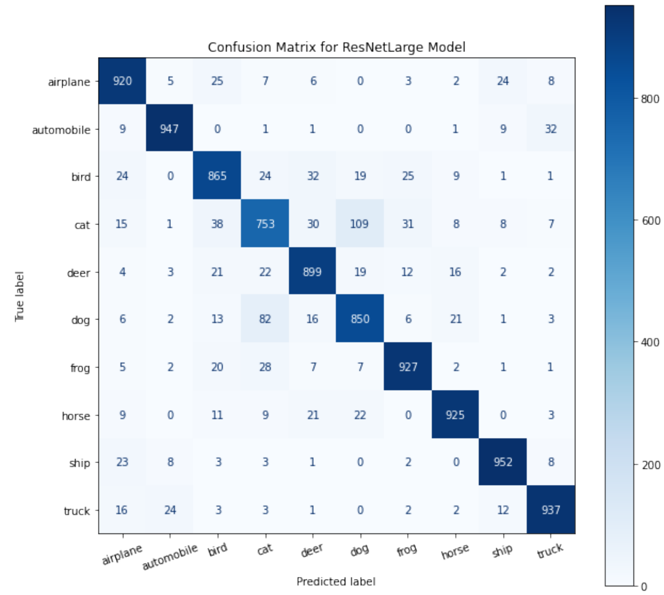


Figure 4: Confusion Matrix LargeModel

Basic block The BasicBlock class in PyTorch is a building block for the ResNet neural network architecture. It consists of two convolutional layers, batch normalization, and ReLU activation. The first convolutional layer applies a 3x3 convolution and batch normalization, followed by a second convolutional layer with shortcut connections. The output is passed through ReLU activation and returned as the output of the BasicBlock layer.

Skip Connection in basic block The skip connection in the BasicBlock is implemented through a shortcut layer as we can see in Figure 1, which directly connects the input to the output of the block through element-wise addition. This helps the network learn identity mappings, which can improve gradient propagation in deep networks. The shortcut connection is only applied when input and output have different dimensions, and it consists of Conv2d and BatchNorm2d layers to adjust dimensions and channels. If input and output have the same dimensions, the shortcut layer is an identity mapping with no additional computation.

Optimizer After experimenting with various optimizers for training our model, we concluded that using Stochastic Gradient Descent (SGD) with Momentum and Nesterov Accelerated Gradient (NAG) resulted in the highest accuracy. The optimizer configuration with the highest accuracy with $learningrate = 0.01, momentum = 0.9$ achieved an accuracy of above 94% on the large model. Other optimizers such as Adam achieved an accuracy of about 85%.

Hyper-parameters In the project, we utilized several hyperparameters to configure the learning rate (LR) during the training process. The LR was set to a minimum value of 1e-6 and a maximum value of 1e-2, spanning a wide range to enable effective model optimization. We trained the model for a total of 30 epochs, which represents the number of complete passes through the entire training dataset. To dynamically adjust the LR during training, we employed a cyclic learning rate (CLR) strategy. The CLR was implemented using the CyclicLR scheduler from the PyTorch optimizer module.

Criterion In our project, we used the cross-entropy loss (denoted as nn.CrossEntropyLoss() in PyTorch) as the objective function, or criterion, for training our model. The cross-entropy loss is a common choice for multi-class classification tasks, such as image classification, where the goal is to classify input data into multiple mutually exclusive classes. It measures the dissimilarity between the predicted class probabilities and the true class labels and provides a scalar value that reflects the model's performance. During training, the model's parameters are updated based on the gradient of the cross-entropy loss, with the aim of minimizing the loss and improving the model's accuracy in predicting the correct class labels.

Data Augmentation In our project, we used data augmentation techniques to enhance the training dataset and improve the model's ability to generalize to unseen data. We used the torchvision.transforms module in PyTorch to apply various image transformations to the input images before feeding them into the model for training.
For the training dataset, we applied the following transformations using the transforms.Compose() function:
Randomly rotating the image by a maximum of 5 degrees in a counter-clockwise or clockwise direction, which introduces diversity in the orientation of the images in the training set.
Horizontally flipping the image with a probability of 0.5, introduces diversity in the horizontal orientation of the images in the training set.
Randomly cropping a 32x32 pixel patch from the image with a padding of 2 pixels, introduces diversity in the spatial location of the images in the training set.

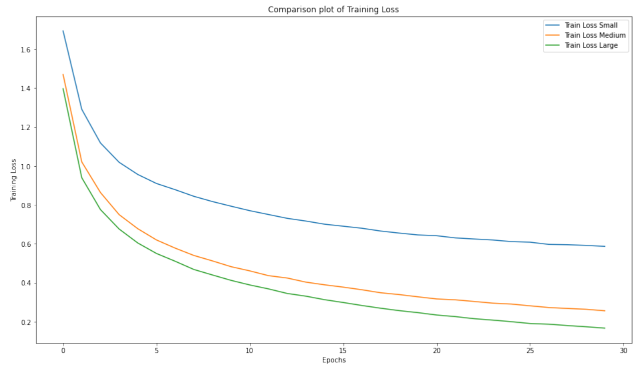


Figure 5: Training loss comparison of the three models

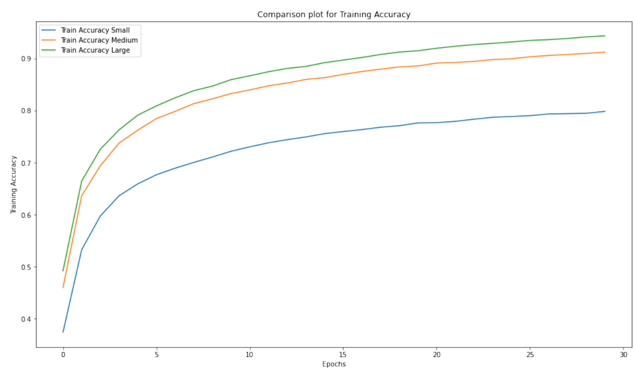


Figure 6: Training accuracy comparison of the three models

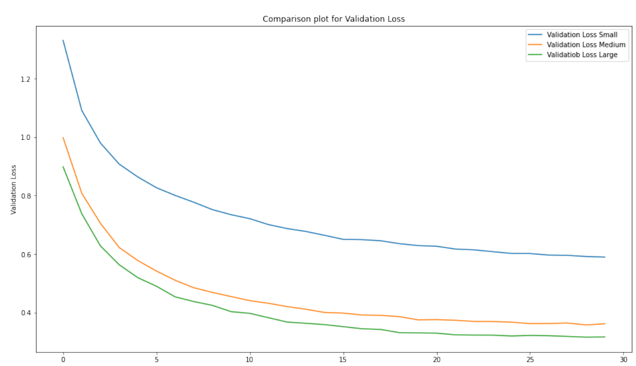


Figure 7: Test loss comparison of the three models

Evaluation

The three proposed models were evaluated using multiple metrics. Cross Entropy Loss was chosen for training purposes, and the models were compared based on their training loss and accuracy across epochs. As shown in Figure 5 and Figure 6, the large model outperformed the small model, exhibiting the lowest loss and highest accuracy throughout the epochs. To further visualize the results, confusion matrices were plotted in Figures 2, 3, and 4. It was observed that certain labels, such as 'airplane' and 'automobile', were classified more accurately by all three models, while the 'cat' label had the highest misclassification rate, often being misclassified as 'dog'. Overall, the larger model demonstrated better performance in terms of both accuracy and loss, with the other models showing similar performance in comparison.

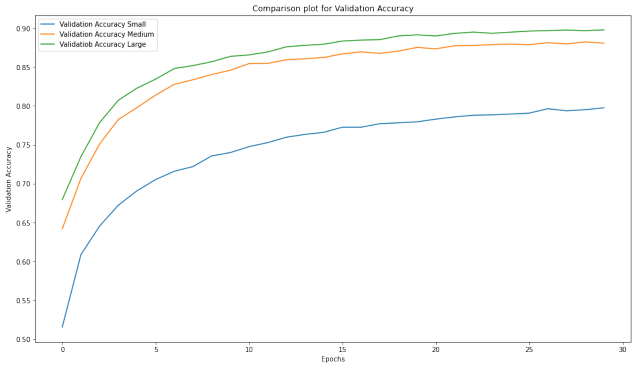


Figure 8: Test accuracy comparison of the three models

Table 1: Finding best λ for different noise level

Models	Parameters	Train Accuracy	Test Accuracy
ResNetSmall	$78,042$	24.97	16.88
ResNetMedium	$1,228,970$	24.97	16.88
ResNetLarge	$4,903,242$	28.68	19.53

System Specification

NYU HPC VM
CPU: 8 Virtualized Cores of Intel Xeon-Platinum 8286
GPU: Nvidia Quadro RTX 8000
System Memory: 96 GB
Python Version: 3.8.6
CUDA version: v11.8
Torch Version: 2.0.0

Acknowledgment

We would like to acknowledge the use of OpenAI's GPT-3.5 language model, commonly referred to as ChatGPT, for providing assistance with generating content for certain sections of this report.

