In [112…

```
%pip install livelossplot
%pip install tensorflow
%pip install certifi
```

```
Requirement already satisfied: livelossplot in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (0.5.5)
Requirement already satisfied: matplotlib in /Users/stephanie/miniforge3/envs/ne
w_env/lib/python3.8/site-packages (from livelossplot) (3.7.5)
Requirement already satisfied: bokeh in /Users/stephanie/miniforge3/envs/new_en
v/lib/python3.8/site-packages (from livelossplot) (3.1.1)
Requirement already satisfied: Jinja2>=2.9 in /Users/stephanie/miniforge3/envs/n
ew_env/lib/python3.8/site-packages (from bokeh->livelossplot) (3.1.3)
Requirement already satisfied: contourpy>=1 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from bokeh->livelossplot) (1.1.1)
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ew_env/lib/python3.8/site-packages (from bokeh->livelossplot) (1.22.3)
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ew_env/lib/python3.8/site-packages (from bokeh->livelossplot) (2.0.3)
Requirement already satisfied: pillow>=7.1.0 in /Users/stephanie/miniforge3/env
s/new_env/lib/python3.8/site-packages (from bokeh->livelossplot) (10.2.0)
Requirement already satisfied: PyYAML>=3.10 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from bokeh->livelossplot) (6.0.1)
Requirement already satisfied: tornado>=5.1 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from bokeh->livelossplot) (6.4)
Requirement already satisfied: xyzservices>=2021.09.1 in /Users/stephanie/minifo
rge3/envs/new_env/lib/python3.8/site-packages (from bokeh->livelossplot) (2023.1
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Requirement already satisfied: cycler>=0.10 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from matplotlib->livelossplot) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /Users/stephanie/miniforge3/
envs/new_env/lib/python3.8/site-packages (from matplotlib->livelossplot) (4.50.
0)
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nvs/new_env/lib/python3.8/site-packages (from matplotlib->livelossplot) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /Users/stephanie/miniforg
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9.0)
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niforge3/envs/new_env/lib/python3.8/site-packages (from matplotlib->livelossplo
t) (6.3.0)
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ew_env/lib/python3.8/site-packages (from importlib-resources>=3.2.0->matplotlib-
>livelossplot) (3.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in /Users/stephanie/miniforge3/en
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Requirement already satisfied: pytz>=2020.1 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from pandas>=1.2->bokeh->livelossplot) (202
4.1)
Requirement already satisfied: tzdata>=2022.1 in /Users/stephanie/miniforge3/env
s/new_env/lib/python3.8/site-packages (from pandas>=1.2->bokeh->livelossplot) (2
024.1)
Requirement already satisfied: six>=1.5 in /Users/stephanie/miniforge3/envs/new_
env/lib/python3.8/site-packages (from python-dateutil>=2.7->matplotlib->liveloss
plot) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
Requirement already satisfied: tensorflow in /Users/stephanie/miniforge3/envs/ne
w_env/lib/python3.8/site-packages (2.13.0)
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```

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Requirement already satisfied: absl-py>=1.0.0 in /Users/stephanie/miniforge3/env
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Requirement already satisfied: astunparse>=1.6.0 in /Users/stephanie/miniforge3/
envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorf
low) (1.6.3)
Requirement already satisfied: flatbuffers>=23.1.21 in /Users/stephanie/miniforg
e3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tens
orflow) (24.3.7)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tenso
rflow) (0.4.0)
Requirement already satisfied: google-pasta>=0.1.1 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tenso
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Requirement already satisfied: h5py>=2.9.0 in /Users/stephanie/miniforge3/envs/n
ew_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorflow)
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Requirement already satisfied: libclang>=13.0.0 in /Users/stephanie/miniforge3/e
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Requirement already satisfied: numpy<=1.24.3,>=1.22 in /Users/stephanie/miniforg
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orflow) (1.22.3)
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_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorflow) (2
4.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.2
1.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /Users/stephanie/miniforge3/envs/new_env/lib/
python3.8/site-packages (from tensorflow-macos==2.13.0->tensorflow) (4.25.3)
Requirement already satisfied: setuptools in /Users/stephanie/miniforge3/envs/ne
w_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorflow) (6
8.2.2)
Requirement already satisfied: six>=1.12.0 in /Users/stephanie/miniforge3/envs/n
ew_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorflow)
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Requirement already satisfied: termcolor>=1.1.0 in /Users/stephanie/miniforge3/e
nvs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tensorfl
ow) (2.4.0)
Requirement already satisfied: typing-extensions<4.6.0,>=3.6.6 in /Users/stephan
ie/miniforge3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==
2.13.0->tensorflow) (4.5.0)
Requirement already satisfied: wrapt>=1.11.0 in /Users/stephanie/miniforge3/env
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Requirement already satisfied: grpcio<2.0,>=1.24.3 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tenso
rflow) (1.48.2)
Requirement already satisfied: tensorboard<2.14,>=2.13 in /Users/stephanie/minif
orge3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->t
ensorflow) (2.13.0)
Requirement already satisfied: tensorflow-estimator<2.14,>=2.13.0 in /Users/step
hanie/miniforge3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos
==2.13.0->tensorflow) (2.13.0)
Requirement already satisfied: keras<2.14,>=2.13.1 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from tensorflow-macos==2.13.0->tenso
rflow) (2.13.1)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from astunparse>=1.6.0->tensorflow-m
acos==2.13.0->tensorflow) (0.41.2)
Requirement already satisfied: google-auth<3,>=1.6.3 in /Users/stephanie/minifor
ge3/envs/new_env/lib/python3.8/site-packages (from tensorboard<2.14,>=2.13->tens
```

