```python
import tensorflow as tf
import cv2
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings("ignore")

import torch
import torch.nn as nn
import torch.optim as optim
from kerastuner import RandomSearch
from torch.utils.data import DataLoader, TensorDataset,Subset,
random_split#changed
import torchvision.transforms as transforms#changed
from torchvision.datasets import ImageFolder#changed
from sklearn.model_selection import KFold #changed
from torchvision import transforms
import torch.nn.functional as F
import random
import time
```

1. Load the datasets

For the project, we provide a training set with 50000 images in the directory `../data/images/` with:

- noisy labels for all images provided in `../data/noisy_label.csv`;
- clean labels for the first 10000 images provided in `../data/clean_labels.csv`.

```python
# Get time consumption
def getTime(func):
    def _wrapper(*args, **kwargs):
        start = time.time()
        res = func(*args, **kwargs)
        end = time.time()
        print(f"Total time consumption:{end-start:.3f}s")
        return res
    return _wrapper

# load the images
n_img = 50000
n_noisy = 40000
n_clean_noisy = n_img - n_noisy
imgs = np.empty((n_img,32,32,3))
for i in range(n_img):
    img_fn = f'train_data/images/{i+1:05d}.png'
```

```
    imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)

# load the labels
clean_labels = np.genfromtxt('train_data/clean_labels.csv',
delimiter=',', dtype="int8")
noisy_labels = np.genfromtxt('train_data/noisy_labels.csv',
delimiter=',', dtype="int8")
```

For illustration, we present a small subset (of size 8) of the images with their clean and noisy labels in `clean_noisy_trainset`. You are encouraged to explore more characteristics of the label noises on the whole dataset.

```
fig = plt.figure()

ax1 = fig.add_subplot(2,4,1)
ax1.imshow(imgs[0]/255)
ax2 = fig.add_subplot(2,4,2)
ax2.imshow(imgs[1]/255)
ax3 = fig.add_subplot(2,4,3)
ax3.imshow(imgs[2]/255)
ax4 = fig.add_subplot(2,4,4)
ax4.imshow(imgs[3]/255)
ax1 = fig.add_subplot(2,4,5)
ax1.imshow(imgs[4]/255)
ax2 = fig.add_subplot(2,4,6)
ax2.imshow(imgs[5]/255)
ax3 = fig.add_subplot(2,4,7)
ax3.imshow(imgs[6]/255)
ax4 = fig.add_subplot(2,4,8)
ax4.imshow(imgs[7]/255)

# The class-label correspondence
classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')

# print clean labels
print('Clean labels:')
print(' '.join('%5s' % classes[clean_labels[j]] for j in range(8)))
# print noisy labels
print('Noisy labels:')
print(' '.join('%5s' % classes[noisy_labels[j]] for j in range(8)))
```

```
Clean labels:
 frog truck truck  deer   car   car  bird horse
Noisy labels:
  cat   dog truck  frog   dog  ship  bird  deer
```

2. The predictive model

We consider a baseline model directly on the noisy dataset without any label corrections. RGB histogram features are extracted to fit a logistic regression model.

2.1. Baseline Model

```
# [DO NOT MODIFY THIS CELL]
# RGB histogram dataset construction
no_bins = 6
bins = np.linspace(0,255,no_bins) # the range of the rgb histogram
target_vec = np.empty(n_img)
feature_mtx = np.empty((n_img,3*(len(bins)-1)))
i = 0
for i in range(n_img):
    # The target vector consists of noisy labels
    target_vec[i] = noisy_labels[i]

    # Use the numbers of pixels in each bin for all three channels as the features
    feature1 = np.histogram(imgs[i][:,:,0],bins=bins)[0]
    feature2 = np.histogram(imgs[i][:,:,1],bins=bins)[0]
    feature3 = np.histogram(imgs[i][:,:,2],bins=bins)[0]

    # Concatenate three features
    feature_mtx[i,] = np.concatenate((feature1, feature2, feature3), axis=None)
    i += 1
```

```
# Train a logistic regression model
clf = LogisticRegression(random_state=0).fit(feature_mtx, target_vec)
```

