CIFAR-100 Homework_v002

February 23, 2023

You can check and explore further methods applied the tasks we have previously covered from the following link: https://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html#43494641522d313030

Skeleton code is provided from the following tutorial: https://pytorch.org/tutorials/beginner/blitz/cifar10_tutoria

Dataset: https://pytorch.org/docs/stable/_modules/torchvision/datasets/cifar.html#CIFAR100

[ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
import torchvision
import torchvision.transforms as transforms
import numpy as np
import pandas as pd
import cv2
from scipy.ndimage.interpolation import map_coordinates
from scipy.ndimage.filters import gaussian_filter
import matplotlib.pyplot as plt
import math
from timeit import default_timer as timer

print("Versions.........")
print("torch:       ", torch.__version__)
print("torchvision: ", torchvision.__version__)
```

```
D:\Anaconda3\envs\myEnv001\lib\site-packages\numpy\_distributor_init.py:30:
UserWarning: loaded more than 1 DLL from .libs:
D:\Anaconda3\envs\myEnv001\lib\site-
packages\numpy\.libs\libopenblas.EL2C6PLE4ZYW3ECEVIV3OXXGRN2NRFM2.gfortran-
win_amd64.dll
D:\Anaconda3\envs\myEnv001\lib\site-
packages\numpy\.libs\libopenblas.PYQHXLVVQ7VESDPUVUADXEVJOBGHJPAY.gfortran-
win_amd64.dll
  warnings.warn("loaded more than 1 DLL from .libs:"
```

```
Versions…
torch:       1.10.1+cu102
```

```
torchvision:  0.11.2+cu102
```

0.0.1 Defining and testing custom image transformation

```
[ ]: # [DONE] TODO: write at least one data transform or augmentation method␣
     ↪yourself ==> DONE
     class ElasticDeformation(object):
         """Elastic deformation used as image augmentation for classification task,␣
     ↪as per the follwoing paper.
         Simard, Steinkraus and Platt, "Best Practices for Convolutional Neural␣
     ↪Networks applied to Visual Document Analysis",
         in Proc. of the International Conference on Document Analysis and␣
     ↪Recognition, 2003.

         Note that calling this class's function will treat its image input␣
     ↪according to its class.
         If the image is a numpy array, it will be treated like an OpenCV image␣
     ↪(channels last; H,W,C)
         If the image is a torch.tensor, it will be treated accordingly (channels␣
     ↪first; C,H,W)

         Args:

         :param alpha: Size of distortion (pixels). typical value is between 1.5 and␣
     ↪3 x image height
         :param sigma: Variance of the Gaussian distribution with whom the uniform␣
     ↪random displacement fields will be convolved. Typical value is between 0.01␣
     ↪and 0.1 image height.
         :param alpha_affine: Size of the affine transformations. Typical value is␣
     ↪between 0.01 and 0.1 image height.
         :param random_state: State of the RNG for reproducibility of random␣
     ↪displacement fields. Default is None.
         :param probability: Chance of the transform happening (it is a random␣
     ↪deformation). Default is 1.0, meaning the transformation will definitely␣
     ↪happen.
         :param output: Type of output for its callable function. Options are␣
     ↪'array' for OpenCV output (channels last), or 'tensor' for PyTorch Tensor␣
     ↪(channels first)
         """
         def __init__(self, alpha, sigma, alpha_affine, random_state=None,␣
     ↪probability=1.0, output='array'):
             self.alpha = alpha
             self.sigma = sigma
             self.alpha_affine = alpha_affine
             self.random_state = random_state
             self.probability = probability
```

```
        self.output = output


    def __call__(self, image):
        """Perform elastic transformation on an image using the class␣
↪parameters for transformation.

        Args:
            :param image (numpy.ndarray or torch.tensor): Input image or tensor␣
↪of image.
                Note that calling this class's function will treat its image␣
↪input according to its class.
                If the image is a numpy array, it will be treated like an␣
↪OpenCV image (channels last; H,W,C)
                If the image is a torch.tensor, it will be treated accordingly␣
↪(channels first; C,H,W)

        Returns:
            :return image: If output=='array' in constructor, output will be an␣
↪OpenCV array (channels last), if output=='tensor', a PyTorch tensor␣
↪(channels first) will be returned.
        """
        if self.random_state is None:
            random_state = np.random.RandomState(None)

        if np.random.uniform() > self.probability:
            if 'tensor' in type(image).__name__.lower():
                if self.output=='tensor':
                    return image
                else:
                    return image.numpy().transpose((1,2,0))
            else:
                if self.output=='tensor':
                    return torch.tensor(image.transpose((2,0,1)))
                else:
                    return image

        image = image.numpy().transpose((1,2,0)) if 'tensor' in type(image).
↪__name__.lower() else image

        shape = image.shape
        shape_size = shape[:2]

        # Random affine
        center_square = np.float32(shape_size) // 2
        square_size = min(shape_size) // 3
```

```python
        pts1 = np.float32([center_square + square_size,␣
↪[center_square[0]+square_size, center_square[1]-square_size], center_square␣
↪- square_size])
        pts2 = pts1 + random_state.uniform(-self.alpha_affine, self.
↪alpha_affine, size=pts1.shape).astype(np.float32)
        M = cv2.getAffineTransform(pts1, pts2)
        image = cv2.warpAffine(image, M, shape_size[::-1], borderMode=cv2.
↪BORDER_REFLECT_101)

        dx = gaussian_filter((random_state.rand(*shape) * 2 - 1), self.sigma) *␣
↪self.alpha
        dy = gaussian_filter((random_state.rand(*shape) * 2 - 1), self.sigma) *␣
↪self.alpha
        dz = np.zeros_like(dx)

        x, y, z = np.meshgrid(np.arange(shape[1]), np.arange(shape[0]), np.
↪arange(shape[2]))
        indices = np.reshape(y+dy, (-1, 1)), np.reshape(x+dx, (-1, 1)), np.
↪reshape(z, (-1, 1))

        out = map_coordinates(image, indices, order=1, mode='reflect').
↪reshape(shape)
        return out if self.output=='array' else torch.tensor(out.
↪transpose((2,0,1)))


    def __repr__(self):
        return self.__class__.__name__+"(\n"+\
            "    alpha = {},\n".format(self.alpha)+\
            "    sigma = {},\n".format(self.sigma)+\
            "    alpha_affine = {},\n".format(self.alpha_affine)+\
            "    random_state = {},\n".format(self.random_state)+\
            "    probability = {},\n".format(self.probability)+\
            "    output = {})".format(self.output)


def elastic_transform_batch(batch, alpha, sigma, alpha_affine,␣
↪random_state=None, probability=1.0):
    # Perform Elastic Deformation on a whole batch. Here, batch can also be a␣
↪torch tensor from a dataloader or something.
    distorter = ElasticDeformation(alpha, sigma, alpha_affine, random_state,␣
↪probability, output='array')
    return np.concatenate([distorter(img) for img in batch]).reshape(batch.
↪shape)
```

```python
# Testing the elastic distorter
sampleset = torchvision.datasets.CIFAR100(root='./data/sample', train=False,␣
↪download=True)
sampledata = sampleset.data[np.random.choice(len(sampleset),10),...]
h,w = sampledata.shape[1:3]
sampledata_deformed = elastic_transform_batch(sampledata, w*1.1, w*0.1, w*0.02)
plt.figure(figsize = (5,25))
i = 0
for idx in range(10):
    i += 1
    plt.subplot(10,2,i)
    plt.imshow(sampledata[idx,...])
    plt.axis('off')
    if i == 1: plt.title('Original')
    i += 1
    plt.subplot(10,2,i)
    plt.imshow(sampledata_deformed[idx,...])
    if i == 2: plt.title('Deformed')
    plt.axis('off')
plt.show()
```

```
Files already downloaded and verified
```


Original
Deformed

0.0.2 Preliminaries and Data Loaders

[ ]:
```
# [DONE] TODO: You may consider appyling more transform such as data␣
 ↪augmentation methods, etc.
# TODO: You may consider hyperparameter optimization: in this cell, we have␣
 ↪batch_size!
# [DONE] TODO: use the previously defined data transform/augmentation method in␣
 ↪the following transform.