References

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2015. Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

Krizhevsky, A. 2009. Learning multiple layers of features from tiny images. Technical report.

Liu, Y.; Gao, Y.; and Yin, W. 2020. An improved analysis of stochastic gradient descent with momentum. *Advances in Neural Information Processing Systems*, 33: 18261–18271.
.

In [ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.datasets as datasets
import torchvision.transforms as transforms
import torch.nn.functional as F
from torchsummary import summary
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn import decomposition
from sklearn import manifold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
import numpy as np
from tqdm import tqdm
import random
```

In [ ]:
```
SEED = 1234

random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed(SEED)
torch.backends.cudnn.deterministic = True
```

In [ ]:
```
class BasicBlock(nn.Module):

    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 != planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, planes, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(planes)
            )
    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out
```

In [ ]:
```
class ResNetSmall(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNetSmall, self).__init__()
        self.in_planes = 16

        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(16)
        self.layer1 = self._make_layer(block, 16, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 32, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 64, num_blocks[2], stride=2)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(64, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        downsample = None
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes
        return nn.Sequential(*layers)

    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), -1)
        x = self.linear(x)
        return x


device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
layers=[1, 1, 1, 1]
modelsmall = ResNetSmall(BasicBlock, layers).to(device)
summary(modelsmall, input_size=(3, 32, 32))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 16, 32, 32]             432
       BatchNorm2d-2           [-1, 16, 32, 32]              32
            Conv2d-3           [-1, 16, 32, 32]           2,304
       BatchNorm2d-4           [-1, 16, 32, 32]              32
            Conv2d-5           [-1, 16, 32, 32]           2,304
       BatchNorm2d-6           [-1, 16, 32, 32]              32
        BasicBlock-7           [-1, 16, 32, 32]               0
            Conv2d-8           [-1, 32, 16, 16]           4,608
       BatchNorm2d-9           [-1, 32, 16, 16]              64
           Conv2d-10           [-1, 32, 16, 16]           9,216
      BatchNorm2d-11           [-1, 32, 16, 16]              64
           Conv2d-12           [-1, 32, 16, 16]             512
      BatchNorm2d-13           [-1, 32, 16, 16]              64
       BasicBlock-14           [-1, 32, 16, 16]               0
           Conv2d-15             [-1, 64, 8, 8]          18,432
      BatchNorm2d-16             [-1, 64, 8, 8]             128
           Conv2d-17             [-1, 64, 8, 8]          36,864
      BatchNorm2d-18             [-1, 64, 8, 8]             128
           Conv2d-19             [-1, 64, 8, 8]           2,048
      BatchNorm2d-20             [-1, 64, 8, 8]             128
       BasicBlock-21             [-1, 64, 8, 8]               0
AdaptiveAvgPool2d-22             [-1, 64, 1, 1]               0
           Linear-23                   [-1, 10]             650
================================================================
Total params: 78,042
Trainable params: 78,042
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 1.53
Params size (MB): 0.30
Estimated Total Size (MB): 1.84
----------------------------------------------------------------
```

In [ ]:
```
class ResNetMedium(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
```

```
        super(ResNetMedium, self).__init__()
        self.in_planes = 32

        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(32)
        self.layer1 = self._make_layer(block, 32, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 64, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 128, num_blocks[2], stride=2)
        self.layer4 = self._make_layer(block, 256, num_blocks[2], stride=2)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(256, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        downsample = None
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes
        return nn.Sequential(*layers)


    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.layer4(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), -1)
        x = self.linear(x)
        return x

modelmedium = ResNetMedium(BasicBlock, layers).to(device)
summary(modelmedium, input_size=(3, 32, 32))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 32, 32]             864
       BatchNorm2d-2           [-1, 32, 32, 32]              64
            Conv2d-3           [-1, 32, 32, 32]           9,216
       BatchNorm2d-4           [-1, 32, 32, 32]              64
            Conv2d-5           [-1, 32, 32, 32]           9,216
       BatchNorm2d-6           [-1, 32, 32, 32]              64
        BasicBlock-7           [-1, 32, 32, 32]               0
            Conv2d-8           [-1, 64, 16, 16]          18,432
       BatchNorm2d-9           [-1, 64, 16, 16]             128
           Conv2d-10           [-1, 64, 16, 16]          36,864
      BatchNorm2d-11           [-1, 64, 16, 16]             128
           Conv2d-12           [-1, 64, 16, 16]           2,048
      BatchNorm2d-13           [-1, 64, 16, 16]             128
       BasicBlock-14           [-1, 64, 16, 16]               0
           Conv2d-15            [-1, 128, 8, 8]          73,728
      BatchNorm2d-16            [-1, 128, 8, 8]             256
           Conv2d-17            [-1, 128, 8, 8]         147,456
      BatchNorm2d-18            [-1, 128, 8, 8]             256
           Conv2d-19            [-1, 128, 8, 8]           8,192
      BatchNorm2d-20            [-1, 128, 8, 8]             256
       BasicBlock-21            [-1, 128, 8, 8]               0
           Conv2d-22            [-1, 256, 4, 4]         294,912
      BatchNorm2d-23            [-1, 256, 4, 4]             512
           Conv2d-24            [-1, 256, 4, 4]         589,824
      BatchNorm2d-25            [-1, 256, 4, 4]             512
           Conv2d-26            [-1, 256, 4, 4]          32,768
      BatchNorm2d-27            [-1, 256, 4, 4]             512
       BasicBlock-28            [-1, 256, 4, 4]               0
AdaptiveAvgPool2d-29            [-1, 256, 1, 1]               0
           Linear-30                   [-1, 10]           2,570
================================================================
Total params: 1,228,970
Trainable params: 1,228,970
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 3.28
Params size (MB): 4.69
Estimated Total Size (MB): 7.98
----------------------------------------------------------------
```

In [ ]:
```
class ResNetLarge(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNetLarge, 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.layer4 = self._make_layer(block, 512, num_blocks[2], stride=2)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(512, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        downsample = None
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes
        return nn.Sequential(*layers)


    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.layer4(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), -1)
        x = self.linear(x)
        return x

modellarge = ResNetLarge(BasicBlock, layers).to(device)
summary(modellarge, input_size=(3, 32, 32))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 32, 32]           1,728
       BatchNorm2d-2           [-1, 64, 32, 32]             128
            Conv2d-3           [-1, 64, 32, 32]          36,864
       BatchNorm2d-4           [-1, 64, 32, 32]             128
            Conv2d-5           [-1, 64, 32, 32]          36,864
       BatchNorm2d-6           [-1, 64, 32, 32]             128
        BasicBlock-7           [-1, 64, 32, 32]               0
            Conv2d-8          [-1, 128, 16, 16]          73,728
       BatchNorm2d-9          [-1, 128, 16, 16]             256
           Conv2d-10          [-1, 128, 16, 16]         147,456
      BatchNorm2d-11          [-1, 128, 16, 16]             256
           Conv2d-12          [-1, 128, 16, 16]           8,192
      BatchNorm2d-13          [-1, 128, 16, 16]             256
       BasicBlock-14          [-1, 128, 16, 16]               0
           Conv2d-15            [-1, 256, 8, 8]         294,912
      BatchNorm2d-16            [-1, 256, 8, 8]             512
           Conv2d-17            [-1, 256, 8, 8]         589,824
      BatchNorm2d-18            [-1, 256, 8, 8]             512
           Conv2d-19            [-1, 256, 8, 8]          32,768
      BatchNorm2d-20            [-1, 256, 8, 8]             512
       BasicBlock-21            [-1, 256, 8, 8]               0
           Conv2d-22            [-1, 512, 4, 4]       1,179,648
      BatchNorm2d-23            [-1, 512, 4, 4]           1,024
           Conv2d-24            [-1, 512, 4, 4]       2,359,296
      BatchNorm2d-25            [-1, 512, 4, 4]           1,024
           Conv2d-26            [-1, 512, 4, 4]         131,072
      BatchNorm2d-27            [-1, 512, 4, 4]           1,024
       BasicBlock-28            [-1, 512, 4, 4]               0
AdaptiveAvgPool2d-29            [-1, 512, 1, 1]               0
           Linear-30                   [-1, 10]           5,130
================================================================
Total params: 4,903,242
Trainable params: 4,903,242
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 6.57
Params size (MB): 18.70
Estimated Total Size (MB): 25.28
----------------------------------------------------------------
```

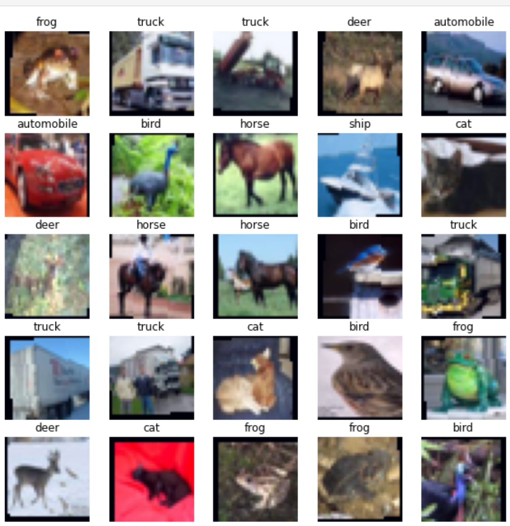
In [ ]:

```python
# Load the dataset
# Defining Transformers for train and test set differently
train_transform = transforms.Compose([
    transforms.RandomRotation(5),
    transforms.RandomHorizontalFlip(0.5),
    transforms.RandomCrop(32, padding=2),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.4914, 0.4822, 0.4465], std=[0.2023, 0.1994, 0.2010])
])
test_transform = transforms.Compose([
                           transforms.ToTensor(),
                           transforms.Normalize(mean = [0.4914, 0.4822, 0.4465],
                                                std = [0.2023, 0.1994, 0.2010])
                       ])
train_dataset = datasets.CIFAR10(root='./data', train=True, download=True, transform=train_transform)
test_dataset = datasets.CIFAR10(root='./data', train=False, download=True, transform=test_transform)
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=4)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64, shuffle=False, num_workers=4)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [ ]:

```python
def plot_images(images, labels, classes, normalize = False):
    n_images = len(images)
    rows = int(np.sqrt(n_images))
    cols = int(np.sqrt(n_images))
    fig = plt.figure(figsize = (10, 10))
    for i in range(rows*cols):
        ax = fig.add_subplot(rows, cols, i+1)
        image = images[i]
        if normalize:
            image_min = image.min()
            image_max = image.max()
            image.clamp_(min = image_min, max = image_max)
            image.add_(-image_min).div_(image_max - image_min + 1e-5)
        ax.imshow(image.permute(1, 2, 0).cpu().numpy())
        ax.set_title(classes[labels[i]])
        ax.axis('off')

N_IMAGES = 25
images, labels = zip(*[(image, label) for image, label in [train_dataset[i] for i in range(N_IMAGES)]])
classes = test_dataset.classes
plot_images(images, labels, classes, normalize = True)
```



In [ ]:

```python
def train(data_loader, model, criterion, optimizer, scheduler = None, early_stop=None):
    learning_rate_tracker = {}
    epoch_correct = 0
    running_loss = 0.0
    model.train()
```

```
    for i, (images, labels) in tqdm(enumerate(data_loader)):
        learning_rate_tracker[i] = optimizer.param_groups[0]['lr']

        images = images.to(device)
        labels = labels.to(device)

        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        running_loss += loss.item()
        predicted = torch.max(outputs.data, 1)[1]
        epoch_correct += (predicted == labels).sum().item()

        if early_stop and i==early_stop:
            break

        loss.backward()
        optimizer.step()
        if scheduler:
            scheduler.step()


    return epoch_correct , running_loss, learning_rate_tracker

def evaluate(data_loader, model, criterion):
    epoch_correct = 0
    running_loss = 0.0
    y_true = []
    y_pred = []
    model.eval()
    with torch.no_grad():
        for images, labels in data_loader:
            images = images.to(device)
            labels = labels.to(device)
            outputs = model(images)
            loss = criterion(outputs, labels)
            running_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            epoch_correct += (predicted == labels).sum().item()
            y_true.extend(labels.cpu().numpy())
            y_pred.extend(predicted.cpu().numpy())

    return epoch_correct, running_loss, y_true, y_pred
```

In [ ]:

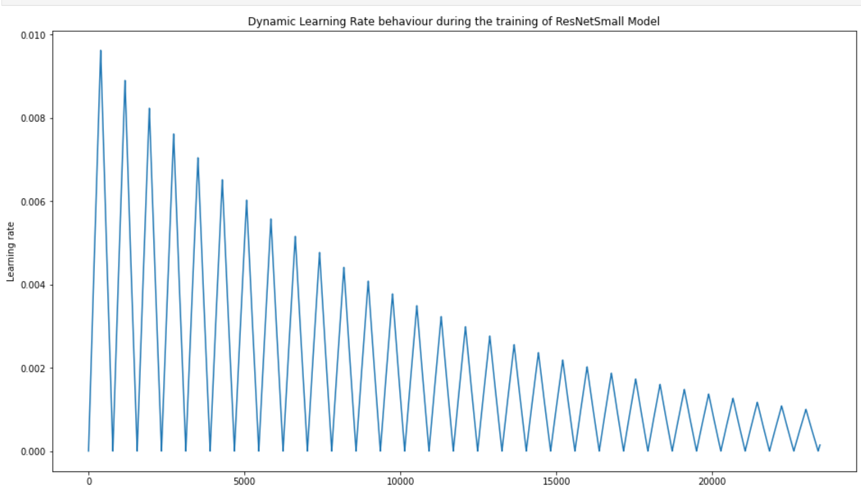
```
lr_min = 1e-6
lr_max = 1e-2
epochs = 30
step_size = (len(train_dataset)/64) // 2

model = modelsmall
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=lr_min, momentum=0.9, nesterov=True)
scheduler = optim.lr_scheduler.CyclicLR(optimizer, base_lr=lr_min, max_lr=lr_max, step_size_up=step_size, step_size_down=step_size, gamma=0.9999, mode="exp_range", cycle_momentum=False)
lr_tracker = {}

train_loss_history_small = []
train_acc_history_small = []
val_loss_history_small = []
val_acc_history_small = []
y_pred_small = []
y_true_small = []
best_valid_loss = float('inf')

for epoch in range(epochs):
    print(f"Epoch: {epoch+1}/{epochs}")
    correct, loss, rate_tracker = train(data_loader=train_loader, model=model, criterion=criterion, optimizer=optimizer, scheduler=scheduler)
    accuracy = correct / len(train_loader.dataset)
    loss = loss / len(train_loader)
    train_loss = loss
    train_acc_history_small.append(accuracy)
    train_loss_history_small.append(loss)
    for key in rate_tracker.keys():
        lr_tracker[(epoch,key)] = rate_tracker[key]
    correct, loss, y_true_small, y_pred_small = evaluate(data_loader = test_loader, model=model, criterion=criterion)
    validation_accuracy = correct / len(test_loader.dataset)
    validation_loss = loss / len(test_loader)
    print(f"Train Accuracy: {accuracy*100:.2f}%, Train Loss: {train_loss}")
    print(f"Test Accuracy: {validation_accuracy*100:.2f}%, Test Loss: {validation_loss}")
    if validation_loss < best_valid_loss:
        best_valid_loss = validation_loss
        torch.save(model.state_dict(), 'ResNetSmall.pt')
    val_acc_history_small.append(validation_accuracy)
    val_loss_history_small.append(validation_loss)
```

```
Epoch: 1/30
782it [00:07, 111.24it/s]
Train Accuracy: 37.43%, Train Loss: 1.6959722177756718
Test Accuracy: 51.58%, Test Loss: 1.3311625202749944
Epoch: 2/30
782it [00:06, 112.60it/s]
Train Accuracy: 53.40%, Train Loss: 1.2890575701165992
Test Accuracy: 60.55%, Test Loss: 1.09142566448564
Epoch: 3/30
782it [00:07, 110.35it/s]
Train Accuracy: 59.81%, Train Loss: 1.118633839251745
Test Accuracy: 64.86%, Test Loss: 0.9786295127716793
Epoch: 4/30
782it [00:07, 110.35it/s]
Train Accuracy: 63.56%, Train Loss: 1.020845061754022
Test Accuracy: 67.33%, Test Loss: 0.9052985675016026
Epoch: 5/30
782it [00:07, 109.85it/s]
Train Accuracy: 65.61%, Train Loss: 0.9602375282046131
Test Accuracy: 68.86%, Test Loss: 0.8616930933514978
Epoch: 6/30
782it [00:07, 109.27it/s]
Train Accuracy: 67.60%, Train Loss: 0.9112818957975758
Test Accuracy: 70.44%, Test Loss: 0.8231870995205679
Epoch: 7/30
782it [00:07, 110.69it/s]
Train Accuracy: 68.71%, Train Loss: 0.8794156540842617
Test Accuracy: 71.47%, Test Loss: 0.7964165343600473
Epoch: 8/30
782it [00:07, 111.09it/s]
Train Accuracy: 70.22%, Train Loss: 0.8425300571772144
Test Accuracy: 72.51%, Test Loss: 0.7651751240727248
Epoch: 9/30
782it [00:07, 111.42it/s]
Train Accuracy: 71.13%, Train Loss: 0.8148341079807038
Test Accuracy: 73.77%, Test Loss: 0.745846070681408
Epoch: 10/30
782it [00:06, 112.79it/s]
Train Accuracy: 71.87%, Train Loss: 0.7913056919184487
Test Accuracy: 74.29%, Test Loss: 0.7224326752553321
Epoch: 11/30
```

```
782it [00:07, 111.35it/s]
Train Accuracy: 73.18%, Train Loss: 0.7659507257401791
Test Accuracy: 74.92%, Test Loss: 0.7140307705493489
Epoch: 12/30
782it [00:07, 110.72it/s]
Train Accuracy: 73.66%, Train Loss: 0.7492306252650898
Test Accuracy: 75.81%, Test Loss: 0.6892960978921052
Epoch: 13/30
782it [00:06, 111.93it/s]
Train Accuracy: 74.45%, Train Loss: 0.731330990219665
Test Accuracy: 76.36%, Test Loss: 0.6842481922951473
Epoch: 14/30
782it [00:06, 113.17it/s]
Train Accuracy: 75.05%, Train Loss: 0.715022104742277
Test Accuracy: 77.13%, Test Loss: 0.6654635948739993
Epoch: 15/30
782it [00:06, 113.00it/s]
Train Accuracy: 75.32%, Train Loss: 0.6988651131653725
Test Accuracy: 77.40%, Test Loss: 0.6576877752686762
Epoch: 16/30
782it [00:07, 109.40it/s]
Train Accuracy: 75.88%, Train Loss: 0.6891592695661213
Test Accuracy: 77.66%, Test Loss: 0.6454789684076977
Epoch: 17/30
782it [00:07, 110.57it/s]
Train Accuracy: 76.33%, Train Loss: 0.6753186381152828
Test Accuracy: 77.92%, Test Loss: 0.6449884510344002
Epoch: 18/30
782it [00:07, 111.69it/s]
Train Accuracy: 77.09%, Train Loss: 0.6616063108072257
Test Accuracy: 78.02%, Test Loss: 0.6358467556868389
Epoch: 19/30
782it [00:06, 113.52it/s]
Train Accuracy: 77.25%, Train Loss: 0.6518765431840706
Test Accuracy: 78.43%, Test Loss: 0.6307068647472722
Epoch: 20/30
782it [00:07, 111.69it/s]
Train Accuracy: 77.57%, Train Loss: 0.6439396278632571
Test Accuracy: 78.46%, Test Loss: 0.6210683910710038
Epoch: 21/30
782it [00:06, 114.93it/s]
Train Accuracy: 77.38%, Train Loss: 0.6418194395425679
Test Accuracy: 78.78%, Test Loss: 0.6212930916600926
Epoch: 22/30
782it [00:07, 111.04it/s]
Train Accuracy: 78.13%, Train Loss: 0.62728391763042
Test Accuracy: 79.12%, Test Loss: 0.6053212379953664
Epoch: 23/30
782it [00:07, 111.57it/s]
Train Accuracy: 78.29%, Train Loss: 0.6244190858148247
Test Accuracy: 79.18%, Test Loss: 0.6040606601223065
Epoch: 24/30
782it [00:06, 112.70it/s]
Train Accuracy: 78.73%, Train Loss: 0.6179643522976609
Test Accuracy: 79.66%, Test Loss: 0.5983337256938789
Epoch: 25/30
782it [00:07, 110.78it/s]
Train Accuracy: 78.62%, Train Loss: 0.610577220692659
Test Accuracy: 79.37%, Test Loss: 0.5925299094361105
Epoch: 26/30
782it [00:06, 114.91it/s]
Train Accuracy: 79.08%, Train Loss: 0.6071711327794873
Test Accuracy: 79.83%, Test Loss: 0.591618735888961
Epoch: 27/30
782it [00:07, 111.57it/s]
Train Accuracy: 78.88%, Train Loss: 0.6008793675457426
Test Accuracy: 79.73%, Test Loss: 0.5894581791321942
Epoch: 28/30
782it [00:06, 112.79it/s]
Train Accuracy: 79.23%, Train Loss: 0.5939635429769525
Test Accuracy: 79.88%, Test Loss: 0.5892057268862512
Epoch: 29/30
782it [00:07, 111.01it/s]
Train Accuracy: 79.61%, Train Loss: 0.5923109132310619
Test Accuracy: 79.77%, Test Loss: 0.5877943929213627
Epoch: 30/30
782it [00:07, 110.57it/s]
Train Accuracy: 79.62%, Train Loss: 0.5894994664832455
Test Accuracy: 80.44%, Test Loss: 0.5786285602552875
```

In [ ]:

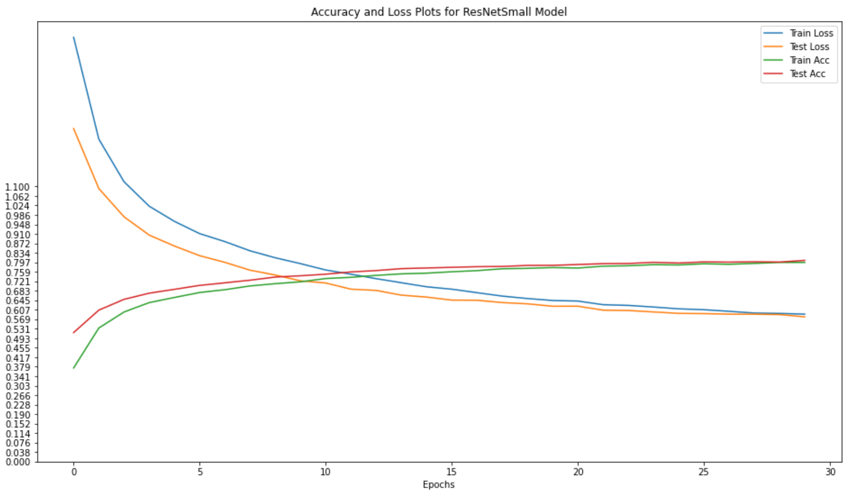
```python
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Dynamic Learning Rate behaviour during the training of ResNetSmall Model')
plt.plot(range(len(lr_tracker)), lr_tracker.values())
plt.xlabel('Batches')
plt.ylabel('Learning rate')
plt.show()
```



In [ ]:

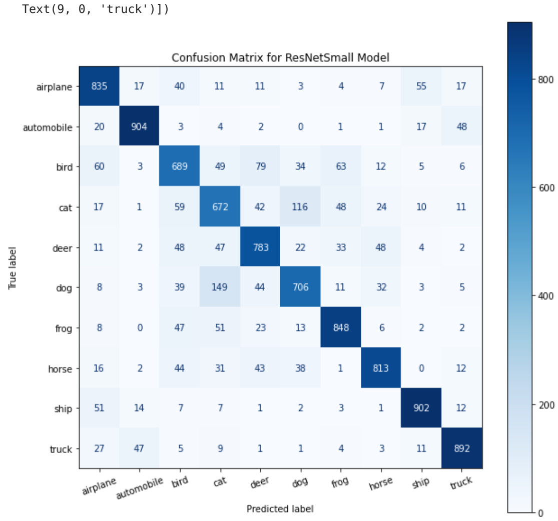
```python
fig, ax = plt.subplots(figsize=(16,9))
```

```
plt.title('Accuracy and Loss Plots for ResNetSmall Model')
plt.plot(train_loss_history_small, label='Train Loss')
plt.plot(val_loss_history_small, label='Test Loss')
plt.plot(train_acc_history_small, label='Train Acc')
plt.plot(val_acc_history_small, label='Test Acc')
plt.legend()
plt.xlabel("Epochs")
yticks = np.linspace(0, 1.1, num=30)
ax.set_yticks(yticks)
plt.show()
```