For the convenience of evaluation, we write the following function `predictive_model` that does the label prediction. **For your predictive model, feel free to modify the function, but make sure the function takes an RGB image of numpy.array format with dimension $32 \times 32 \times 3$ as input, and returns one single label as output.**

```
def baseline_model(image):
    '''
    This is the baseline predictive model that takes in the image and
returns a label prediction
    '''
    feature1 = np.histogram(image[:,:,0],bins=bins)[0]
    feature2 = np.histogram(image[:,:,1],bins=bins)[0]
    feature3 = np.histogram(image[:,:,2],bins=bins)[0]
    feature = np.concatenate((feature1, feature2, feature3),
axis=None).reshape(1,-1)
    return clf.predict(feature)
```

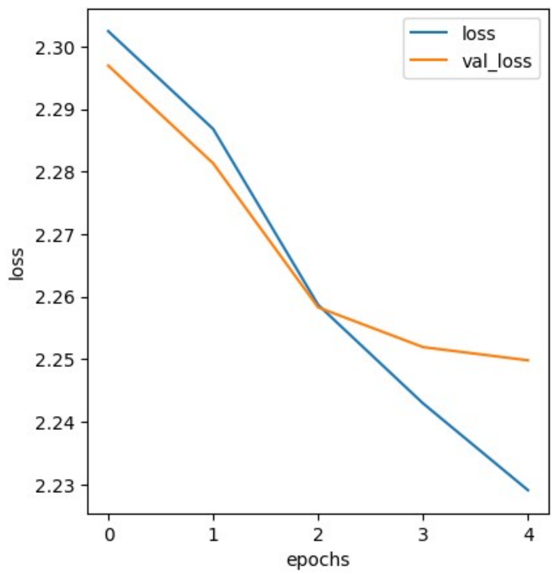
2.2. Model I

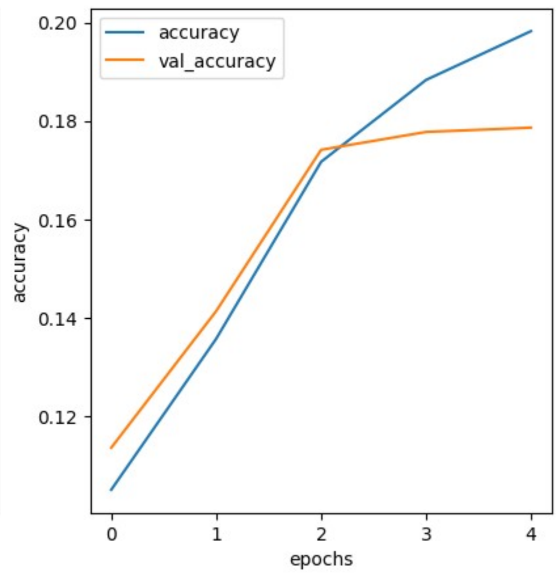
```
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)
aug_df = train_datagen.flow(imgs,noisy_labels,batch_size =
50000,seed=1,shuffle=False)
imgs1,noisy = aug_df.next()
# Split the dataset into training and testing sets
random.seed(2023)
X_train, X_val,y_train, y_val =
train_test_split(imgs1,noisy,test_size=0.2)
X_train, X_val= X_train.astype('float32'), X_val.astype('float32')

# Create a Sequential model using keras. This is a baseline cnn to
compare with the tuner result.
cnn1 = keras.Sequential()
# Add a Conv2D layer with 6 filters of size 3x3, using ReLU activation
function, with an input shape of 32x32x3
cnn1.add(layers.Conv2D(6, kernel_size=(3,3),
activation='relu',input_shape = (32,32,3)))
# Add a MaxPooling2D layer with pool size of 2x2
cnn1.add(layers.MaxPooling2D(pool_size=(2,2)))
# Add another Conv2D layer with 120 filters of size 5x5, using ReLU
activation function
cnn1.add(layers.Conv2D(120,kernel_size=(5,5),activation='relu'))
# Flatten the output from the previous layer
```

```
cnn1.add(layers.Flatten())
# Add a Dense layer with 32 units and ReLU activation function
cnn1.add(layers.Dense(32,activation='relu'))
# Add a Dense layer with 10 units and softmax activation function
cnn1.add(layers.Dense(10,activation='softmax'))

# Compile the model with Adam optimizer, categorical_crossentropy loss
function, and accuracy as the evaluation metric
cnn1.compile('adam','sparse_categorical_crossentropy',metrics=['accura
cy'])
# Train the model using the fit() method, with batch size of 128, 40
epochs, and 20% of the data as validation set
history =
cnn1.fit(X_train,y_train,batch_size=128,epochs=5,verbose=1,validation_
split=0.2)