# Global constants
ELASTIC_ALPHA = 32*1.1
ELASTIC_SIGMA = 32*0.1
ELASTIC_ALPHA_AFFINE = 32*0.02
ELASTIC_PROBABILITY = 0.5
P_VERT_FLIP = 0.5
P_HORZ_FLIP = 0.5
JITTER_BRIGHTNESS = 0.1
JITTER_SATURATION = 0.1
JITTER_CONTRAST = 0.2
AFFINE_ROTATION = 50
AFFINE_TRANSLATION = (0.1, 0.1)
AFFINE_SCALE = (0.5, 1.5)
AFFINE_SHEAR = 20
NORM_MEAN = (0.5, 0.5, 0.5)
NORM_STD = (0.5, 0.5, 0.5)
VALIDATION_DATA = 0.2
NUM_HPO_TRIALS = 10
HPO_TIMEOUT_SEC = 3600 * 5
NUM_HPO_JOBS = 1

# Hyperparameters
hparams = {
    'input_image_size':[32, 32],
    'batch_size': 256,
    'epochs': 10,
    'lr': 0.001,
    'loss_function': nn.CrossEntropyLoss(),
    'optimizer':'adam',
    'optimizer_params':None,
    'num_conv_blocks': 3,
    'num_dense_layers':3,
    'conv_kernel_size':5,
    'pool_kernel_size':2,
    'conv_padding':0,
```

```
    'pool_padding':0,
    'conv_activations':'relu',
    'dense_activations':'relu',
    'conv_batchnorm':'before',
    'dense_batchnorm':'before',
    'conv_stride':1,
    'pool_stride':1,
    'dense_sizes':[256,128],
    'conv_dropout':0.2,
    'dense_dropout':0.2,
    'L2':0.001,
    'num_classes':100}


transform = transforms.Compose([
        transforms.ToTensor(),
        ElasticDeformation(ELASTIC_ALPHA, ELASTIC_SIGMA, ELASTIC_ALPHA_AFFINE,␣
 ↪random_state=None, probability=ELASTIC_PROBABILITY, output='tensor'),
        transforms.RandomVerticalFlip(P_VERT_FLIP),
        transforms.RandomHorizontalFlip(P_HORZ_FLIP),
        transforms.ColorJitter(brightness=JITTER_BRIGHTNESS,␣
 ↪contrast=JITTER_CONTRAST, saturation=JITTER_SATURATION),
        transforms.RandomAffine(AFFINE_ROTATION, AFFINE_TRANSLATION,␣
 ↪AFFINE_SCALE, AFFINE_SHEAR),
        transforms.Normalize(NORM_MEAN, NORM_STD)])


allset = torchvision.datasets.CIFAR100(root='./data/CIFAR100', train=True,␣
 ↪download=True, transform=transform)
num_all_data = len(allset.data)
num_val_data, num_train_data = int(VALIDATION_DATA*num_all_data),␣
 ↪int((1-VALIDATION_DATA)*num_all_data)
(trainset, valset) = random_split(allset, (num_train_data, num_val_data),␣
 ↪generator=torch.Generator().manual_seed(42))
trainloader = DataLoader(trainset, batch_size=hparams['batch_size'],␣
 ↪shuffle=True, num_workers=0)
validloader = DataLoader(valset, batch_size=hparams['batch_size'],␣
 ↪shuffle=True, num_workers=0)
testset = torchvision.datasets.CIFAR100(root='./data/CIFAR100', train=False,␣
 ↪download=True, transform=transform)
testloader = DataLoader(testset, batch_size=hparams['batch_size'],␣
 ↪shuffle=False, num_workers=0)

classes = ('apples', 'aquarium fish', 'baby', 'bear', 'beaver', 'bed', 'bee',␣
 ↪'beetle', 'bicycle', 'bottles',
```

```
          'bowls', 'boy', 'bridge', 'bus', 'butterfly', 'camel', 'cans',␣
↪'castle', 'caterpillar', 'cattle', 'chair',
          'chimpanzee', 'clock', 'cloud', 'cockroach', 'computer keyboard',␣
↪'couch', 'crab', 'crocodile',
          'cups', 'dinosaur', 'dolphin', 'elephant', 'flatfish', 'forest',␣
↪'fox', 'girl', 'hamster', 'house',
          'kangaroo', 'lamp', 'lawn-mower', 'leopard', 'lion', 'lizard',␣
↪'lobster', 'man', 'maple', 'motorcycle',
          'mountain', 'mouse', 'mushrooms', 'oak', 'oranges', 'orchids',␣
↪'otter', 'palm', 'pears', 'pickup truck',
          'pine', 'plain', 'plates', 'poppies', 'porcupine', 'possum',␣
↪'rabbit', 'raccoon', 'ray', 'road', 'rocket',
          'roses', 'sea', 'seal', 'shark', 'shrew', 'skunk', 'skyscraper',␣
↪'snail', 'snake', 'spider', 'squirrel',
          'streetcar', 'sunflowers', 'sweet peppers', 'table', 'tank',␣
↪'telephone', 'television', 'tiger', 'tractor',
          'train', 'trout', 'tulips', 'turtle', 'wardrobe', 'whale', 'willow',␣
↪'wolf', 'woman', 'worm')
```

```
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Files already downloaded and verified
```

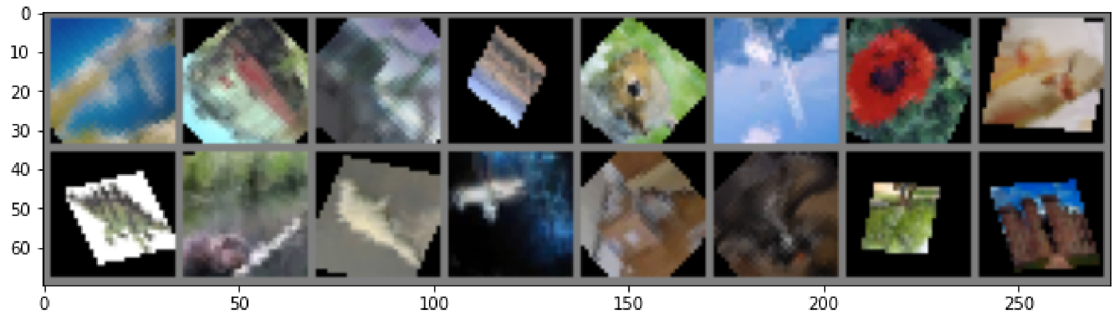
0.0.3 Visualizing some normalized images

[ ]:
```
def imshow(img):
    img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.figure(figsize=(12,3))
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# get some random training images
dataiter = iter(trainloader)

images, labels = dataiter.next()
#images, labels = testloader[0]
print("Shape of images: ", images.shape)
print("Shape of labels: ", labels.shape)
print(labels)
# show images
imshow(torchvision.utils.make_grid(images[:16]))
# print labels
print(', '.join('%5s' % classes[labels[j]] for j in range(16)))
```

```
Shape of images:  torch.Size([1024, 3, 32, 32])
Shape of labels:  torch.Size([1024])
tensor([49, 90,  8,  …, 82,  9, 84])
```




```
mountain, train, bicycle, plain, squirrel, mountain, poppies, trout,  cups,
beaver,  crab, shark, rabbit, motorcycle, willow, castle
```

0.0.4 Constructing CNN model