In [ ]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_true_small, y_pred_small)
fig = plt.figure(figsize = (10, 10));
ax = fig.add_subplot(1, 1, 1);
ax.set_title('Confusion Matrix for ResNetSmall Model')
cm = ConfusionMatrixDisplay(cm, display_labels = classes);
cm.plot(values_format = 'd', cmap = 'Blues', ax = ax)
plt.xticks(rotation = 20)
```

Out[ ]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'airplane'),
  Text(1, 0, 'automobile'),
  Text(2, 0, 'bird'),
  Text(3, 0, 'cat'),
  Text(4, 0, 'deer'),
  Text(5, 0, 'dog'),
  Text(6, 0, 'frog'),
  Text(7, 0, 'horse'),
  Text(8, 0, 'ship'),
  Text(9, 0, 'truck')])
```



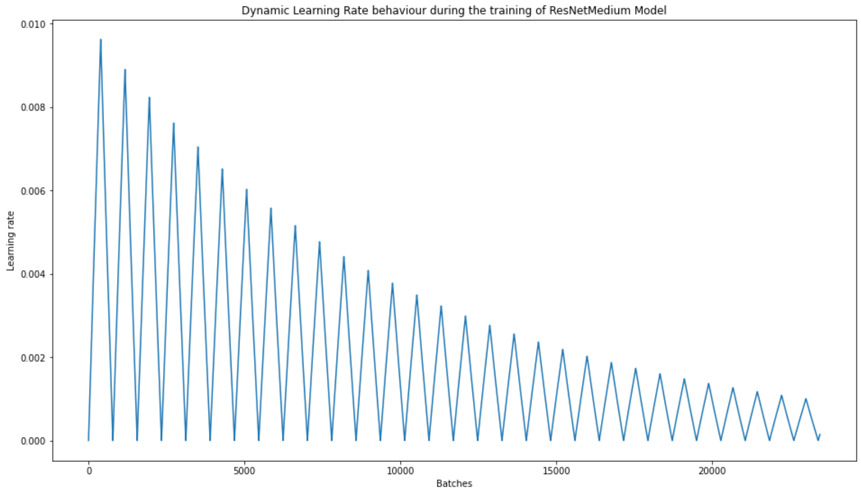
In [ ]:
```
lr_min = 1e-6
lr_max = 1e-2
epochs = 30
step_size = (len(train_dataset)/64) // 2

model = modelmedium
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=lr_min, momentum=0.9, nesterov=True)
scheduler = optim.lr_scheduler.CyclicLR(optimizer, base_lr=lr_min, max_lr=lr_max, step_size_up=step_size, step_size_down=step_size, gamma=0.9999, mode="exp_range", cycle_momentum=False)
lr_tracker = {}

train_loss_history_medium = []
train_acc_history_medium = []
val_loss_history_medium = []
val_acc_history_medium = []
y_pred_medium = []
y_true_medium = []
best_valid_loss = float('inf')

for epoch in range(epochs):
    print(f"Epoch: {epoch+1}/{epochs}")
    correct, loss, rate_tracker = train(data_loader=train_loader, model=model, criterion=criterion, optimizer=optimizer, scheduler=scheduler)
    accuracy = correct / len(train_loader.dataset)
    loss = loss / len(train_loader)
    train_loss = loss
    train_acc_history_medium.append(accuracy)
    train_loss_history_medium.append(loss)
    for key in rate_tracker.keys():
        lr_tracker[(epoch,key)] = rate_tracker[key]
```

```
    correct, loss, y_true_medium, y_pred_medium = evaluate(data_loader = test_loader, model=model, criterion=criterion)
    validation_accuracy = correct / len(test_loader.dataset)
    validation_loss = loss / len(test_loader)
    print(f"Train Accuracy: {accuracy*100:.2f}%, Train Loss: {train_loss}")
    print(f"Test Accuracy: {validation_accuracy*100:.2f}%, Test Loss: {validation_loss}")
    if validation_loss < best_valid_loss:
        best_valid_loss = validation_loss
        torch.save(model.state_dict(), 'ResNetMedium.pt')
    val_acc_history_medium.append(validation_accuracy)
    val_loss_history_medium.append(validation_loss)
```

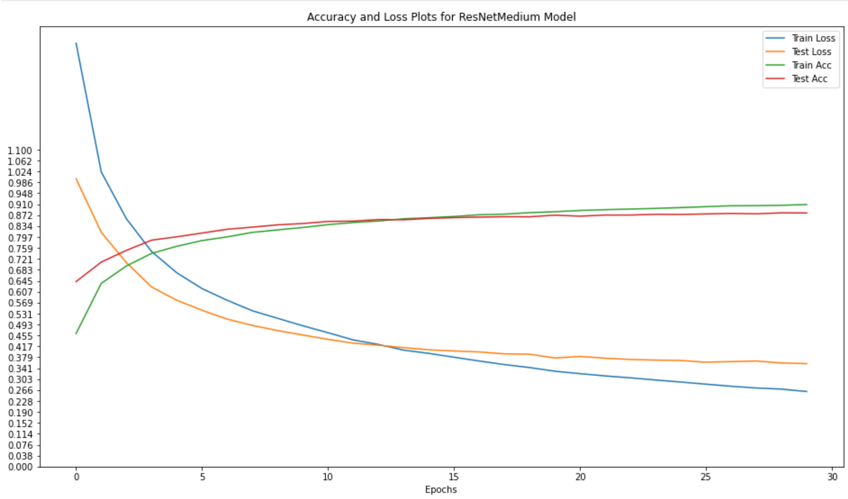
```
Epoch: 1/30
782it [00:07, 105.48it/s]
Train Accuracy: 46.18%, Train Loss: 1.4688814467633777
Test Accuracy: 64.18%, Test Loss: 0.9985658879492693
Epoch: 2/30
782it [00:07, 105.16it/s]
Train Accuracy: 63.56%, Train Loss: 1.0222012444072976
Test Accuracy: 70.96%, Test Loss: 0.812827889327031
Epoch: 3/30
782it [00:07, 106.27it/s]
Train Accuracy: 69.63%, Train Loss: 0.8594880220682725
Test Accuracy: 75.03%, Test Loss: 0.7075042455059708
Epoch: 4/30
782it [00:07, 106.92it/s]
Train Accuracy: 73.98%, Train Loss: 0.7459845128647812
Test Accuracy: 78.56%, Test Loss: 0.6229665603986971
Epoch: 5/30
782it [00:07, 107.37it/s]
Train Accuracy: 76.44%, Train Loss: 0.6723040058027447
Test Accuracy: 79.73%, Test Loss: 0.5769824285036439
Epoch: 6/30
782it [00:07, 106.98it/s]
Train Accuracy: 78.42%, Train Loss: 0.6175326255657484
Test Accuracy: 81.03%, Test Loss: 0.5423921880069053
Epoch: 7/30
782it [00:07, 104.66it/s]
Train Accuracy: 79.71%, Train Loss: 0.5769456775901872
Test Accuracy: 82.35%, Test Loss: 0.511577048783849
Epoch: 8/30
782it [00:07, 106.10it/s]
Train Accuracy: 81.26%, Train Loss: 0.5404994655638704
Test Accuracy: 83.08%, Test Loss: 0.4897377863051785
Epoch: 9/30
782it [00:07, 108.86it/s]
Train Accuracy: 82.12%, Train Loss: 0.5144487246870995
Test Accuracy: 83.87%, Test Loss: 0.4717256900421373
Epoch: 10/30
782it [00:07, 106.89it/s]
Train Accuracy: 82.97%, Train Loss: 0.4885648795787026
Test Accuracy: 84.34%, Test Loss: 0.456546327775451
Epoch: 11/30
782it [00:07, 106.55it/s]
Train Accuracy: 83.94%, Train Loss: 0.4644170618804215
Test Accuracy: 85.06%, Test Loss: 0.4415438612745066
Epoch: 12/30
782it [00:07, 103.43it/s]
Train Accuracy: 84.69%, Train Loss: 0.43958293130178283
Test Accuracy: 85.16%, Test Loss: 0.4281866009922544
Epoch: 13/30
782it [00:07, 105.33it/s]
Train Accuracy: 85.20%, Train Loss: 0.42381607920236297
Test Accuracy: 85.72%, Test Loss: 0.42119093191851475
Epoch: 14/30
782it [00:07, 108.28it/s]
Train Accuracy: 85.98%, Train Loss: 0.4039933187577426
Test Accuracy: 85.64%, Test Loss: 0.41263495081928886
Epoch: 15/30
782it [00:07, 103.39it/s]
Train Accuracy: 86.34%, Train Loss: 0.3928191062739438
Test Accuracy: 86.10%, Test Loss: 0.40537300136438603
Epoch: 16/30
782it [00:07, 107.83it/s]
Train Accuracy: 86.77%, Train Loss: 0.37938593587149744
Test Accuracy: 86.39%, Test Loss: 0.4011301859548897
Epoch: 17/30
782it [00:07, 104.63it/s]
Train Accuracy: 87.37%, Train Loss: 0.36636039492724193
Test Accuracy: 86.56%, Test Loss: 0.3977719046128024
Epoch: 18/30
782it [00:07, 108.38it/s]
Train Accuracy: 87.60%, Train Loss: 0.3539097967660031
Test Accuracy: 86.69%, Test Loss: 0.3911374845797089
Epoch: 19/30
782it [00:07, 106.17it/s]
Train Accuracy: 88.11%, Train Loss: 0.3435981313285925
Test Accuracy: 86.67%, Test Loss: 0.3899396312464574
Epoch: 20/30
782it [00:07, 103.32it/s]
Train Accuracy: 88.42%, Train Loss: 0.33097044855851654
Test Accuracy: 87.23%, Test Loss: 0.37678804993629456
Epoch: 21/30
782it [00:07, 106.50it/s]
Train Accuracy: 88.86%, Train Loss: 0.3224521252848303
Test Accuracy: 86.88%, Test Loss: 0.3822112738326856
Epoch: 22/30
782it [00:07, 106.45it/s]
Train Accuracy: 89.14%, Train Loss: 0.3145800076729959
Test Accuracy: 87.27%, Test Loss: 0.3760678332512546
Epoch: 23/30
782it [00:07, 105.88it/s]
Train Accuracy: 89.36%, Train Loss: 0.3078972375129952
Test Accuracy: 87.27%, Test Loss: 0.37165280327105976
Epoch: 24/30
782it [00:07, 107.70it/s]
Train Accuracy: 89.57%, Train Loss: 0.3004054766138801
Test Accuracy: 87.54%, Test Loss: 0.3694511747853771
Epoch: 25/30
782it [00:07, 107.85it/s]
Train Accuracy: 89.86%, Train Loss: 0.2933846808817533
Test Accuracy: 87.48%, Test Loss: 0.368121220142978
Epoch: 26/30
782it [00:07, 104.21it/s]
Train Accuracy: 90.18%, Train Loss: 0.2858991510213336
Test Accuracy: 87.67%, Test Loss: 0.36210738222120675
Epoch: 27/30
782it [00:07, 103.29it/s]
Train Accuracy: 90.49%, Train Loss: 0.27874315253761417
Test Accuracy: 87.84%, Test Loss: 0.36425760867679197
Epoch: 28/30
```

```
782it [00:07, 106.63it/s]
Train Accuracy: 90.53%, Train Loss: 0.27268813739118675
Test Accuracy: 87.72%, Test Loss: 0.36632380762677286
Epoch: 29/30
782it [00:07, 107.13it/s]
Train Accuracy: 90.67%, Train Loss: 0.2687381294262988
Test Accuracy: 88.04%, Test Loss: 0.3595244288444519
Epoch: 30/30
782it [00:07, 103.98it/s]
Train Accuracy: 90.93%, Train Loss: 0.2604838322724223
Test Accuracy: 87.99%, Test Loss: 0.3572485315002454
```