hist = pd.DataFrame(history.history)
# Extract the loss, validation loss, accuracy, and validation accuracy
from the history
loss = hist['loss']
val_loss = hist['val_loss']
accuracy = hist['accuracy']
val_accuracy = hist['val_accuracy']

# Plot the loss and validation loss over epochs in the first subplot
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(10,5))
ax1.plot(hist.index,loss,label='loss')
ax1.plot(hist.index,val_loss,label='val_loss')
ax1.set_xlabel('epochs')
ax1.set_ylabel('loss')
ax1.legend()

# Plot the accuracy and validation accuracy over epochs in the second
subplot
ax2.plot(hist.index,accuracy,label='accuracy')
ax2.plot(hist.index,val_accuracy,label='val_accuracy')
ax2.set_xlabel('epochs')
ax2.set_ylabel('accuracy')
ax2.legend()

# Evaluate the model on the validation set and print the test loss and
test accuracy
scores = cnn1.evaluate(X_val,y_val,verbose=0)
print('test loss:',scores[0])
print('test accuracy:',scores[1])
```

```
Epoch 1/5
250/250 [==============================] - 8s 29ms/step - loss: 2.3025
- accuracy: 0.1051 - val_loss: 2.2970 - val_accuracy: 0.1136
Epoch 2/5
250/250 [==============================] - 7s 29ms/step - loss: 2.2868
```

```
- accuracy: 0.1357 - val_loss: 2.2813 - val_accuracy: 0.1414
Epoch 3/5
250/250 [==============================] - 7s 29ms/step - loss: 2.2587
- accuracy: 0.1717 - val_loss: 2.2583 - val_accuracy: 0.1741
Epoch 4/5
250/250 [==============================] - 7s 28ms/step - loss: 2.2429
- accuracy: 0.1883 - val_loss: 2.2519 - val_accuracy: 0.1778
Epoch 5/5
250/250 [==============================] - 7s 30ms/step - loss: 2.2291
- accuracy: 0.1982 - val_loss: 2.2498 - val_accuracy: 0.1786
test loss: 2.2497026920318604
test accuracy: 0.18870000541210175
```






```python
def build_model(hp):
    # create model object
    model = keras.Sequential([
    #adding first convolutional layer
    keras.layers.Conv2D(
        #adding filter
        filters=hp.Int('conv_1_filter', min_value=8, max_value=16,
step=4),
        # adding filter size or kernel size
        kernel_size=hp.Choice('conv_1_kernel', values = [3,5]),
        #activation function
        activation='relu',
        input_shape=(32,32,3)),
    #keras.layers.BatchNormalization(),
    # adding second convolutional layer
    keras.layers.MaxPooling2D(
        pool_size=hp.Choice('maxpool_1_size', values = [2]),
    ),
    keras.layers.Dropout(0.3),
```

```
    keras.layers.Conv2D(
        #adding filter
        filters=hp.Int('conv_2_filter', min_value=128, max_value=256,
step=64),