```
[ ]: # Base model, not to be used here
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 16, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(16, 32, 5)
        self.fc1 = nn.Linear(32 * 5 * 5, 200)
        self.fc2 = nn.Linear(200, 128)
        self.fc3 = nn.Linear(128, 100)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 32 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

```
[ ]: # [DONE] (Optional but highly recommended) TODO: You can define your own neural␣
 ↪network to create a better performing model!
class ConvNet(nn.Module):
    def __init__(self, hparams:dict):
        super(ConvNet, self).__init__()
        self.hparams = hparams
        self.layers = []
        self._img_size = self.hparams['input_image_size']
        self._h, self._w = self._img_size
        self._img_size_list = [[3, self._h, self._w]]
```

```
        self._actdict = {'relu':nn.ReLU(), 'leakyrelu':nn.LeakyReLU(0.1),␣
↪'sigmoid':nn.Sigmoid(), 'tanh':nn.Tanh()}

        # Constructing the encoder (feature extractor)
        in_channels = 3
        out_channels = 16
        for i in range(self.hparams['num_conv_blocks']):
            self.layers.append(nn.Conv2d(in_channels, out_channels, self.
↪hparams['conv_kernel_size'], padding=self.hparams['conv_padding'],␣
↪stride=self.hparams['conv_stride']))
            self._update_image_size(out_channels, 'conv')
            if self.hparams['conv_batchnorm']=='before':
                self.layers.append(nn.BatchNorm2d(out_channels))
            self.layers.append(self._actdict[self.hparams['conv_activations']])
            if self.hparams['conv_batchnorm']=='after':
                self.layers.append(nn.BatchNorm2d(out_channels))
            self.layers.append(nn.MaxPool2d(self.hparams['pool_kernel_size'],␣
↪padding=self.hparams['pool_padding'], stride=self.hparams['pool_stride']))
            self._update_image_size(out_channels, 'pool')
            if self.hparams.get('conv_dropout'):
                self.layers.append(nn.Dropout2d(self.hparams['conv_dropout']))
            if i < self.hparams['num_conv_blocks'] - 1:
                in_channels = out_channels
                out_channels *= 2

        # Flattening (Image embedding)
        self.layers.append(nn.Flatten())

        # Constructing the decoder (classifier)
        if self.hparams.get('dense_sizes'):
            size_vec = self.hparams.get('dense_sizes')
        else:
            size_vec = [0] * self.hparams['num_dense_layers']
            size_vec[-1] = np.power(2, np.ceil(np.log2(self.
↪hparams['num_classes']))).astype(int)
            for i in range(self.hparams['num_dense_layers']-2, -1, -1):
                size_vec[i] = size_vec[i+1] * 2
        in_size = out_channels*self._h*self._w
        out_size = size_vec[0]
        for i in range(len(size_vec)):
            self.layers.append(nn.Linear(in_size, out_size))
            if self.hparams['dense_batchnorm'] == 'before':
                self.layers.append(nn.BatchNorm1d(out_size))
            self.layers.append(self._actdict[self.hparams['dense_activations']])
            if self.hparams['dense_batchnorm'] == 'after':
                self.layers.append(nn.BatchNorm1d(out_size))
            if self.hparams.get('dense_dropout'):
```

```python
                self.layers.append(nn.Dropout(self.hparams['dense_dropout']))
            if i < len(size_vec) - 1:
                in_size = out_size
                out_size = size_vec[i+1]
        self.layers.append(nn.Linear(out_size, self.hparams['num_classes']))

        # Constructing model
        self.net = nn.Sequential(*self.layers)


    def _calc_size(self, size_in:int, padding:int, kernel_size:int, stride:int):
        if padding == 'valid':
            padding=0
        if padding=='same':
            return size_in
        else:
            return math.floor((size_in + 2*padding - (kernel_size-1) - 1)/
↪stride + 1)


    def _update_image_size(self, out_channels, ops:str='conv'):
        (self._h, self._w) = (self._calc_size(sz, self.hparams[ops+'_padding'],␣
↪self.hparams[ops+'_kernel_size'], self.hparams[ops+'_stride']) for sz in␣
↪(self._h,self._w))
        self._img_size = (self._h, self._w)
        #print("new size: ",self._img_size)
        self._img_size_list.append([out_channels, self._h, self._w])

    def forward(self, x:torch.Tensor):
        return self.net(x)


# Instantiation
inzvaNet = ConvNet(hparams)
print("Built network is:")
print(inzvaNet)
print("Image sizes as they go through the convolution blocks:")
print(np.array(inzvaNet._img_size_list))
```

```
Built network is:
ConvNet(
  (net): Sequential(
    (0): Conv2d(3, 16, kernel_size=(5, 5), stride=(1, 1))
    (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1,
```

```
ceil_mode=False)
    (4): Dropout2d(p=0.2, inplace=False)
    (5): Conv2d(16, 32, kernel_size=(5, 5), stride=(1, 1))
    (6): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (7): ReLU()
    (8): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1,
ceil_mode=False)
    (9): Dropout2d(p=0.2, inplace=False)
    (10): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
    (11): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (12): ReLU()
    (13): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1,
ceil_mode=False)
    (14): Dropout2d(p=0.2, inplace=False)
    (15): Flatten(start_dim=1, end_dim=-1)
    (16): Linear(in_features=18496, out_features=256, bias=True)
    (17): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (18): ReLU()
    (19): Dropout(p=0.2, inplace=False)
    (20): Linear(in_features=256, out_features=128, bias=True)
    (21): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (22): ReLU()
    (23): Dropout(p=0.2, inplace=False)
    (24): Linear(in_features=128, out_features=100, bias=True)
  )
)
Image sizes as they go through the convolution blocks:
[[ 3 32 32]
 [16 28 28]
 [16 27 27]
 [32 23 23]
 [32 22 22]
 [64 18 18]
 [64 17 17]]
```

0.0.5 Checking GPU availability

[ ]:
```python
# if you want to train on GPU:
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

0.0.6 Instantiating CNN and defining training procedure

[ ]:
```python
inzvaNet.to(device)
inzvaNet.train()

# base optimizer with following parameters:
criterion = hparams['loss_function']
if hparams['optimizer']=='adam':
    if hparams.get('optimizer_params'):
        optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'],␣
 ↪**hparams['optimizer_params'])
    else:
        optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'])
elif hparams['optimizer']=='sgd':
    if hparams.get('optimizer_params'):
        optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'],␣
 ↪**hparams['optimizer_params'])
    else:
        optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'])
else:
    raise ValueError("Sorry, only 'adam' and 'sgd' are supported for now.")

# optimizer = optim.SGD(inzvaNet.parameters(), lr=0.001, momentum=0.9)
# TODO: play with hyperparameters and chosen methods to achieve higher accuracy!
 ↪ You can apply grid or random search.
```

0.0.7 Training

[ ]:
```python
# Training loop
print('training starts!')
num_training_batches = len(trainloader)
num_validation_batches = len(validloader)
num_testing_batches = len(testloader)

tStart = timer()
for epoch in range(hparams["epochs"]):

    epoch_loss_training = 0.0
    epoch_loss_validation = 0.0

    inzvaNet.train()
    for i, data in enumerate(trainloader):
        images, labels = data[0].to(device), data[1].to(device)
        optimizer.zero_grad()
        predictions = inzvaNet(images)
        loss = criterion(predictions, labels)
        loss.backward()
```

```
        optimizer.step()
        epoch_loss_training += loss.item()

    inzvaNet.eval()
    with torch.no_grad():
        for i, data in enumerate(validloader):
            images, labels = data[0].to(device), data[1].to(device)
            predictions = inzvaNet(images)
            loss = criterion(predictions, labels)
            epoch_loss_validation += loss.item()

    print("Epoch:  %2d\t|Training Loss:   %.3f\t|Validation Loss:   %.3f" %␣
↪(epoch + 1,
        epoch_loss_training / num_training_batches,
        epoch_loss_validation / num_validation_batches))

tFinish = timer()
print('Finished Training.')
print("Training process took %.2f seconds."%(tFinish-tStart))
print("Saving model...")
try:
    torch.save(inzvaNet, "ConvNet.pth")
except Exception as e:
    print(e)
    print("Failed to save the model.")
print("Done.")
```

```
training starts!
Epoch:   1      |Training Loss:   4.454 |Validation Loss:   4.230
Epoch:   2      |Training Loss:   4.253 |Validation Loss:   4.105
Epoch:   3      |Training Loss:   4.166 |Validation Loss:   4.021
Epoch:   4      |Training Loss:   4.112 |Validation Loss:   3.967
Epoch:   5      |Training Loss:   4.058 |Validation Loss:   3.917
Epoch:   6      |Training Loss:   4.019 |Validation Loss:   3.857
Epoch:   7      |Training Loss:   3.985 |Validation Loss:   3.860
Epoch:   8      |Training Loss:   3.957 |Validation Loss:   3.836
Epoch:   9      |Training Loss:   3.921 |Validation Loss:   3.783
Epoch:  10      |Training Loss:   3.908 |Validation Loss:   3.780
Finished Training.
Training process took 842.76 seconds.
Saving model…
Done.
```

[ ]:
```
dataiter = iter(testloader)
images, labels = dataiter.next()
images, labels = images[:8].to(device), labels[:8].to(device)
```

```
outputs = inzvaNet(images)
_, predicted = torch.max(outputs.data, 1)
# print images
imshow(torchvision.utils.make_grid(images.cpu()))
print('GroundTruth: ', ', '.join('%10s' % classes[labels[j]] for j in range(8)))
print('Predicted:   ', ', '.join('%10s' % classes[predicted[j]]for j in␣
 ↪range(8)))
```

```
GroundTruth:    mountain,   flatfish,       seal,  mushrooms,        sea,
tulips,      camel,  butterfly
Predicted:         cloud,    leopard,      train,       wolf,     apples,
tiger,    leopard,      skunk
```

[ ]:
```
# test on all test data
inzvaNet.eval()
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = inzvaNet(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print("correct predictions: ", correct)
print("total number of data: ", total)
print('Accuracy of the network on the 10000 test images: %d %%' % (100 *␣
 ↪correct / total))
```

```
correct predictions:  1229
total number of data:  10000
Accuracy of the network on the 10000 test images: 12 %
```

[ ]:
```
# class-wise accuracy
class_correct = list(0. for i in range(100))
class_total = list(0. for i in range(100))
with torch.no_grad():
```