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orflow-macos==2.13.0->tensorflow) (2.28.2)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /Users/stephani
e/miniforge3/envs/new_env/lib/python3.8/site-packages (from tensorboard<2.14,>=
2.13->tensorflow-macos==2.13.0->tensorflow) (1.0.0)
Requirement already satisfied: markdown>=2.6.8 in /Users/stephanie/miniforge3/en
vs/new_env/lib/python3.8/site-packages (from tensorboard<2.14,>=2.13->tensorflow
-macos==2.13.0->tensorflow) (3.6)
Requirement already satisfied: requests<3,>=2.21.0 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from tensorboard<2.14,>=2.13->tensor
flow-macos==2.13.0->tensorflow) (2.31.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /Users/s
tephanie/miniforge3/envs/new_env/lib/python3.8/site-packages (from tensorboard<
2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in /Users/stephanie/miniforge3/en
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-macos==2.13.0->tensorflow) (3.0.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /Users/stephanie/minifo
rge3/envs/new_env/lib/python3.8/site-packages (from google-auth<3,>=1.6.3->tenso
rboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (5.3.3)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /Users/stephanie/minifor
ge3/envs/new_env/lib/python3.8/site-packages (from google-auth<3,>=1.6.3->tensor
board<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in /Users/stephanie/miniforge3/env
s/new_env/lib/python3.8/site-packages (from google-auth<3,>=1.6.3->tensorboard<
2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /Users/stephanie/mini
forge3/envs/new_env/lib/python3.8/site-packages (from google-auth-oauthlib<1.1,>
=0.5->tensorboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (1.4.0)
Requirement already satisfied: importlib-metadata>=4.4 in /Users/stephanie/minif
orge3/envs/new_env/lib/python3.8/site-packages (from markdown>=2.6.8->tensorboar
d<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (7.0.2)
Requirement already satisfied: charset-normalizer<4,>=2 in /Users/stephanie/mini
forge3/envs/new_env/lib/python3.8/site-packages (from requests<3,>=2.21.0->tenso
rboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /Users/stephanie/miniforge3/envs/
new_env/lib/python3.8/site-packages (from requests<3,>=2.21.0->tensorboard<2.14,
>=2.13->tensorflow-macos==2.13.0->tensorflow) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from requests<3,>=2.21.0->tensorboar
d<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (2.2.1)
Requirement already satisfied: certifi>=2017.4.17 in /Users/stephanie/miniforge
3/envs/new_env/lib/python3.8/site-packages (from requests<3,>=2.21.0->tensorboar
d<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (2024.2.2)
Requirement already satisfied: MarkupSafe>=2.1.1 in /Users/stephanie/miniforge3/
envs/new_env/lib/python3.8/site-packages (from werkzeug>=1.0.1->tensorboard<2.1
4,>=2.13->tensorflow-macos==2.13.0->tensorflow) (2.1.5)
Requirement already satisfied: zipp>=0.5 in /Users/stephanie/miniforge3/envs/new
_env/lib/python3.8/site-packages (from importlib-metadata>=4.4->markdown>=2.6.8-
>tensorboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow) (3.17.0)
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in /Users/stephanie/miniforg
e3/envs/new_env/lib/python3.8/site-packages (from pyasn1-modules>=0.2.1->google-
auth<3,>=1.6.3->tensorboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensorflow)
(0.5.1)
Requirement already satisfied: oauthlib>=3.0.0 in /Users/stephanie/miniforge3/en
vs/new_env/lib/python3.8/site-packages (from requests-oauthlib>=0.7.0->google-au
th-oauthlib<1.1,>=0.5->tensorboard<2.14,>=2.13->tensorflow-macos==2.13.0->tensor
flow) (3.2.2)
Note: you may need to restart the kernel to use updated packages.
Requirement already satisfied: certifi in /Users/stephanie/miniforge3/envs/new_e
nv/lib/python3.8/site-packages (2024.2.2)
Note: you may need to restart the kernel to use updated packages.
```

In [119…