        #adding filter size or kernel size
        kernel_size=hp.Choice('conv_2_kernel', values = [3,5]),
        #activation function
        activation='relu'
    ),
    #keras.layers.BatchNormalization(),
    keras.layers.MaxPooling2D(
        pool_size=hp.Choice('maxpool_1_size', values = [2]),
    ),
    keras.layers.Dropout(0.3),
    # adding flatten layer
    keras.layers.Flatten(),
    # adding dense layer
    keras.layers.Dense(
        units=hp.Int('dense_1_units', min_value=128, max_value=256,
step=64),
        activation='relu'
    ),
    keras.layers.Dropout(0.3),
    # output layer
    keras.layers.Dense(10, activation='softmax')
    ])
    #compilation of model

model.compile(optimizer=keras.optimizers.Adam(hp.Choice('learning_rate
', values=[1e-2, 1e-3])),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
    return model

tuner = RandomSearch(build_model,
                    objective='val_accuracy',
                    max_trials = 5,
                    overwrite=True)
tuner.search(X_train,y_train,epochs=5,validation_split = 0.2)
```

```
Trial 5 Complete [00h 01m 30s]
val_accuracy: 0.19550000131130219

Best val_accuracy So Far: 0.2083750069141388
Total elapsed time: 00h 10m 18s
INFO:tensorflow:Oracle triggered exit
```

```
model1=tuner.get_best_models(num_models=1)[0]
#summary of best model
model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 16)        448

 max_pooling2d (MaxPooling2D  (None, 15, 15, 16)       0
 )

 dropout (Dropout)           (None, 15, 15, 16)        0

 conv2d_1 (Conv2D)           (None, 13, 13, 256)       37120

 max_pooling2d_1 (MaxPooling  (None, 6, 6, 256)        0
 2D)

 dropout_1 (Dropout)         (None, 6, 6, 256)         0

 flatten (Flatten)           (None, 9216)              0

 dense (Dense)               (None, 128)               1179776

 dropout_2 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 1,218,634
Trainable params: 1,218,634
Non-trainable params: 0
_________________________________________________________________
```

```
model1.evaluate(X_val,y_val,verbose=1)
```

```
313/313 [==============================] - 2s 6ms/step - loss: 2.2283
- accuracy: 0.2188

[2.2283196449279785, 0.21879999339580536]
```

```
# [BUILD A MORE SOPHISTICATED PREDICTIVE MODEL]

# write your code here...

def model_I(image):
    '''
    This function should takes in the image of dimension 32*32*3 as
input and returns a label prediction
    '''
    img_reshape = np.expand_dims(image/225,0)
    pred = model1.predict(img_reshape)
    return np.argmax(pred,1)[0]
```