```python
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = inzvaNet(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
        for i in range(len(labels)):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

print("Accuracy of classes:")
for i in range(100):
    print('%3d- %20s : %5.3f %%' % (
        i+1, classes[i], 100 * class_correct[i] / class_total[i]))
```

```
Accuracy of classes:
  1-               apples : 23.000 %
  2-        aquarium fish : 9.000 %
  3-                 baby : 10.000 %
  4-                 bear : 9.000 %
  5-               beaver : 12.000 %
  6-                  bed : 1.000 %
  7-                  bee : 4.000 %
  8-               beetle : 13.000 %
  9-              bicycle : 2.000 %
 10-              bottles : 0.000 %
 11-                bowls : 0.000 %
 12-                  boy : 0.000 %
 13-               bridge : 4.000 %
 14-                  bus : 7.000 %
 15-            butterfly : 6.000 %
 16-                camel : 8.000 %
 17-                 cans : 0.000 %
 18-               castle : 26.000 %
 19-          caterpillar : 28.000 %
 20-               cattle : 2.000 %
 21-                chair : 13.000 %
 22-           chimpanzee : 36.000 %
 23-                clock : 0.000 %
 24-                cloud : 52.000 %
 25-            cockroach : 44.000 %
 26-    computer keyboard : 0.000 %
 27-                couch : 1.000 %
 28-                 crab : 2.000 %
 29-            crocodile : 0.000 %
 30-                 cups : 4.000 %
 31-             dinosaur : 13.000 %
```

32- dolphin : 14.000 %
33- elephant : 0.000 %
34- flatfish : 6.000 %
35- forest : 4.000 %
36- fox : 6.000 %
37- girl : 22.000 %
38- hamster : 4.000 %
39- house : 6.000 %
40- kangaroo : 0.000 %
41- lamp : 0.000 %
42- lawn-mower : 6.000 %
43- leopard : 31.000 %
44- lion : 34.000 %
45- lizard : 1.000 %
46- lobster : 5.000 %
47- man : 10.000 %
48- maple : 2.000 %
49- motorcycle : 7.000 %
50- mountain : 24.000 %
51- mouse : 0.000 %
52- mushrooms : 4.000 %
53- oak : 66.000 %
54- oranges : 57.000 %
55- orchids : 17.000 %
56- otter : 0.000 %
57- palm : 3.000 %
58- pears : 10.000 %
59- pickup truck : 1.000 %
60- pine : 4.000 %
61- plain : 18.000 %
62- plates : 20.000 %
63- poppies : 39.000 %
64- porcupine : 4.000 %
65- possum : 4.000 %
66- rabbit : 0.000 %
67- raccoon : 9.000 %
68- ray : 14.000 %
69- road : 31.000 %
70- rocket : 5.000 %
71- roses : 32.000 %
72- sea : 13.000 %
73- seal : 1.000 %
74- shark : 41.000 %
75- shrew : 1.000 %
76- skunk : 32.000 %
77- skyscraper : 4.000 %
78- snail : 3.000 %
79- snake : 1.000 %

```
 80-              spider : 3.000 %
 81-            squirrel : 0.000 %
 82-           streetcar : 1.000 %
 83-          sunflowers : 73.000 %
 84-       sweet peppers : 3.000 %
 85-               table : 0.000 %
 86-                tank : 11.000 %
 87-           telephone : 22.000 %
 88-          television : 1.000 %
 89-               tiger : 4.000 %
 90-             tractor : 7.000 %
 91-               train : 5.000 %
 92-               trout : 1.000 %
 93-              tulips : 5.000 %
 94-              turtle : 2.000 %
 95-            wardrobe : 33.000 %
 96-               whale : 36.000 %
 97-              willow : 39.000 %
 98-                wolf : 11.000 %
 99-               woman : 5.000 %
100-                worm : 1.000 %
```

0.0.8 Hyper-Parameter Optimization

[ ]:
```
# installing optuna
import subprocess
command = "pip install --no-input optuna"
process = subprocess.run(command, stdout=subprocess.PIPE, stderr=subprocess.
 ↪PIPE, universal_newlines=True, shell=True)
stdout_raw = process.stdout.strip().upper()
stderr_raw = process.stderr.strip().upper()
if len(stderr_raw) > 0:
    print(stderr_raw)
    raise RuntimeError("ERROR: Could not execute shell command '{}'".
 ↪format(command))
print(stdout_raw)
print("Done.")
```

```
REQUIREMENT ALREADY SATISFIED: OPTUNA IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (2.10.0)
REQUIREMENT ALREADY SATISFIED: SQLALCHEMY>=1.1.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM OPTUNA) (1.4.29)
REQUIREMENT ALREADY SATISFIED: SCIPY!=1.4.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM OPTUNA) (1.5.2)
REQUIREMENT ALREADY SATISFIED: COLORLOG IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (6.6.0)
REQUIREMENT ALREADY SATISFIED: TQDM IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (4.62.3)
```

```
REQUIREMENT ALREADY SATISFIED: CMAES>=0.8.2 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM OPTUNA) (0.8.2)
REQUIREMENT ALREADY SATISFIED: ALEMBIC IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (1.7.5)
REQUIREMENT ALREADY SATISFIED: PYYAML IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (6.0)
REQUIREMENT ALREADY SATISFIED: PACKAGING>=20.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM OPTUNA) (21.3)
REQUIREMENT ALREADY SATISFIED: CLIFF IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (3.10.0)
REQUIREMENT ALREADY SATISFIED: NUMPY IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM OPTUNA) (1.22.1)
REQUIREMENT ALREADY SATISFIED: PYPARSING!=3.0.5,>=2.0.2 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM PACKAGING>=20.0->OPTUNA)
(3.0.6)
REQUIREMENT ALREADY SATISFIED: GREENLET!=0.4.17 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM SQLALCHEMY>=1.1.0->OPTUNA)
(1.1.2)
REQUIREMENT ALREADY SATISFIED: IMPORTLIB-METADATA IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM ALEMBIC->OPTUNA) (4.10.0)
REQUIREMENT ALREADY SATISFIED: IMPORTLIB-RESOURCES IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM ALEMBIC->OPTUNA) (5.4.0)
REQUIREMENT ALREADY SATISFIED: MAKO IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM ALEMBIC->OPTUNA) (1.1.6)
REQUIREMENT ALREADY SATISFIED: CMD2>=1.0.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CLIFF->OPTUNA) (2.3.3)
REQUIREMENT ALREADY SATISFIED: PBR!=2.1.0,>=2.0.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CLIFF->OPTUNA) (5.8.0)
REQUIREMENT ALREADY SATISFIED: STEVEDORE>=2.0.1 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CLIFF->OPTUNA) (3.5.0)
REQUIREMENT ALREADY SATISFIED: PRETTYTABLE>=0.7.2 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CLIFF->OPTUNA) (2.5.0)
REQUIREMENT ALREADY SATISFIED: AUTOPAGE>=0.4.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CLIFF->OPTUNA) (0.4.0)
REQUIREMENT ALREADY SATISFIED: COLORAMA IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM COLORLOG->OPTUNA) (0.4.4)
REQUIREMENT ALREADY SATISFIED: PYREADLINE3 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CMD2>=1.0.0->CLIFF->OPTUNA)
(3.3)
REQUIREMENT ALREADY SATISFIED: ATTRS>=16.3.0 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CMD2>=1.0.0->CLIFF->OPTUNA)
(21.2.0)
REQUIREMENT ALREADY SATISFIED: WCWIDTH>=0.1.7 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CMD2>=1.0.0->CLIFF->OPTUNA)
(0.2.5)
REQUIREMENT ALREADY SATISFIED: PYPERCLIP>=1.6 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM CMD2>=1.0.0->CLIFF->OPTUNA)
(1.8.2)
```

```
REQUIREMENT ALREADY SATISFIED: ZIPP>=0.5 IN D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-
PACKAGES (FROM IMPORTLIB-METADATA->ALEMBIC->OPTUNA) (3.7.0)
REQUIREMENT ALREADY SATISFIED: MARKUPSAFE>=0.9.2 IN
D:\ANACONDA3\ENVS\MYENV001\LIB\SITE-PACKAGES (FROM MAKO->ALEMBIC->OPTUNA)
(2.0.1)
Done.
```

[ ]:
```
import optuna
from optuna.samplers import TPESampler
```

[ ]:
```
# Function that runs through training and returns the validation loss to be␣
 ↪optimized
def objective(trial):