In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Dynamic Learning Rate behaviour during the training of ResNetMedium Model')
plt.plot(range(len(lr_tracker)), lr_tracker.values())
plt.xlabel('Batches')
plt.ylabel('Learning rate')
plt.show()
```

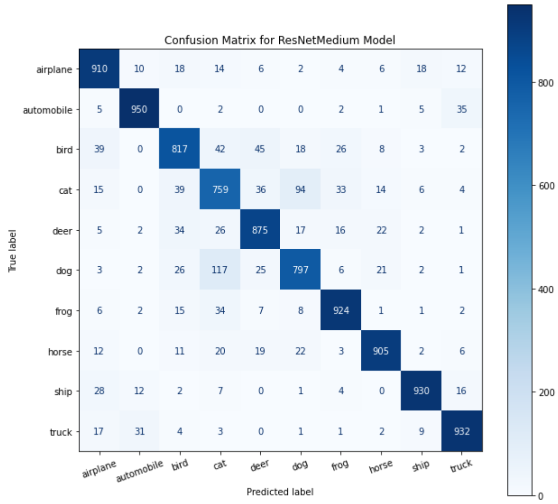


In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))

plt.title('Accuracy and Loss Plots for ResNetMedium Model')
plt.plot(train_loss_history_medium, label='Train Loss')
plt.plot(val_loss_history_medium, label='Test Loss')
plt.plot(train_acc_history_medium, label='Train Acc')
plt.plot(val_acc_history_medium, label='Test Acc')
plt.legend()
plt.xlabel("Epochs")
yticks = np.linspace(0, 1.1, num=30)
ax.set_yticks(yticks)
plt.show()
```



In [ ]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_true_medium, y_pred_medium)
fig = plt.figure(figsize = (10, 10));
ax = fig.add_subplot(1, 1, 1);
ax.set_title('Confusion Matrix for ResNetMedium Model')
cm = ConfusionMatrixDisplay(cm, display_labels = classes);
cm.plot(values_format = 'd', cmap = 'Blues', ax = ax)
plt.xticks(rotation = 20)
```

Out[ ]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'airplane'),
  Text(1, 0, 'automobile'),
  Text(2, 0, 'bird'),
  Text(3, 0, 'cat'),
  Text(4, 0, 'deer'),
  Text(5, 0, 'dog'),
  Text(6, 0, 'frog'),
  Text(7, 0, 'horse'),
  Text(8, 0, 'ship'),
  Text(9, 0, 'truck')])
```