2.3. Model II

```
# split data
clean_x = imgs1[0:10000]
noisy_x = imgs1[10000:]
noisy_labels_4w =  noisy[10000:]

# split the clean dataset into train and test
random.seed(2023)
#changed
x_train_clean, x_test, y_train_clean, y_test =
train_test_split(clean_x, clean_labels, test_size=0.2)

# combine the clean train dataset with noisy dataset
x_train_combined = np.concatenate((x_train_clean, noisy_x))
#y_train_combined = np.concatenate((y_train_clean, noisy_labels_4w))

# normalization
#x_test = x_test/255.0
#x_train_combined = x_train_combined/255.0
#x_train_clean = x_train_clean/255.0

# CNN
class CNN(nn.Module):
    def __init__(self, num_classes=10):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, stride=1,
padding=1)
        self.bn1 = nn.BatchNorm2d(16)
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(16, 32, kernel_size=3, stride=1,
padding=1)
        self.bn2 = nn.BatchNorm2d(32)
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv3 = nn.Conv2d(32, 64, kernel_size=3, stride=1,
padding=1)
        self.bn3 = nn.BatchNorm2d(64)
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.fc1 = nn.Linear(64 * 4 * 4, 512)
        self.bn4 = nn.BatchNorm1d(512)
        self.fc2 = nn.Linear(512, 10)

    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = self.pool1(x)
        x = F.relu(self.bn2(self.conv2(x)))
        x = self.pool2(x)
        x = F.relu(self.bn3(self.conv3(x)))
        x = self.pool3(x)
        x = x.view(-1, 64 * 4 * 4)
        x = F.relu(self.bn4(self.fc1(x)))
```

```
        x = self.fc2(x)
        return x


# train model once and return loss

@getTime
def train_model(model, train_loader, loss_function, optimizer,
device):
    model.train()
    running_loss = 0.0 # big diff between 0.01 and 0.0
    for x, label in train_loader:
        x, label = x.to(device), label.to(device)
        optimizer.zero_grad()
        fitted = model(x)
        loss = loss_function(fitted, label)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()


    # update learning rate
    lr = 0.1 * (0.1 ** (epoch // 20))
    for param_group in optimizer.param_groups:
        param_group['lr'] = lr

    #update batch normalization layers
    model.eval()
    with torch.no_grad():
        for input_data, ground_truth_labels in train_loader:
            input_data = input_data.to(device)
            output = model(input_data)

    return running_loss / len(train_loader)

#calculate loss function
def get_loss(model,loader):
    running_loss = 0.0
    for x, label in loader:
        x, label = x.to(device), label.to(device)
        fitted = model(x)
        loss = loss_function(fitted, label)
        running_loss += loss.item()
    return running_loss / len(loader)

# validation
def validate_model(model, loader, device,sample_size):
    model.eval()
    num_correct_predictions = 0
    num_total_samples = 0
```

```
    with torch.no_grad(): # disable the gradient calculation
        for x, labels in loader:
            x, labels = x.to(device), labels.to(device)
            fitted = model(x)
            max_, predicted = torch.max(fitted.data, 1)
            num_correct_predictions += (predicted ==
labels).sum().item()

    accuracy = 100 * num_correct_predictions /sample_size
    return accuracy

# prepare the dataset and data loaders
# 'permute()' change the dimensions from (batch_size, height, width,
num_channels) to (batch_size, num_channels, height, width).
y_clean_tensor = torch.tensor(clean_labels).long()
x_clean_tensor = torch.tensor(clean_x).float().permute(0, 3, 1, 2)

dataset = TensorDataset(x_clean_tensor, y_clean_tensor)

# set up training parameters, loss function, and optimizer
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
k_folds = 4
loss_function = nn.CrossEntropyLoss()
kfold = KFold(n_splits=k_folds, shuffle=True, random_state=42)
max_acc = []
fold_train_losses=[]
fold_test_losses=[]
fold_train_accuracys=[]
fold_test_accuracys=[]
fold_models=[]

#changed
#k-fold cross-validation
for fold, (train_ids, val_ids) in enumerate(kfold.split(dataset)):
    print(f"Fold {fold+1}/{k_folds}")

    # Create data loaders for the current fold
    train_loader = DataLoader(Subset(dataset,train_ids),
batch_size=64, shuffle=True)
    test_loader = DataLoader(Subset(dataset,val_ids), batch_size=64,
shuffle=False)

    # Initialize the model, optimizer, and scheduler
    model = CNN().to(device)
    optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

    #Train the model
    train_losses=[]
    test_losses=[]
```

```
    train_accuracys=[]
    test_accuracys=[]
    models=[]
    num_epochs = 15
    for epoch in range(num_epochs):

        models.append(model)

        train_loss = train_model(model, train_loader, loss_function, 
optimizer, device)
        train_losses.append(train_loss)
        train_acc=validate_model(model, 
train_loader,device,len(Subset(dataset,train_ids)))
        train_accuracys.append(train_acc)

        test_loss=get_loss(model,test_loader)
        test_losses.append(test_loss)

test_acc=validate_model(model,test_loader,device,len(Subset(dataset,va
l_ids)))
        test_accuracys.append(test_acc)

    del model, optimizer
    #get max acc for each fold
    max_acc.append(np.max(test_accuracys))
    fold_test_accuracys.append(test_accuracys)
    fold_train_losses.append(train_losses)
    fold_test_losses.append(test_losses)
    fold_train_accuracys.append(train_accuracys)
    fold_models.append(models)

#find best fold
best_fold = np.argmax(max_acc)
best_fold_test_accuracys = fold_test_accuracys[best_fold]
best_fold_test_losses = fold_test_losses[best_fold]
best_fold_train_accuracys = fold_train_accuracys[best_fold]
best_fold_train_losses = fold_train_losses[best_fold]
best_fold_models = fold_models[best_fold]
```