    # Cleaning up GPU
    torch.cuda.empty_cache()

    # Defining hyperparameter space
    hparams = {
    'input_image_size':[32, 32],
    'batch_size': 256,
    'epochs': 10,
    'lr': 0.001,
    'loss_function': nn.CrossEntropyLoss(),
    'optimizer':trial.suggest_categorical('optimizer', ['adam', 'sgd']),
    'optimizer_params':None,
    'num_conv_blocks': trial.suggest_int("num_conv_blocks", 2, 5),
    'num_dense_layers':trial.suggest_int("num_dense_layers", 1, 5),
    'conv_kernel_size':trial.suggest_int("conv_kernel_size", 2, 10),
    'pool_kernel_size':trial.suggest_int("pool_kernel_size", 2, 5),
    'conv_padding':'same',
    'pool_padding':0,
    'conv_activations':trial.suggest_categorical("conv_activations", ['relu',␣
 ↪'leakyrelu', 'sigmoid', 'tanh']),
    'dense_activations':trial.suggest_categorical("dense_activations", ['relu',␣
 ↪'leakyrelu', 'sigmoid', 'tanh']),
    'conv_batchnorm':trial.suggest_categorical("conv_batchnorm", ["before",␣
 ↪"after"]),
    'dense_batchnorm':trial.suggest_categorical("dense_batchnorm", ["before",␣
 ↪"after"]),
    'conv_stride':1,
    'pool_stride':1,
    'conv_dropout':trial.suggest_float("conv_dropout", 0.1, 0.5),
    'dense_dropout':trial.suggest_float("dense_dropout", 0.1, 0.5),
    'L2':0.001,
    'num_classes':100}
```

```
    # Defining hyperparameter conditions
    hparams['pool_padding'] = hparams['pool_kernel_size']//2
    if hparams['optimizer'] == 'sgd':
        hparams['optimizer_params'] = {'momentum':0.9}


    # Generate data
    allset = torchvision.datasets.CIFAR100(root='./data/CIFAR100', train=True,␣
↪download=True, transform=transform)
    num_all_data = len(allset.data)
    num_val_data, num_train_data = int(VALIDATION_DATA*num_all_data),␣
↪int((1-VALIDATION_DATA)*num_all_data)
    (trainset, valset) = random_split(allset, (num_train_data, num_val_data),␣
↪generator=torch.Generator().manual_seed(42))
    trainloader = DataLoader(trainset, batch_size=hparams['batch_size'],␣
↪shuffle=True, num_workers=0)
    validloader = DataLoader(valset, batch_size=hparams['batch_size'],␣
↪shuffle=True, num_workers=0)

    # Build and train the model as we did before
    inzvaNet = ConvNet(hparams)
    inzvaNet.to(device)
    inzvaNet.train()
    criterion = hparams['loss_function']
    if hparams['optimizer']=='adam':
        if hparams.get('optimizer_params'):
            optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'],␣
↪**hparams['optimizer_params'])
        else:
            optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'])
    elif hparams['optimizer']=='sgd':
        if hparams.get('optimizer_params'):
            optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'],␣
↪**hparams['optimizer_params'])
        else:
            optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'])
    num_training_batches = len(trainloader)
    num_validation_batches = len(validloader)

    for epoch in range(hparams["epochs"]):

        epoch_loss_training = 0.0
        epoch_loss_validation = 0.0

        inzvaNet.train()
        for i, data in enumerate(trainloader):
```

```
            images, labels = data[0].to(device), data[1].to(device)
            optimizer.zero_grad()
            predictions = inzvaNet(images)
            loss = criterion(predictions, labels)
            loss.backward()
            optimizer.step()
            epoch_loss_training += loss.item()

        inzvaNet.eval()
        with torch.no_grad():
            for i, data in enumerate(validloader):
                images, labels = data[0].to(device), data[1].to(device)
                predictions = inzvaNet(images)
                loss = criterion(predictions, labels)
                epoch_loss_validation += loss.item()

        print("Epoch:  %2d\t|Training Loss:   %.3f\t|Validation Loss:   %.3f" %␣
 ↪(epoch + 1,
            epoch_loss_training / num_training_batches,
            epoch_loss_validation / num_validation_batches))

    return epoch_loss_validation
```

[ ]:
```
# Create HPO study
study = optuna.create_study(sampler=TPESampler(), direction="minimize")

# Optimize HPO study
tStart = timer()
study.optimize(objective, n_trials=NUM_HPO_TRIALS, timeout=HPO_TIMEOUT_SEC,␣
 ↪n_jobs=NUM_HPO_JOBS, catch=(Exception,))
tFinish = timer()

# Report
print("HPO process took %d seconds."%(tFinish-tStart))
print("Number of completed trials: {}".format(len(study.trials)))
print("Best trial:")
trial = study.best_trial
print(trial)
print("\tBest Validation Loss: {}".format(trial.value))
print("\tBest Params: ")
for key, value in trial.params.items():
    print("    {}: {}".format(key, value))
```

```
[I 2022-01-24 03:21:21,604] A new study created in memory with name:
no-name-1f2b7940-f244-4b78-be45-831a171969cd
```

```
Files already downloaded and verified
```

```
D:\Anaconda3\envs\myEnv001\lib\site-packages\torch\nn\modules\conv.py:442:
```

```
UserWarning: Using padding='same' with even kernel lengths and odd dilation may
require a zero-padded copy of the input be created (Triggered internally at
..\aten\src\ATen\native\Convolution.cpp:647.)
  return F.conv2d(input, weight, bias, self.stride,

Epoch:   1      |Training Loss:   4.679 |Validation Loss:   4.425
Epoch:   2      |Training Loss:   4.527 |Validation Loss:   4.337
Epoch:   3      |Training Loss:   4.447 |Validation Loss:   4.281
Epoch:   4      |Training Loss:   4.389 |Validation Loss:   4.231
Epoch:   5      |Training Loss:   4.342 |Validation Loss:   4.189
Epoch:   6      |Training Loss:   4.290 |Validation Loss:   4.148
Epoch:   7      |Training Loss:   4.260 |Validation Loss:   4.120
Epoch:   8      |Training Loss:   4.226 |Validation Loss:   4.071
Epoch:   9      |Training Loss:   4.197 |Validation Loss:   4.063

[I 2022-01-24 03:38:16,548] Trial 0 finished with value:
160.976891040802 and parameters: {'optimizer': 'sgd', 'num_conv_blocks': 3,
'num_dense_layers': 4, 'conv_kernel_size': 4, 'pool_kernel_size': 5,
'conv_activations': 'relu', 'dense_activations': 'leakyrelu', 'conv_batchnorm':
'before', 'dense_batchnorm': 'after', 'conv_dropout': 0.19179270727092163,
'dense_dropout': 0.25768620210213067}. Best is trial 0 with value:
160.976891040802.

Epoch:  10      |Training Loss:   4.172 |Validation Loss:   4.024
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.667 |Validation Loss:   4.611
Epoch:   2      |Training Loss:   4.628 |Validation Loss:   4.510
Epoch:   3      |Training Loss:   4.547 |Validation Loss:   4.428
Epoch:   4      |Training Loss:   4.485 |Validation Loss:   4.387
Epoch:   5      |Training Loss:   4.445 |Validation Loss:   4.362
Epoch:   6      |Training Loss:   4.424 |Validation Loss:   4.356
Epoch:   7      |Training Loss:   4.407 |Validation Loss:   4.330
Epoch:   8      |Training Loss:   4.395 |Validation Loss:   4.330
Epoch:   9      |Training Loss:   4.377 |Validation Loss:   4.362

[I 2022-01-24 03:55:07,186] Trial 1 finished with value:
171.43050575256348 and parameters: {'optimizer': 'adam', 'num_conv_blocks': 4,
'num_dense_layers': 2, 'conv_kernel_size': 2, 'pool_kernel_size': 5,
'conv_activations': 'sigmoid', 'dense_activations': 'leakyrelu',
'conv_batchnorm': 'before', 'dense_batchnorm': 'before', 'conv_dropout':
0.4005373293909916, 'dense_dropout': 0.12951364524530612}. Best is trial 0 with
value: 160.976891040802.