```
# Import required packages
import numpy as np
import cv2
```

```
import time
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
import torch.nn.functional as F
from sklearn.model_selection import train_test_split
import time
import cv2
import numpy as np
import tensorflow as tf
import warnings
warnings.filterwarnings("ignore")
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers.legacy import Adam
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.keras.layers import Dense, Dropout, Flatten, Input, Concatenate
from tensorflow.keras.applications import InceptionV3
from sklearn.model_selection import KFold, train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_mat
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from keras.applications import resnet, inception_v3, MobileNetV3Small, mobilenet
from keras.preprocessing.image import ImageDataGenerator
from keras.utils import to_categorical
from livelossplot.inputs.keras import PlotLossesCallback
from tensorflow.keras import backend as K
```

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` .

In [113…

```
# [DO NOT MODIFY THIS CELL]

# 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'../data/images/{i+1:05d}.png'
    imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)

# load the labels
clean_labels = np.genfromtxt('../data/clean_labels.csv', delimiter=',', dtype="i
noisy_labels = np.genfromtxt('../data/noisy_labels.csv', delimiter=',', dtype="i
```

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.

In [4]:
```
# [DO NOT MODIFY THIS CELL]

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

In [120…

```
# [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 featur
    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
```

In [121…

```
# [DO NOT MODIFY THIS CELL]
# 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.

In [122…

```
# [DO NOT MODIFY THIS CELL]
def baseline_model(image):
    '''
    This is the baseline predictive model that takes in the image and returns a
    '''
    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(
    return clf.predict(feature)
```

In [123…

```
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)

print('Clean labels:')
print(' '.join('%5s' % classes[clean_labels[j]] for j in range(8)))
print('Predicted baseline labels:')
print(' '.join('%5s' % classes[int(baseline_model(imgs[j])[0])] for j in range(8
```

```
Clean labels:
 frog truck truck  deer   car   car  bird horse
Predicted baseline labels:
 frog  ship truck  frog  ship   cat  deer horse
```

2.2. Model I (Convolutional Neural Network)

In model I, we first train our Convolutional Neural Network model with clean labels. The parameters of this CNN are updated by gradients to find the parameter with the smallest loss. This model uses 2 convolutional layers and 3 fully connected layers. Activation functions are RELU.

In [125…

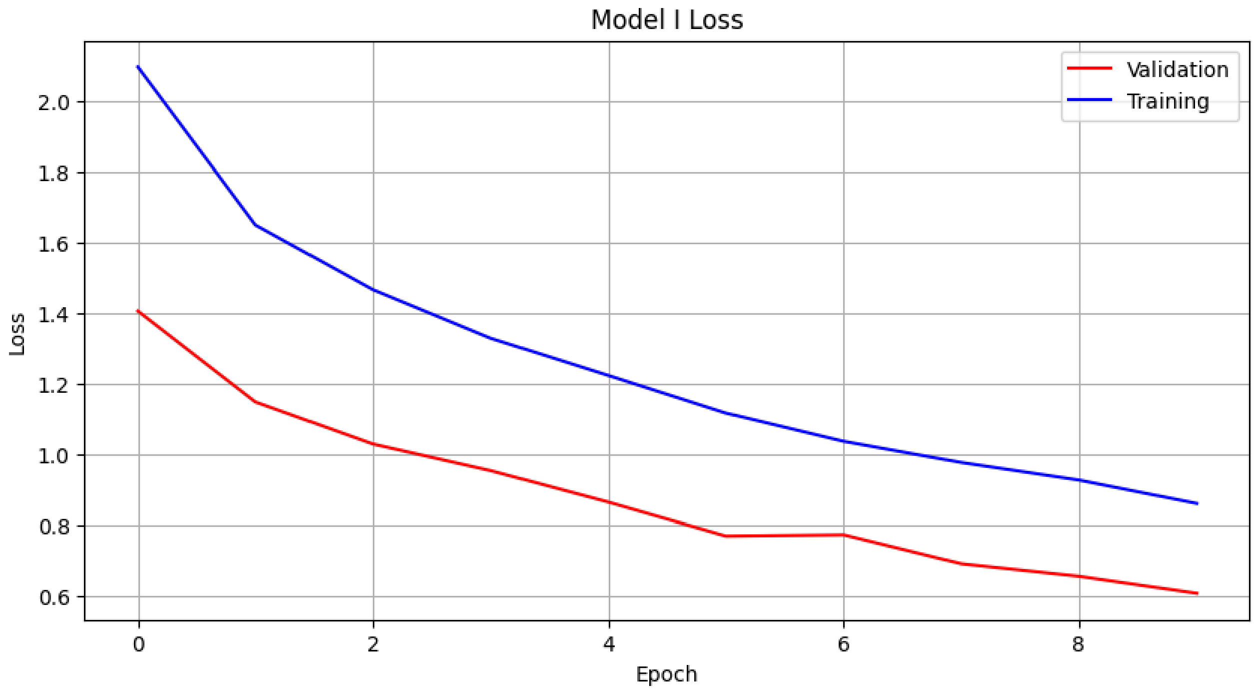
```
## Define