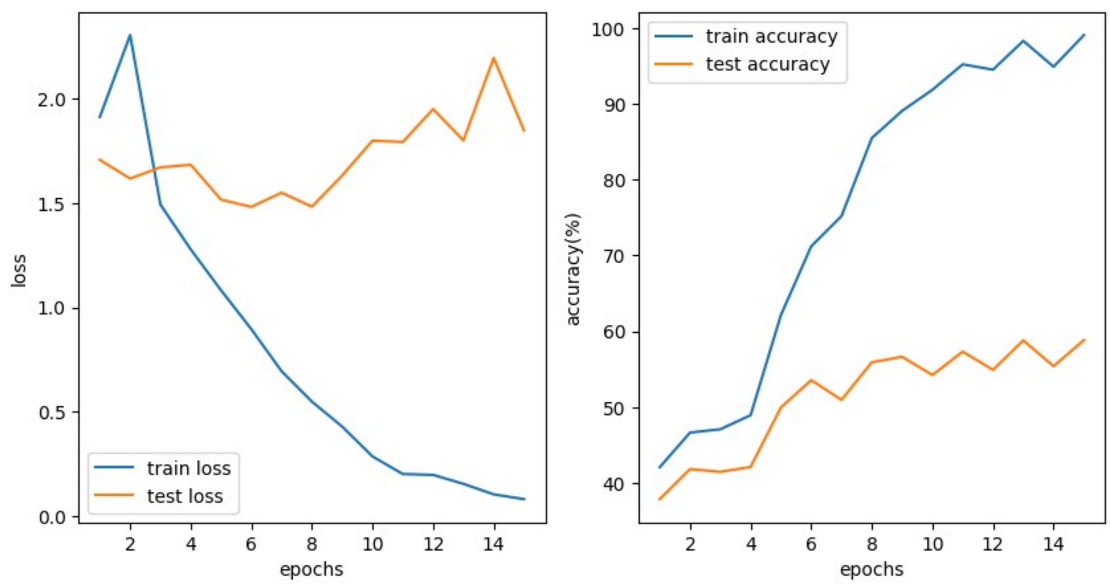
```
Fold 1/4
Total time consumption:4.894s
Total time consumption:0.668s
Total time consumption:0.679s
Total time consumption:0.659s
Total time consumption:0.665s
Total time consumption:0.661s
Total time consumption:0.700s
Total time consumption:0.784s
Total time consumption:0.834s
Total time consumption:0.675s
```

```
Total time consumption:0.723s
Total time consumption:0.653s
Total time consumption:0.679s
Total time consumption:0.821s
Total time consumption:0.662s
Fold 2/4
Total time consumption:0.661s
Total time consumption:0.664s
Total time consumption:0.668s
Total time consumption:0.662s
Total time consumption:0.664s
Total time consumption:0.661s
Total time consumption:0.662s
Total time consumption:0.655s
Total time consumption:0.660s
Total time consumption:0.857s
Total time consumption:0.680s
Total time consumption:0.774s
Total time consumption:0.668s
Total time consumption:0.663s
Total time consumption:0.672s
Fold 3/4
Total time consumption:0.748s
Total time consumption:0.723s
Total time consumption:0.722s
Total time consumption:0.797s
Total time consumption:0.810s
Total time consumption:0.724s
Total time consumption:0.687s
Total time consumption:0.779s
Total time consumption:0.920s
Total time consumption:0.718s
Total time consumption:0.683s
Total time consumption:0.675s
Total time consumption:0.749s
Total time consumption:0.689s
Total time consumption:0.706s
Fold 4/4
Total time consumption:0.721s
Total time consumption:0.708s
Total time consumption:0.676s
Total time consumption:0.798s
Total time consumption:0.790s
Total time consumption:0.678s
Total time consumption:0.747s
Total time consumption:0.670s
Total time consumption:0.778s
Total time consumption:0.706s
Total time consumption:0.750s
Total time consumption:0.724s
```

```
Total time consumption:0.674s
Total time consumption:0.754s
Total time consumption:0.780s
```

```
#Visualization to determine the optimal number of epoches
fig,(ax1,ax2)=plt.subplots(1,2,figsize=(10,5))
axes_x=list(range(1,num_epochs+1 ))
ax1.plot(axes_x,best_fold_train_losses,label='train loss')
ax1.plot(axes_x,best_fold_test_losses,label='test loss')

ax2.plot(axes_x,best_fold_train_accuracys,label='train accuracy')
ax2.plot(axes_x,best_fold_test_accuracys,label='test accuracy')

ax1.set_xlabel('epochs')
ax1.set_ylabel('loss')
ax1.legend()
ax2.set_xlabel('epochs')
ax2.set_ylabel('accuracy(%)')
ax2.legend()
```

```
<matplotlib.legend.Legend at 0x266fcfe78e0>
```




```
#Choose the final cleaning model with the chosen number of epoches：9
#best epoch
best_epoch = np.argmax(best_fold_test_accuracys)
model=models[best_epoch]    # image change, where is the randomness
comes from
print(f'Accuracy on test data:
{validate_model(model,test_loader,device,len(y_test))}%')
```

```
Accuracy on test data: 70.95%
```

```
#Function of implementing the cleaning model
def clean_label(image):
    # Convert the input images
    noisy_x_tensor = torch.tensor(image).float().permute(0, 3, 1, 2)
    noisy_dataset = TensorDataset(noisy_x_tensor)
    noisy_loader = DataLoader(noisy_dataset, batch_size=64,
shuffle=False)

    # evaluation mode
    model.eval()
    predicted_outputs = torch.tensor([], dtype=torch.long)

    with torch.no_grad():
        for x in noisy_loader:
            x = x[0].to(device)
            fitted = model(x)