Epoch:  10      |Training Loss:   4.350 |Validation Loss:   4.286
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.657 |Validation Loss:   4.359
Epoch:   2      |Training Loss:   4.520 |Validation Loss:   4.283
Epoch:   3      |Training Loss:   4.457 |Validation Loss:   4.221
Epoch:   4      |Training Loss:   4.417 |Validation Loss:   4.192
Epoch:   5      |Training Loss:   4.373 |Validation Loss:   4.179
```

```
Epoch:   6      |Training Loss:   4.348 |Validation Loss:   4.124
Epoch:   7      |Training Loss:   4.326 |Validation Loss:   4.100
Epoch:   8      |Training Loss:   4.298 |Validation Loss:   4.081
Epoch:   9      |Training Loss:   4.287 |Validation Loss:   4.062
```

```
[I 2022-01-24 04:10:04,541] Trial 2 finished with value:
162.40307450294495 and parameters: {'optimizer': 'sgd', 'num_conv_blocks': 2,
'num_dense_layers': 2, 'conv_kernel_size': 5, 'pool_kernel_size': 2,
'conv_activations': 'tanh', 'dense_activations': 'tanh', 'conv_batchnorm':
'after', 'dense_batchnorm': 'after', 'conv_dropout': 0.4945721582411171,
'dense_dropout': 0.3600449294674264}. Best is trial 0 with value:
160.976891040802.
```

```
Epoch:  10      |Training Loss:   4.265 |Validation Loss:   4.060
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.657 |Validation Loss:   4.467
Epoch:   2      |Training Loss:   4.554 |Validation Loss:   4.378
Epoch:   3      |Training Loss:   4.483 |Validation Loss:   4.323
Epoch:   4      |Training Loss:   4.425 |Validation Loss:   4.269
Epoch:   5      |Training Loss:   4.385 |Validation Loss:   4.225
Epoch:   6      |Training Loss:   4.348 |Validation Loss:   4.194
Epoch:   7      |Training Loss:   4.313 |Validation Loss:   4.181
Epoch:   8      |Training Loss:   4.289 |Validation Loss:   4.124
Epoch:   9      |Training Loss:   4.263 |Validation Loss:   4.107
```

```
[I 2022-01-24 04:29:34,390] Trial 3 finished with value:
163.596444606781 and parameters: {'optimizer': 'sgd', 'num_conv_blocks': 4,
'num_dense_layers': 3, 'conv_kernel_size': 8, 'pool_kernel_size': 3,
'conv_activations': 'tanh', 'dense_activations': 'leakyrelu', 'conv_batchnorm':
'before', 'dense_batchnorm': 'before', 'conv_dropout': 0.12940670912374097,
'dense_dropout': 0.44156351204304856}. Best is trial 0 with value:
160.976891040802.
```

```
Epoch:  10      |Training Loss:   4.241 |Validation Loss:   4.090
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.611 |Validation Loss:   4.347
Epoch:   2      |Training Loss:   4.466 |Validation Loss:   4.303
Epoch:   3      |Training Loss:   4.411 |Validation Loss:   4.263
Epoch:   4      |Training Loss:   4.372 |Validation Loss:   4.198
Epoch:   5      |Training Loss:   4.334 |Validation Loss:   4.168
Epoch:   6      |Training Loss:   4.317 |Validation Loss:   4.127
Epoch:   7      |Training Loss:   4.296 |Validation Loss:   4.145
Epoch:   8      |Training Loss:   4.286 |Validation Loss:   4.138
Epoch:   9      |Training Loss:   4.272 |Validation Loss:   4.077
```

```
[I 2022-01-24 04:45:15,816] Trial 4 finished with value:
163.43482208251953 and parameters: {'optimizer': 'adam', 'num_conv_blocks': 3,
'num_dense_layers': 4, 'conv_kernel_size': 2, 'pool_kernel_size': 4,
'conv_activations': 'relu', 'dense_activations': 'tanh', 'conv_batchnorm':
'before', 'dense_batchnorm': 'after', 'conv_dropout': 0.3430825134068658,
```

```
'dense_dropout': 0.21658675460165494}. Best is trial 0 with value:
160.976891040802.

Epoch:  10      |Training Loss:   4.262 |Validation Loss:   4.086
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.370 |Validation Loss:   4.137
Epoch:   2      |Training Loss:   4.197 |Validation Loss:   4.026
Epoch:   3      |Training Loss:   4.119 |Validation Loss:   3.950
Epoch:   4      |Training Loss:   4.071 |Validation Loss:   3.899
Epoch:   5      |Training Loss:   4.032 |Validation Loss:   3.854
Epoch:   6      |Training Loss:   3.994 |Validation Loss:   3.795
Epoch:   7      |Training Loss:   3.966 |Validation Loss:   3.783
Epoch:   8      |Training Loss:   3.938 |Validation Loss:   3.760
Epoch:   9      |Training Loss:   3.911 |Validation Loss:   3.724

[I 2022-01-24 05:00:24,257] Trial 5 finished with value:
148.07879781723022 and parameters: {'optimizer': 'adam', 'num_conv_blocks': 2,
'num_dense_layers': 1, 'conv_kernel_size': 9, 'pool_kernel_size': 2,
'conv_activations': 'relu', 'dense_activations': 'leakyrelu', 'conv_batchnorm':
'after', 'dense_batchnorm': 'before', 'conv_dropout': 0.41786473811059455,
'dense_dropout': 0.16982388420062394}. Best is trial 5 with value:
148.07879781723022.

Epoch:  10      |Training Loss:   3.894 |Validation Loss:   3.702
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.674 |Validation Loss:   4.626
Epoch:   2      |Training Loss:   4.651 |Validation Loss:   4.614
Epoch:   3      |Training Loss:   4.644 |Validation Loss:   4.606
Epoch:   4      |Training Loss:   4.637 |Validation Loss:   4.602
Epoch:   5      |Training Loss:   4.637 |Validation Loss:   4.599
Epoch:   6      |Training Loss:   4.631 |Validation Loss:   4.597
Epoch:   7      |Training Loss:   4.631 |Validation Loss:   4.594
Epoch:   8      |Training Loss:   4.628 |Validation Loss:   4.590
Epoch:   9      |Training Loss:   4.629 |Validation Loss:   4.587

[I 2022-01-24 05:15:32,249] Trial 6 finished with value:
183.25664234161377 and parameters: {'optimizer': 'sgd', 'num_conv_blocks': 2,
'num_dense_layers': 2, 'conv_kernel_size': 8, 'pool_kernel_size': 3,
'conv_activations': 'sigmoid', 'dense_activations': 'sigmoid', 'conv_batchnorm':
'before', 'dense_batchnorm': 'before', 'conv_dropout': 0.4962010530402665,
'dense_dropout': 0.3713930295322787}. Best is trial 5 with value:
148.07879781723022.

Epoch:  10      |Training Loss:   4.623 |Validation Loss:   4.581
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.581 |Validation Loss:   4.283
Epoch:   2      |Training Loss:   4.339 |Validation Loss:   4.136
Epoch:   3      |Training Loss:   4.235 |Validation Loss:   4.068
Epoch:   4      |Training Loss:   4.180 |Validation Loss:   3.992
Epoch:   5      |Training Loss:   4.137 |Validation Loss:   3.953
```

```
Epoch:   6      |Training Loss:   4.099 |Validation Loss:   3.913
Epoch:   7      |Training Loss:   4.071 |Validation Loss:   3.878
Epoch:   8      |Training Loss:   4.047 |Validation Loss:   3.841
Epoch:   9      |Training Loss:   4.031 |Validation Loss:   3.812
```

```
[I 2022-01-24 05:31:27,581] Trial 7 finished with value:
152.01260638237 and parameters: {'optimizer': 'adam', 'num_conv_blocks': 4,
'num_dense_layers': 1, 'conv_kernel_size': 3, 'pool_kernel_size': 5,
'conv_activations': 'relu', 'dense_activations': 'leakyrelu', 'conv_batchnorm':
'after', 'dense_batchnorm': 'after', 'conv_dropout': 0.4260640048050487,
'dense_dropout': 0.3556335650272967}. Best is trial 5 with value:
148.07879781723022.
```

```
Epoch:  10      |Training Loss:   4.008 |Validation Loss:   3.800
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.494 |Validation Loss:   4.186
Epoch:   2      |Training Loss:   4.301 |Validation Loss:   4.124
Epoch:   3      |Training Loss:   4.243 |Validation Loss:   4.094
Epoch:   4      |Training Loss:   4.201 |Validation Loss:   4.067
Epoch:   5      |Training Loss:   4.179 |Validation Loss:   4.045
Epoch:   6      |Training Loss:   4.157 |Validation Loss:   4.019
Epoch:   7      |Training Loss:   4.144 |Validation Loss:   4.027
Epoch:   8      |Training Loss:   4.145 |Validation Loss:   4.001
Epoch:   9      |Training Loss:   4.122 |Validation Loss:   3.987
```

```
[I 2022-01-24 05:47:01,481] Trial 8 finished with value:
160.26873660087585 and parameters: {'optimizer': 'adam', 'num_conv_blocks': 3,
'num_dense_layers': 3, 'conv_kernel_size': 6, 'pool_kernel_size': 2,
'conv_activations': 'leakyrelu', 'dense_activations': 'sigmoid',
'conv_batchnorm': 'before', 'dense_batchnorm': 'after', 'conv_dropout':
0.13013382314348784, 'dense_dropout': 0.40888582990951783}. Best is trial 5 with
value: 148.07879781723022.
```