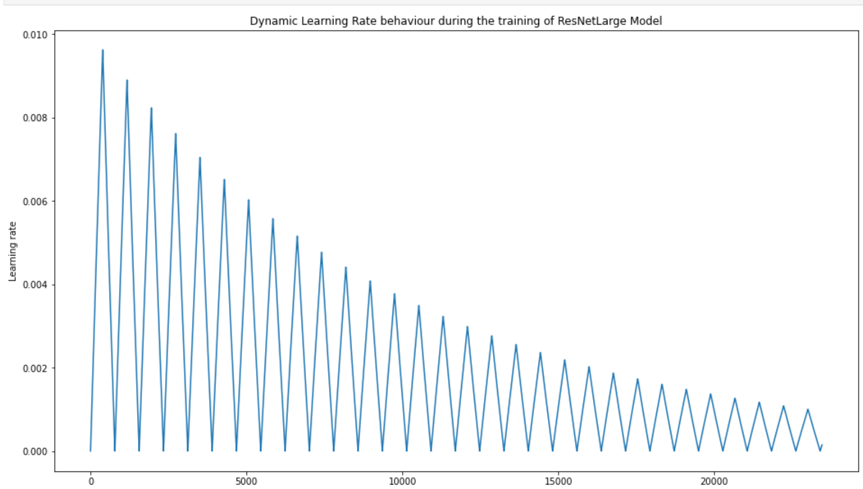
In [ ]:
```python
lr_min = 1e-6
lr_max = 1e-2
epochs = 30
step_size = (len(train_dataset)/64) // 2

model = modellarge
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=lr_min, momentum=0.9, nesterov=True)
scheduler = optim.lr_scheduler.CyclicLR(optimizer, base_lr=lr_min, max_lr=lr_max, step_size_up=step_size, step_size_down=step_size, gamma=0.9999, mode="exp_range", cycle_momentum=False)
lr_tracker = {}

train_loss_history_large = []
train_acc_history_large = []
val_loss_history_large = []
val_acc_history_large = []
y_pred_large = []
y_true_large = []
best_valid_loss = float('inf')

for epoch in range(epochs):
    print(f"Epoch: {epoch+1}/{epochs}")
    correct, loss, rate_tracker = train(data_loader=train_loader, model=model, criterion=criterion, optimizer=optimizer, scheduler=scheduler)
    accuracy = correct / len(train_loader.dataset)
    loss = loss / len(train_loader)
    train_loss = loss
    train_acc_history_large.append(accuracy)
    train_loss_history_large.append(loss)
    for key in rate_tracker.keys():
        lr_tracker[(epoch,key)] = rate_tracker[key]
    correct, loss, y_true_large, y_pred_large = evaluate(data_loader = test_loader, model=model, criterion=criterion)
    validation_accuracy = correct / len(test_loader.dataset)
    validation_loss = loss / len(test_loader)
    print(f"Train Accuracy: {accuracy*100:.2f}%, Train Loss: {train_loss}")
    print(f"Test Accuracy: {validation_accuracy*100:.2f}%, Test Loss: {validation_loss}")
    if validation_loss < best_valid_loss:
        best_valid_loss = validation_loss
        torch.save(model.state_dict(), 'ResNetLarge.pt')
    val_acc_history_large.append(validation_accuracy)
    val_loss_history_large.append(validation_loss)
```

```
Epoch: 1/30
782it [00:10, 77.87it/s]
Train Accuracy: 48.92%, Train Loss: 1.4058114572254288
Test Accuracy: 67.16%, Test Loss: 0.9061055942705483
Epoch: 2/30
782it [00:09, 78.98it/s]
Train Accuracy: 66.51%, Train Loss: 0.9404833051935791
Test Accuracy: 73.88%, Test Loss: 0.7336463125268365
Epoch: 3/30
782it [00:10, 78.02it/s]
Train Accuracy: 72.53%, Train Loss: 0.77577556170466
Test Accuracy: 77.88%, Test Loss: 0.6237734108214166
Epoch: 4/30
782it [00:10, 78.19it/s]
Train Accuracy: 76.42%, Train Loss: 0.6752028043389016
Test Accuracy: 81.01%, Test Loss: 0.5592745715265821
Epoch: 5/30
782it [00:10, 77.55it/s]
Train Accuracy: 78.86%, Train Loss: 0.6052702906567727
Test Accuracy: 82.03%, Test Loss: 0.5175294848574195
Epoch: 6/30
782it [00:09, 78.68it/s]
Train Accuracy: 81.01%, Train Loss: 0.5501928740297742
Test Accuracy: 83.42%, Test Loss: 0.4905243561526013
Epoch: 7/30
782it [00:09, 78.51it/s]
Train Accuracy: 82.43%, Train Loss: 0.5081557086323534
Test Accuracy: 84.51%, Test Loss: 0.4533748639996644
Epoch: 8/30
782it [00:09, 79.31it/s]
Train Accuracy: 83.75%, Train Loss: 0.4682275569995346
Test Accuracy: 85.21%, Test Loss: 0.44090694616175
Epoch: 9/30
782it [00:09, 78.73it/s]
Train Accuracy: 84.74%, Train Loss: 0.44072029074592056
Test Accuracy: 85.90%, Test Loss: 0.4206506500768054
Epoch: 10/30
782it [00:09, 78.85it/s]
Train Accuracy: 85.72%, Train Loss: 0.4126177037425358
Test Accuracy: 86.30%, Test Loss: 0.40764474109479576
Epoch: 11/30
782it [00:09, 78.94it/s]
Train Accuracy: 86.45%, Train Loss: 0.3917580034841052
Test Accuracy: 86.57%, Test Loss: 0.39937475295203506
Epoch: 12/30
782it [00:09, 78.92it/s]
Train Accuracy: 87.17%, Train Loss: 0.37006695851531174
Test Accuracy: 87.03%, Test Loss: 0.383157089827167
Epoch: 13/30
782it [00:10, 77.75it/s]
```

```
Train Accuracy: 88.11%, Train Loss: 0.3458830364753523
Test Accuracy: 87.59%, Test Loss: 0.36779645512438125
Epoch: 14/30
782it [00:09, 78.64it/s]
Train Accuracy: 88.46%, Train Loss: 0.3313629613889148
Test Accuracy: 87.90%, Test Loss: 0.3625057391869794
Epoch: 15/30
782it [00:09, 79.02it/s]
Train Accuracy: 89.08%, Train Loss: 0.3158440920988769
Test Accuracy: 88.01%, Test Loss: 0.35847265520103416
Epoch: 16/30
782it [00:10, 77.83it/s]
Train Accuracy: 89.57%, Train Loss: 0.3024188351086186
Test Accuracy: 87.97%, Test Loss: 0.3555400956683098
Epoch: 17/30
782it [00:10, 78.17it/s]
Train Accuracy: 90.27%, Train Loss: 0.28528198902792945
Test Accuracy: 88.53%, Test Loss: 0.3485969147010214
Epoch: 18/30
782it [00:09, 78.50it/s]
Train Accuracy: 90.64%, Train Loss: 0.2724381180675438
Test Accuracy: 88.51%, Test Loss: 0.3466635327430288
Epoch: 19/30
782it [00:09, 78.40it/s]
Train Accuracy: 90.91%, Train Loss: 0.2608195971554655
Test Accuracy: 88.87%, Test Loss: 0.3394074491254843
Epoch: 20/30
782it [00:09, 78.74it/s]
Train Accuracy: 91.40%, Train Loss: 0.2494079852309983
Test Accuracy: 88.81%, Test Loss: 0.3330639451742172
Epoch: 21/30
782it [00:10, 77.81it/s]
Train Accuracy: 91.70%, Train Loss: 0.24052330293237706
Test Accuracy: 89.07%, Test Loss: 0.3327259635374804
Epoch: 22/30
782it [00:09, 78.45it/s]
Train Accuracy: 91.98%, Train Loss: 0.23239734841277226
Test Accuracy: 89.14%, Test Loss: 0.32689990112735967
Epoch: 23/30
782it [00:10, 78.02it/s]
Train Accuracy: 92.40%, Train Loss: 0.21973636169986957
Test Accuracy: 89.07%, Test Loss: 0.32861825183128857
Epoch: 24/30
782it [00:09, 78.22it/s]
Train Accuracy: 92.76%, Train Loss: 0.21252951015006094
Test Accuracy: 88.82%, Test Loss: 0.329613656327603
Epoch: 25/30
782it [00:09, 79.11it/s]
Train Accuracy: 93.05%, Train Loss: 0.20455673771917515
Test Accuracy: 89.00%, Test Loss: 0.3305412292195733
Epoch: 26/30
782it [00:10, 77.56it/s]
Train Accuracy: 93.26%, Train Loss: 0.19517021642907348
Test Accuracy: 89.21%, Test Loss: 0.33258719144353444
Epoch: 27/30
782it [00:09, 79.10it/s]
Train Accuracy: 93.64%, Train Loss: 0.18944301981659953
Test Accuracy: 89.11%, Test Loss: 0.32758472826640317
Epoch: 28/30
782it [00:10, 77.56it/s]
Train Accuracy: 93.63%, Train Loss: 0.18426255238673572
Test Accuracy: 89.47%, Test Loss: 0.3239446260082494
Epoch: 29/30
782it [00:09, 79.28it/s]
Train Accuracy: 94.02%, Train Loss: 0.1789445672327143
Test Accuracy: 89.32%, Test Loss: 0.3247904695428101
Epoch: 30/30
782it [00:10, 77.78it/s]
Train Accuracy: 94.10%, Train Loss: 0.17178399384002704
Test Accuracy: 89.34%, Test Loss: 0.3246337286890692
```

In [ ]:

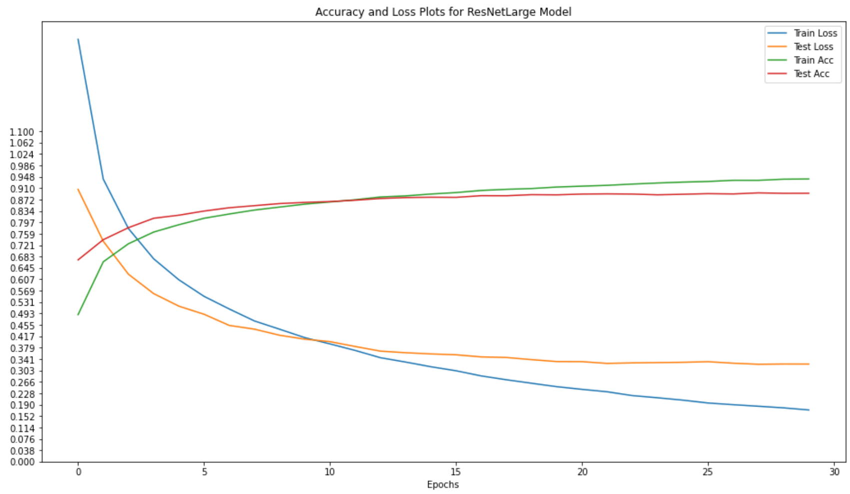
```python
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Dynamic Learning Rate behaviour during the training of ResNetLarge Model')
plt.plot(range(len(lr_tracker)), lr_tracker.values())
plt.xlabel('Batches')
plt.ylabel('Learning rate')
plt.show()
```