            # Get the index of the predicted class for each input
image in the batch
            max_, predicted_classes = torch.max(fitted.data, 1)
            predicted_outputs = torch.cat((predicted_outputs,
predicted_classes.cpu()), dim=0)

    return np.array(predicted_outputs)

#Clean the 40000 noisy labels
cleaned_labels=clean_label(imgs1[10000:])

# Concat both dataset and split into train & test data
labels=np.concatenate((clean_labels, cleaned_labels))
random.seed(2023)
X_train, X_val,y_train, y_val =
train_test_split(imgs1,labels,test_size=0.2)
X_train, X_val= X_train.astype('float32'), X_val.astype('float32')

best_hps = tuner.get_best_hyperparameters(5)
# Build the model with the best hp.
modelx = build_model(best_hps[0])
modelx.fit(X_train,y_train,epochs=15,validation_data =
(X_val,y_val),verbose=1)

Epoch 1/15
1250/1250 [==============================] - 35s 27ms/step - loss:
1.6441 - accuracy: 0.4043 - val_loss: 1.3317 - val_accuracy: 0.5358
Epoch 2/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.3832 - accuracy: 0.5074 - val_loss: 1.2213 - val_accuracy: 0.5789
Epoch 3/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.2813 - accuracy: 0.5434 - val_loss: 1.1339 - val_accuracy: 0.6026
Epoch 4/15
```

```
1250/1250 [==============================] - 35s 28ms/step - loss:
1.2308 - accuracy: 0.5659 - val_loss: 1.0933 - val_accuracy: 0.6126
Epoch 5/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.1824 - accuracy: 0.5834 - val_loss: 1.0743 - val_accuracy: 0.6260
Epoch 6/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.1497 - accuracy: 0.5911 - val_loss: 1.0487 - val_accuracy: 0.6294
Epoch 7/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.1201 - accuracy: 0.6045 - val_loss: 1.0454 - val_accuracy: 0.6330
Epoch 8/15
1250/1250 [==============================] - 34s 27ms/step - loss:
1.0938 - accuracy: 0.6100 - val_loss: 1.1257 - val_accuracy: 0.6135
Epoch 9/15
1250/1250 [==============================] - 36s 29ms/step - loss:
1.0752 - accuracy: 0.6182 - val_loss: 1.0328 - val_accuracy: 0.6406
Epoch 10/15
1250/1250 [==============================] - 36s 28ms/step - loss:
1.0531 - accuracy: 0.6228 - val_loss: 1.0121 - val_accuracy: 0.6447
Epoch 11/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.0368 - accuracy: 0.6289 - val_loss: 1.0081 - val_accuracy: 0.6490
Epoch 12/15
1250/1250 [==============================] - 35s 28ms/step - loss:
1.0158 - accuracy: 0.6347 - val_loss: 1.0036 - val_accuracy: 0.6459
Epoch 13/15
1250/1250 [==============================] - 35s 28ms/step - loss:
0.9976 - accuracy: 0.6435 - val_loss: 1.0207 - val_accuracy: 0.6388
Epoch 14/15
1250/1250 [==============================] - 36s 29ms/step - loss:
0.9889 - accuracy: 0.6451 - val_loss: 1.0181 - val_accuracy: 0.6393
Epoch 15/15
1250/1250 [==============================] - 35s 28ms/step - loss:
0.9712 - accuracy: 0.6533 - val_loss: 1.0057 - val_accuracy: 0.6422

<keras.callbacks.History at 0x2678d0c4220>
```

```python
# [ADD WEAKLY SUPERVISED LEARNING FEATURE TO MODEL I]

# write your code here...

def model_II(image):
    '''
    This function should takes in the image of dimension 32*32*3 as
input and returns a label prediction
    '''
    # write your code here...
    img_reshape = np.expand_dims(image/225,0)
```

```
    pred = model2.predict(img_reshape)
    return np.argmax(pred,1)[0]
```