# Convert images and labels into PyTorch tensors
imgs_tensor = torch.tensor(imgs.transpose((0, 3, 1, 2))).float() / 255.0  # Conv
clean_labels_tensor = torch.tensor(clean_labels, dtype=torch.long) # Ensure labe

# Create a dataset and dataloader for the clean labeled data
dataset_clean = TensorDataset(imgs_tensor[:10000], clean_labels_tensor[:10000])
loader_clean = DataLoader(dataset_clean, batch_size=64, shuffle=True)


class ImprovedCNN(nn.Module):
    def __init__(self, num_classes=10):
        super(ImprovedCNN, self).__init__()
        # Increased depth and complexity
        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm2d(32)  # Batch normalization
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(64)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv3 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.bn3 = nn.BatchNorm2d(128)
        self.dropout = nn.Dropout(0.5)  # Dropout layer
        self.fc1 = nn.Linear(128 * 4 * 4, 256)
        self.fc2 = nn.Linear(256, num_classes)

    def forward(self, x):
        x = self.pool(F.relu(self.bn1(self.conv1(x))))
```

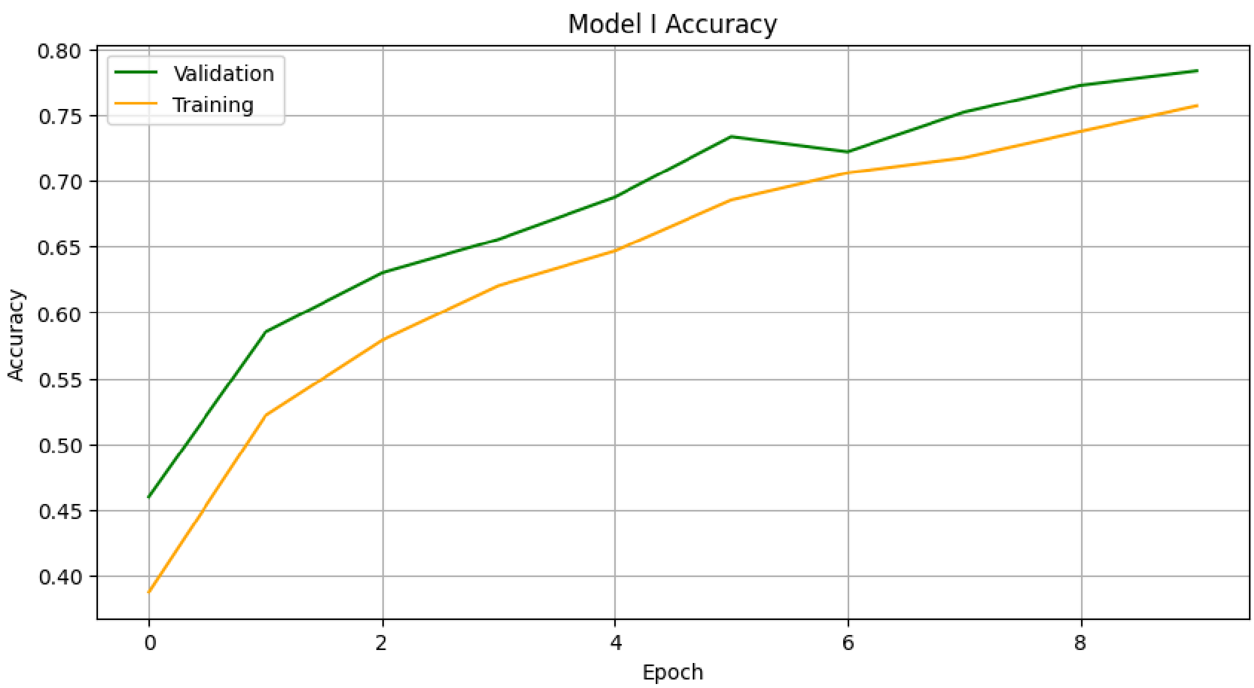
```
        x = self.pool(F.relu(self.bn2(self.conv2(x))))
        x = self.pool(F.relu(self.bn3(self.conv3(x))))
        x = x.view(-1, 128 * 4 * 4)
        x = self.dropout(x)  # Applying dropout
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