```
Epoch:  10      |Training Loss:   4.109 |Validation Loss:   4.007
Files already downloaded and verified
Epoch:   1      |Training Loss:   4.619 |Validation Loss:   4.452
Epoch:   2      |Training Loss:   4.509 |Validation Loss:   4.364
Epoch:   3      |Training Loss:   4.445 |Validation Loss:   4.305
Epoch:   4      |Training Loss:   4.387 |Validation Loss:   4.252
Epoch:   5      |Training Loss:   4.347 |Validation Loss:   4.212
Epoch:   6      |Training Loss:   4.311 |Validation Loss:   4.189
Epoch:   7      |Training Loss:   4.285 |Validation Loss:   4.156
Epoch:   8      |Training Loss:   4.258 |Validation Loss:   4.118
Epoch:   9      |Training Loss:   4.229 |Validation Loss:   4.091
```

```
[I 2022-01-24 06:02:53,443] Trial 9 finished with value:
163.08367204666138 and parameters: {'optimizer': 'sgd', 'num_conv_blocks': 3,
'num_dense_layers': 4, 'conv_kernel_size': 4, 'pool_kernel_size': 2,
'conv_activations': 'tanh', 'dense_activations': 'leakyrelu', 'conv_batchnorm':
'after', 'dense_batchnorm': 'before', 'conv_dropout': 0.3574359087360288,
```

```
'dense_dropout': 0.22527667617198507}. Best is trial 5 with value:
148.07879781723022.

Epoch:  10      |Training Loss:   4.210 |Validation Loss:   4.077
HPO process took 9691 seconds.
Number of completed trials: 10
Best trial:
FrozenTrial(number=5, values=[148.07879781723022],
datetime_start=datetime.datetime(2022, 1, 24, 4, 45, 15, 817464),
datetime_complete=datetime.datetime(2022, 1, 24, 5, 0, 24, 256433),
params={'optimizer': 'adam', 'num_conv_blocks': 2, 'num_dense_layers': 1,
'conv_kernel_size': 9, 'pool_kernel_size': 2, 'conv_activations': 'relu',
'dense_activations': 'leakyrelu', 'conv_batchnorm': 'after', 'dense_batchnorm':
'before', 'conv_dropout': 0.41786473811059455, 'dense_dropout':
0.16982388420062394}, distributions={'optimizer':
CategoricalDistribution(choices=('adam', 'sgd')), 'num_conv_blocks':
IntUniformDistribution(high=5, low=2, step=1), 'num_dense_layers':
IntUniformDistribution(high=5, low=1, step=1), 'conv_kernel_size':
IntUniformDistribution(high=10, low=2, step=1), 'pool_kernel_size':
IntUniformDistribution(high=5, low=2, step=1), 'conv_activations':
CategoricalDistribution(choices=('relu', 'leakyrelu', 'sigmoid', 'tanh')),
'dense_activations': CategoricalDistribution(choices=('relu', 'leakyrelu',
'sigmoid', 'tanh')), 'conv_batchnorm':
CategoricalDistribution(choices=('before', 'after')), 'dense_batchnorm':
CategoricalDistribution(choices=('before', 'after')), 'conv_dropout':
UniformDistribution(high=0.5, low=0.1), 'dense_dropout':
UniformDistribution(high=0.5, low=0.1)}, user_attrs={}, system_attrs={},
intermediate_values={}, trial_id=5, state=TrialState.COMPLETE, value=None)
        Best Validation Loss: 148.07879781723022
        Best Params:
    optimizer: adam
    num_conv_blocks: 2
    num_dense_layers: 1
    conv_kernel_size: 9
    pool_kernel_size: 2
    conv_activations: relu
    dense_activations: leakyrelu
    conv_batchnorm: after
    dense_batchnorm: before
    conv_dropout: 0.41786473811059455
    dense_dropout: 0.16982388420062394
```

[ ]:
```
# Selecting the best algorithm
torch.cuda.empty_cache()
best_hparams = trial.params
hparams.update(best_hparams)

# Training model with these parameters
```

```
hparams['epochs'] = 80
best_model = ConvNet(hparams)

inzvaNet.to(device)
inzvaNet.train()
criterion = hparams['loss_function']
if hparams['optimizer']=='adam':
    if hparams.get('optimizer_params'):
        optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'],␣
 ↪**hparams['optimizer_params'])
    else:
        optimizer = optim.Adam(inzvaNet.parameters(), lr=hparams['lr'])
elif hparams['optimizer']=='sgd':
    if hparams.get('optimizer_params'):
        optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'],␣
 ↪**hparams['optimizer_params'])
    else:
        optimizer = optim.SGD(inzvaNet.parameters(), lr=hparams['lr'])
num_training_batches = len(trainloader)
num_validation_batches = len(validloader)

print('training starts!')
num_training_batches = len(trainloader)
num_validation_batches = len(validloader)
num_testing_batches = len(testloader)

tStart = timer()
for epoch in range(hparams["epochs"]):

    epoch_loss_training = 0.0
    epoch_loss_validation = 0.0

    inzvaNet.train()
    for i, data in enumerate(trainloader):
        images, labels = data[0].to(device), data[1].to(device)
        optimizer.zero_grad()
        predictions = inzvaNet(images)
        loss = criterion(predictions, labels)
        loss.backward()
        optimizer.step()
        epoch_loss_training += loss.item()

    inzvaNet.eval()
    with torch.no_grad():
        for i, data in enumerate(validloader):
            images, labels = data[0].to(device), data[1].to(device)
            predictions = inzvaNet(images)
```

```
            loss = criterion(predictions, labels)
            epoch_loss_validation += loss.item()

    print("Epoch:  %2d\t|Training Loss:   %.3f\t|Validation Loss:   %.3f" %␣
 ↪(epoch + 1,
        epoch_loss_training / num_training_batches,
        epoch_loss_validation / num_validation_batches))

tFinish = timer()
print('Finished Training.')
print("Training process took %.2f seconds."%(tFinish-tStart))
print("Saving model...")
try:
    torch.save(inzvaNet, "ConvNet_best.pth")
except Exception as e:
    print(e)
    print("Failed to save the model.")
print("Done saving.")

# Evaluation of the model on testset
inzvaNet.eval()
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = inzvaNet(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print("correct predictions: ", correct)
print("total number of data: ", total)
print('Accuracy of the network on all of the test images: %d %%' % (100 *␣
 ↪correct / total))

# Class-wise accuracy
class_correct = list(0. for i in range(100))
class_total = list(0. for i in range(100))
with torch.no_grad():
    for data in testloader:
        images, labels = data
        images, labels = images.to(device), labels.to(device)
        outputs = inzvaNet(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
```

```
        for i in range(len(labels)):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

print("Accuracy of classes:")
for i in range(100):
    print('%3d- %20s : %5.3f %%' % (
        i+1, classes[i], 100 * class_correct[i] / class_total[i]))
```

```
training starts!
Epoch:   1      |Training Loss:   3.808 |Validation Loss:   3.634
Epoch:   2      |Training Loss:   3.790 |Validation Loss:   3.617
Epoch:   3      |Training Loss:   3.776 |Validation Loss:   3.596
Epoch:   4      |Training Loss:   3.752 |Validation Loss:   3.581
Epoch:   5      |Training Loss:   3.733 |Validation Loss:   3.582
Epoch:   6      |Training Loss:   3.720 |Validation Loss:   3.579
Epoch:   7      |Training Loss:   3.709 |Validation Loss:   3.541
Epoch:   8      |Training Loss:   3.705 |Validation Loss:   3.539
Epoch:   9      |Training Loss:   3.690 |Validation Loss:   3.539
Epoch:  10      |Training Loss:   3.684 |Validation Loss:   3.532
Epoch:  11      |Training Loss:   3.665 |Validation Loss:   3.492
Epoch:  12      |Training Loss:   3.667 |Validation Loss:   3.477
Epoch:  13      |Training Loss:   3.651 |Validation Loss:   3.494
Epoch:  14      |Training Loss:   3.648 |Validation Loss:   3.491
Epoch:  15      |Training Loss:   3.638 |Validation Loss:   3.463
Epoch:  16      |Training Loss:   3.640 |Validation Loss:   3.478
Epoch:  17      |Training Loss:   3.626 |Validation Loss:   3.437
Epoch:  18      |Training Loss:   3.619 |Validation Loss:   3.435
Epoch:  19      |Training Loss:   3.603 |Validation Loss:   3.407
Epoch:  20      |Training Loss:   3.613 |Validation Loss:   3.434
Epoch:  21      |Training Loss:   3.605 |Validation Loss:   3.439
Epoch:  22      |Training Loss:   3.596 |Validation Loss:   3.405
Epoch:  23      |Training Loss:   3.594 |Validation Loss:   3.408
Epoch:  24      |Training Loss:   3.585 |Validation Loss:   3.438
Epoch:  25      |Training Loss:   3.573 |Validation Loss:   3.402
Epoch:  26      |Training Loss:   3.576 |Validation Loss:   3.383
Epoch:  27      |Training Loss:   3.575 |Validation Loss:   3.399
Epoch:  28      |Training Loss:   3.569 |Validation Loss:   3.372
Epoch:  29      |Training Loss:   3.561 |Validation Loss:   3.379
Epoch:  30      |Training Loss:   3.561 |Validation Loss:   3.369
Epoch:  31      |Training Loss:   3.557 |Validation Loss:   3.344
Epoch:  32      |Training Loss:   3.549 |Validation Loss:   3.370
Epoch:  33      |Training Loss:   3.550 |Validation Loss:   3.359
Epoch:  34      |Training Loss:   3.537 |Validation Loss:   3.332
Epoch:  35      |Training Loss:   3.540 |Validation Loss:   3.324
Epoch:  36      |Training Loss:   3.535 |Validation Loss:   3.320
Epoch:  37      |Training Loss:   3.520 |Validation Loss:   3.321
```