In [ ]:

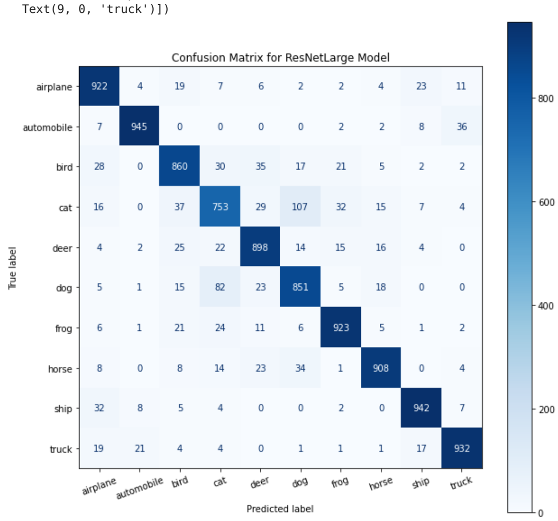
```python
fig, ax = plt.subplots(figsize=(16,9))

plt.title('Accuracy and Loss Plots for ResNetLarge Model')
plt.plot(train_loss_history_large, label='Train Loss')
plt.plot(val_loss_history_large, label='Test Loss')
plt.plot(train_acc_history_large, label='Train Acc')
plt.plot(val_acc_history_large, label='Test Acc')
plt.legend()
plt.xlabel("Epochs")
yticks = np.linspace(0, 1.1, num=30)
```

```
ax.set_yticks(yticks)
plt.show()
```

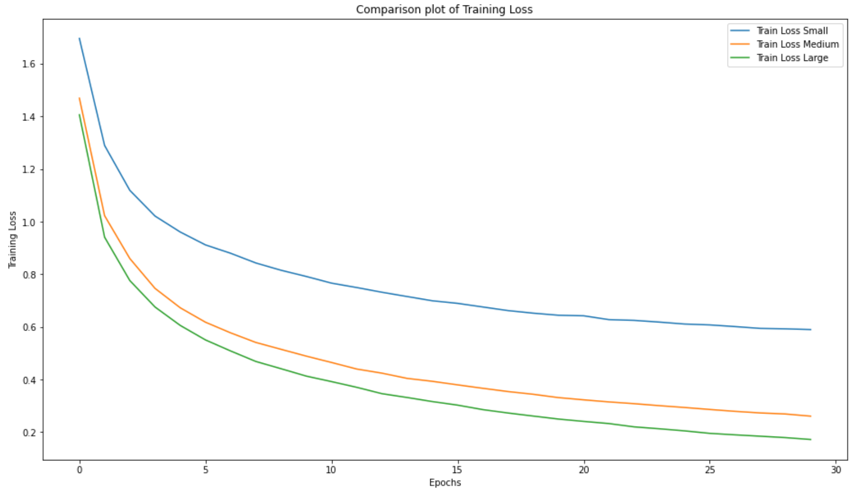


In [ ]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_true_large, y_pred_large)
fig = plt.figure(figsize = (10, 10));
ax = fig.add_subplot(1, 1, 1);
ax.set_title('Confusion Matrix for ResNetLarge Model')
cm = ConfusionMatrixDisplay(cm, display_labels = classes);
cm.plot(values_format = 'd', cmap = 'Blues', ax = ax)
plt.xticks(rotation = 20)
```

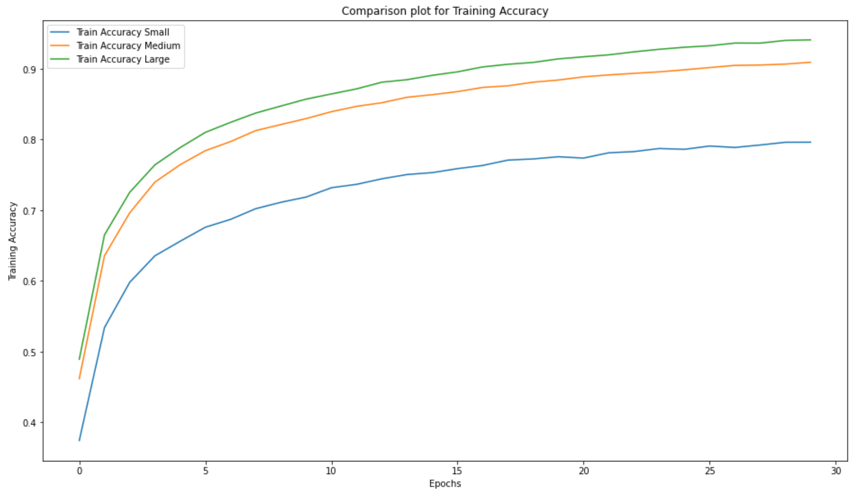
Out[ ]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'airplane'),
  Text(1, 0, 'automobile'),
  Text(2, 0, 'bird'),
  Text(3, 0, 'cat'),
  Text(4, 0, 'deer'),
  Text(5, 0, 'dog'),
  Text(6, 0, 'frog'),
  Text(7, 0, 'horse'),
  Text(8, 0, 'ship'),
  Text(9, 0, 'truck')])
```



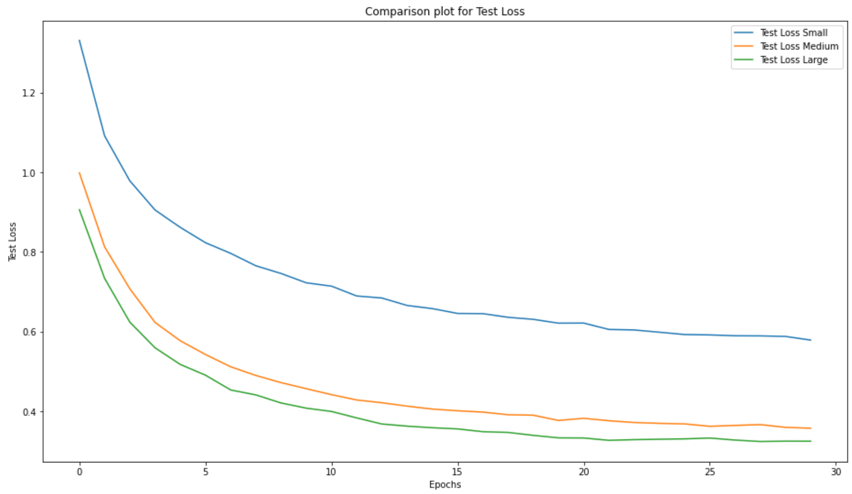
In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Comparison plot of Training Loss')
plt.plot(train_loss_history_small, label='Train Loss Small')
plt.plot(train_loss_history_medium, label='Train Loss Medium')
plt.plot(train_loss_history_large, label='Train Loss Large')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Training Loss")
plt.show()
```



In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Comparison plot for Training Accuracy')
plt.plot(train_acc_history_small, label='Train Accuracy Small')
plt.plot(train_acc_history_medium, label='Train Accuracy Medium')
plt.plot(train_acc_history_large, label='Train Accuracy Large')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Training Accuracy")
plt.show()
```



In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Comparison plot for Test Loss')
plt.plot(val_loss_history_small, label='Test Loss Small')
plt.plot(val_loss_history_medium, label='Test Loss Medium')
plt.plot(val_loss_history_large, label='Test Loss Large')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Test Loss")
plt.show()
```



In [ ]:
```
fig, ax = plt.subplots(figsize=(16,9))
plt.title('Comparison plot for Test Accuracy')
plt.plot(val_acc_history_small, label='Test Accuracy Small')
plt.plot(val_acc_history_medium, label='Test Accuracy Medium')
plt.plot(val_acc_history_large, label='Test Accuracy Large')
plt.legend()
plt.xlabel("Epochs")
```

```
plt.ylabel("Test Accuracy")
plt.show()
```