# Initialize the model, loss function, and optimizer
model = ImprovedCNN()
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Split Train and test set in clean lables
imgs_train, imgs_val, labels_train, labels_val = train_test_split(
    imgs_tensor[:10000], clean_labels_tensor[:10000], test_size=0.2, random_stat
)

# Create DataLoader for training and validation sets
train_dataset = TensorDataset(imgs_train, labels_train)
val_dataset = TensorDataset(imgs_val, labels_val)

train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=64, shuffle=False)

val_loss_list = []
val_accuracy_list = []
train_accuracy_list = []
train_loss_list = []

# Training loop
num_epochs = 10
startTime = time.time()
for epoch in range(num_epochs):
    running_loss = 0.0
    correct_train = 0
    total_train = 0
    for i, data in enumerate(loader_clean, 0):
        inputs, labels = data
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()

        # Compute training accuracy
        _, predicted = torch.max(outputs, 1)
        correct_train += (predicted == labels).sum().item()
        total_train += labels.size(0)

    # Calculate training loss and accuracy for the epoch
    epoch_loss = running_loss / len(train_loader)
    epoch_accuracy = correct_train / total_train
    # Validate the model
    correct_val = 0
    total_val = 0
    val_loss = 0.0
    with torch.no_grad():
        for data in val_loader:
```

```
            inputs, labels = data
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            val_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total_val += labels.size(0)
            correct_val += (predicted == labels).sum().item()

    # Calculate validation loss
    val_loss /= len(val_loader)
    val_loss_list.append(val_loss)

    # Calculate validation accuracy
    val_accuracy = correct_val / total_val
    val_accuracy_list.append(val_accuracy)

    train_loss_list.append(epoch_loss)
    train_accuracy_list.append(epoch_accuracy)
    print(f"Epoch {epoch+1}/{num_epochs} - loss: {epoch_loss:.4f} - accuracy: {e
train_time_model_1 = time.time() - startTime
print(f'Model 1 training time {train_time_model_1} seconds')
print('Finished Training')
# Plot loss
plt.figure(figsize=(10, 5))
plt.plot(val_loss_list, label='Validation', color='red')
plt.plot(train_loss_list, label='Training', color='blue')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Model I Loss')
plt.legend()
plt.grid(True)
plt.show()

# Plot accuracy
plt.figure(figsize=(10, 5))
plt.plot(val_accuracy_list, label='Validation', color='green')
plt.plot(train_accuracy_list, label='Training', color='orange')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Model I Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/10 - loss: 2.0971 - accuracy: 0.39% - val_loss: 0.0439 - val_accuracy:
0.46%
Epoch 2/10 - loss: 1.6495 - accuracy: 0.52% - val_loss: 0.0359 - val_accuracy:
0.58%
Epoch 3/10 - loss: 1.4656 - accuracy: 0.58% - val_loss: 0.0321 - val_accuracy:
0.63%
Epoch 4/10 - loss: 1.3280 - accuracy: 0.62% - val_loss: 0.0298 - val_accuracy:
0.66%
Epoch 5/10 - loss: 1.2224 - accuracy: 0.65% - val_loss: 0.0270 - val_accuracy:
0.69%
Epoch 6/10 - loss: 1.1155 - accuracy: 0.69% - val_loss: 0.0240 - val_accuracy:
0.73%
Epoch 7/10 - loss: 1.0356 - accuracy: 0.71% - val_loss: 0.0241 - val_accuracy:
0.72%
Epoch 8/10 - loss: 0.9754 - accuracy: 0.72% - val_loss: 0.0215 - val_accuracy:
0.75%
Epoch 9/10 - loss: 0.9256 - accuracy: 0.74% - val_loss: 0.0204 - val_accuracy:
0.77%
```