3. Evaluation

For assessment, we will evaluate your final model on a hidden test dataset with clean labels by the `evaluation` function defined as follows. Although you will not have the access to the test set, the function would be useful for the model developments. For example, you can split the small training set, using one portion for weakly supervised learning and the other for validation purpose.

```
# [DO NOT MODIFY THIS CELL]
def evaluation(model, test_labels, test_imgs):
    y_true = test_labels
    y_pred = []
    for image in test_imgs:
        y_pred.append(model(image))
    print(classification_report(y_true, y_pred))
```

```
# [DO NOT MODIFY THIS CELL]
# This is the code for evaluating the prediction performance on a
testset
# You will get an error if running this cell, as you do not have the
testset
# Nonetheless, you can create your own validation set to run the
evlauation
n_test = 10000
test_labels = np.genfromtxt('../data/test_labels.csv', delimiter=',',
dtype="int8")
test_imgs = np.empty((n_test,32,32,3))
for i in range(n_test):
    img_fn = f'../data/test_images/test{i+1:05d}.png'

test_imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)
evaluation(baseline_model, test_labels, test_imgs)
```

```
----------------------------------------------------------------------
-----
FileNotFoundError                         Traceback (most recent call
last)
Cell In[27], line 6
      1 # [DO NOT MODIFY THIS CELL]
      2 # This is the code for evaluating the prediction performance
on a testset
      3 # You will get an error if running this cell, as you do not
have the testset
      4 # Nonetheless, you can create your own validation set to run
the evlauation
      5 n_test = 10000
```

```
----> 6 test_labels = np.genfromtxt('../data/test_labels.csv',
delimiter=',', dtype="int8")
      7 test_imgs = np.empty((n_test,32,32,3))
      8 for i in range(n_test):

File ~\anaconda3\lib\site-packages\numpy\lib\npyio.py:1959, in
genfromtxt(fname, dtype, comments, delimiter, skip_header,
skip_footer, converters, missing_values, filling_values, usecols,
names, excludelist, deletechars, replace_space, autostrip,
case_sensitive, defaultfmt, unpack, usemask, loose, invalid_raise,
max_rows, encoding, ndmin, like)
   1957     fname = os_fspath(fname)
   1958 if isinstance(fname, str):
-> 1959     fid = np.lib._datasource.open(fname, 'rt',
encoding=encoding)
   1960     fid_ctx = contextlib.closing(fid)
   1961 else:

File ~\anaconda3\lib\site-packages\numpy\lib\_datasource.py:193, in
open(path, mode, destpath, encoding, newline)
    156 """
    157 Open `path` with `mode` and return the file object.
    158
   (...)
    189
    190 """
    192 ds = DataSource(destpath)
--> 193 return ds.open(path, mode, encoding=encoding, newline=newline)

File ~\anaconda3\lib\site-packages\numpy\lib\_datasource.py:533, in
DataSource.open(self, path, mode, encoding, newline)
    530     return _file_openers[ext](found, mode=mode,
    531                               encoding=encoding,
newline=newline)
    532 else:
--> 533     raise FileNotFoundError(f"{path} not found.")

FileNotFoundError: ../data/test_labels.csv not found.
```

The overall accuracy is 0.24, which is better than random guess (which should have a accuracy around 0.10). For the project, you should try to improve the performance by the following strategies:

- Consider a better choice of model architectures, hyperparameters, or training scheme for the predictive model;
- Use both `clean_noisy_trainset` and `noisy_trainset` for model training via **weakly supervised learning** methods. One possible solution is to train a "label-correction" model using the former, correct the labels in the latter, and train the final predictive model using the corrected dataset.

- Apply techniques such as k-fold cross validation to avoid overfitting;
- Any other reasonable strategies.