```
Epoch:  38      |Training Loss:   3.526 |Validation Loss:   3.360
Epoch:  39      |Training Loss:   3.524 |Validation Loss:   3.319
Epoch:  40      |Training Loss:   3.520 |Validation Loss:   3.308
Epoch:  41      |Training Loss:   3.513 |Validation Loss:   3.330
Epoch:  42      |Training Loss:   3.513 |Validation Loss:   3.331
Epoch:  43      |Training Loss:   3.509 |Validation Loss:   3.326
Epoch:  44      |Training Loss:   3.509 |Validation Loss:   3.311
Epoch:  45      |Training Loss:   3.505 |Validation Loss:   3.321
Epoch:  46      |Training Loss:   3.502 |Validation Loss:   3.280
Epoch:  47      |Training Loss:   3.500 |Validation Loss:   3.314
Epoch:  48      |Training Loss:   3.500 |Validation Loss:   3.302
Epoch:  49      |Training Loss:   3.500 |Validation Loss:   3.291
Epoch:  50      |Training Loss:   3.488 |Validation Loss:   3.289
Epoch:  51      |Training Loss:   3.486 |Validation Loss:   3.271
Epoch:  52      |Training Loss:   3.480 |Validation Loss:   3.311
Epoch:  53      |Training Loss:   3.480 |Validation Loss:   3.271
Epoch:  54      |Training Loss:   3.476 |Validation Loss:   3.285
Epoch:  55      |Training Loss:   3.476 |Validation Loss:   3.287
Epoch:  56      |Training Loss:   3.470 |Validation Loss:   3.270
Epoch:  57      |Training Loss:   3.481 |Validation Loss:   3.256
Epoch:  58      |Training Loss:   3.466 |Validation Loss:   3.250
Epoch:  59      |Training Loss:   3.473 |Validation Loss:   3.284
Epoch:  60      |Training Loss:   3.477 |Validation Loss:   3.249
Epoch:  61      |Training Loss:   3.474 |Validation Loss:   3.262
Epoch:  62      |Training Loss:   3.462 |Validation Loss:   3.260
Epoch:  63      |Training Loss:   3.457 |Validation Loss:   3.261
Epoch:  64      |Training Loss:   3.460 |Validation Loss:   3.246
Epoch:  65      |Training Loss:   3.455 |Validation Loss:   3.266
Epoch:  66      |Training Loss:   3.455 |Validation Loss:   3.245
Epoch:  67      |Training Loss:   3.451 |Validation Loss:   3.242
Epoch:  68      |Training Loss:   3.446 |Validation Loss:   3.237
Epoch:  69      |Training Loss:   3.448 |Validation Loss:   3.235
Epoch:  70      |Training Loss:   3.444 |Validation Loss:   3.236
Epoch:  71      |Training Loss:   3.448 |Validation Loss:   3.236
Epoch:  72      |Training Loss:   3.438 |Validation Loss:   3.243
Epoch:  73      |Training Loss:   3.436 |Validation Loss:   3.223
Epoch:  74      |Training Loss:   3.440 |Validation Loss:   3.198
Epoch:  75      |Training Loss:   3.436 |Validation Loss:   3.228
Epoch:  76      |Training Loss:   3.440 |Validation Loss:   3.212
Epoch:  77      |Training Loss:   3.442 |Validation Loss:   3.224
Epoch:  78      |Training Loss:   3.429 |Validation Loss:   3.195
Epoch:  79      |Training Loss:   3.436 |Validation Loss:   3.239
Epoch:  80      |Training Loss:   3.436 |Validation Loss:   3.207
Finished Training.
Training process took 7008.78 seconds.
Saving model…
Done saving.
correct predictions:  2151
```

```
total number of data:  10000
Accuracy of the network on all of the test images: 21 %
Accuracy of classes:
  1-            apples : 35.000 %
  2-     aquarium fish : 18.000 %
  3-              baby : 15.000 %
  4-              bear : 10.000 %
  5-            beaver : 10.000 %
  6-               bed : 20.000 %
  7-               bee : 20.000 %
  8-            beetle : 31.000 %
  9-           bicycle : 22.000 %
 10-           bottles : 8.000 %
 11-             bowls : 0.000 %
 12-               boy : 1.000 %
 13-            bridge : 24.000 %
 14-               bus : 17.000 %
 15-         butterfly : 5.000 %
 16-             camel : 18.000 %
 17-              cans : 16.000 %
 18-            castle : 37.000 %
 19-       caterpillar : 25.000 %
 20-            cattle : 5.000 %
 21-             chair : 37.000 %
 22-        chimpanzee : 47.000 %
 23-             clock : 12.000 %
 24-             cloud : 64.000 %
 25-         cockroach : 60.000 %
 26-   computer keyboard : 4.000 %
 27-             couch : 4.000 %
 28-              crab : 9.000 %
 29-         crocodile : 3.000 %
 30-              cups : 7.000 %
 31-          dinosaur : 34.000 %
 32-           dolphin : 23.000 %
 33-          elephant : 2.000 %
 34-          flatfish : 25.000 %
 35-            forest : 12.000 %
 36-               fox : 14.000 %
 37-              girl : 26.000 %
 38-           hamster : 9.000 %
 39-             house : 14.000 %
 40-          kangaroo : 21.000 %
 41-              lamp : 1.000 %
 42-        lawn-mower : 43.000 %
 43-           leopard : 24.000 %
 44-              lion : 53.000 %
 45-            lizard : 12.000 %
```

46- lobster : 20.000 %
47- man : 8.000 %
48- maple : 19.000 %
49- motorcycle : 52.000 %
50- mountain : 14.000 %
51- mouse : 0.000 %
52- mushrooms : 9.000 %
53- oak : 69.000 %
54- oranges : 49.000 %
55- orchids : 49.000 %
56- otter : 1.000 %
57- palm : 36.000 %
58- pears : 12.000 %
59- pickup truck : 13.000 %
60- pine : 9.000 %
61- plain : 54.000 %
62- plates : 23.000 %
63- poppies : 39.000 %
64- porcupine : 27.000 %
65- possum : 6.000 %
66- rabbit : 1.000 %
67- raccoon : 22.000 %
68- ray : 20.000 %
69- road : 59.000 %
70- rocket : 28.000 %
71- roses : 24.000 %
72- sea : 33.000 %
73- seal : 4.000 %
74- shark : 33.000 %
75- shrew : 9.000 %
76- skunk : 45.000 %
77- skyscraper : 37.000 %
78- snail : 10.000 %
79- snake : 6.000 %
80- spider : 24.000 %
81- squirrel : 6.000 %
82- streetcar : 7.000 %
83- sunflowers : 69.000 %
84- sweet peppers : 22.000 %
85- table : 5.000 %
86- tank : 19.000 %
87- telephone : 29.000 %
88- television : 10.000 %
89- tiger : 46.000 %
90- tractor : 41.000 %
91- train : 18.000 %
92- trout : 13.000 %
93- tulips : 8.000 %

94-	turtle : 7.000 %
95-	wardrobe : 45.000 %
96-	whale : 39.000 %
97-	willow : 29.000 %
98-	wolf : 18.000 %
99-	woman : 7.000 %
100-	worm : 7.000 %