```
Epoch 10/10 - loss: 0.8594 - accuracy: 0.76% - val_loss: 0.0189 - val_accuracy:
0.78%
Model 1 training time 250.01520681381226 seconds
Finished Training
```





Next, we wanted to test the accuracy of our model. We took the clean labels and performed a train test split, and then wrote two functions: one to measure the prediction accuracy and the other to visualize some examples of predictions.

In [126…

```
# this function is for Validation Accuracy
def evaluate_model(model, data_loader):
    model.eval()  # Set the model to evaluation mode
    correct = 0
    total = 0
    with torch.no_grad():  # No need to track gradients
        for images, labels in data_loader:
```

```
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
    accuracy = 100 * correct / total
    return accuracy

# Evaluate the model
val_accuracy_model_I = evaluate_model(model, val_loader)
print(f'Validation Accuracy of Model I: {val_accuracy_model_I:.2f}%')
```

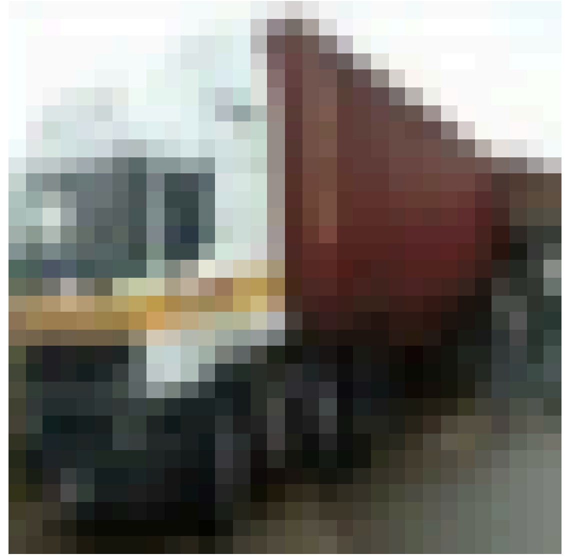
```
Validation Accuracy of Model I: 83.45%
```

In [127…

```
# this function is for visualize some examples of prediciton
def visualize_predictions(model, data_loader, class_names, num_images=5):
    model.eval()
    images, labels = next(iter(data_loader))
    outputs = model(images)
    _, preds = torch.max(outputs, 1)
    num_rows = np.ceil(num_images / 2).astype(int)
    plt.figure(figsize=(10, num_rows * 5))  # Adjust the figure size as needed
    for i in range(num_images):
        ax = plt.subplot(num_rows, 2, i + 1)
        img = images[i].permute(1, 2, 0).numpy()  # Convert to numpy array and c
        plt.imshow(img)
        plt.title(f'Actual: {class_names[labels[i]]}\nPredicted: {class_names[pr
        plt.axis('off')

# Assuming `classes` is defined (as in your provided code)
visualize_predictions(model, val_loader, classes)
```

Actual: frog
Predicted: frog

Actual: truck
Predicted: truck



Actual: car
Predicted: car

Actual: ship
Predicted: ship

Actual: bird
Predicted: frog

Next, the trained CNN model is used in noisy labels to measure the accuracy.

In [128…

```
# Now, we use trained model to noisy labels
noisy_labels_tensor = torch.tensor(noisy_labels, dtype=torch.long)

# Since noisy_labels are for all images, we use the entire imgs_tensor
noisy_dataset = TensorDataset(imgs_tensor, noisy_labels_tensor)
noisy_loader = DataLoader(noisy_dataset, batch_size=64, shuffle=False)

# Evaluating the Models on Noisy Labels
noisy_data_accuracy_model_I = evaluate_model(model, noisy_loader)
print(f'Accuracy of Model I on Noisy Data: {noisy_data_accuracy_model_I:.2f}%')

# Visualizing Predictions On Noisy Data
visualize_predictions(model, noisy_loader, classes, num_images=5)
```

```
Accuracy of Model I on Noisy Data: 30.18%
```

Actual: cat
Predicted: dog

Actual: dog
Predicted: truck

Actual: truck
Predicted: truck

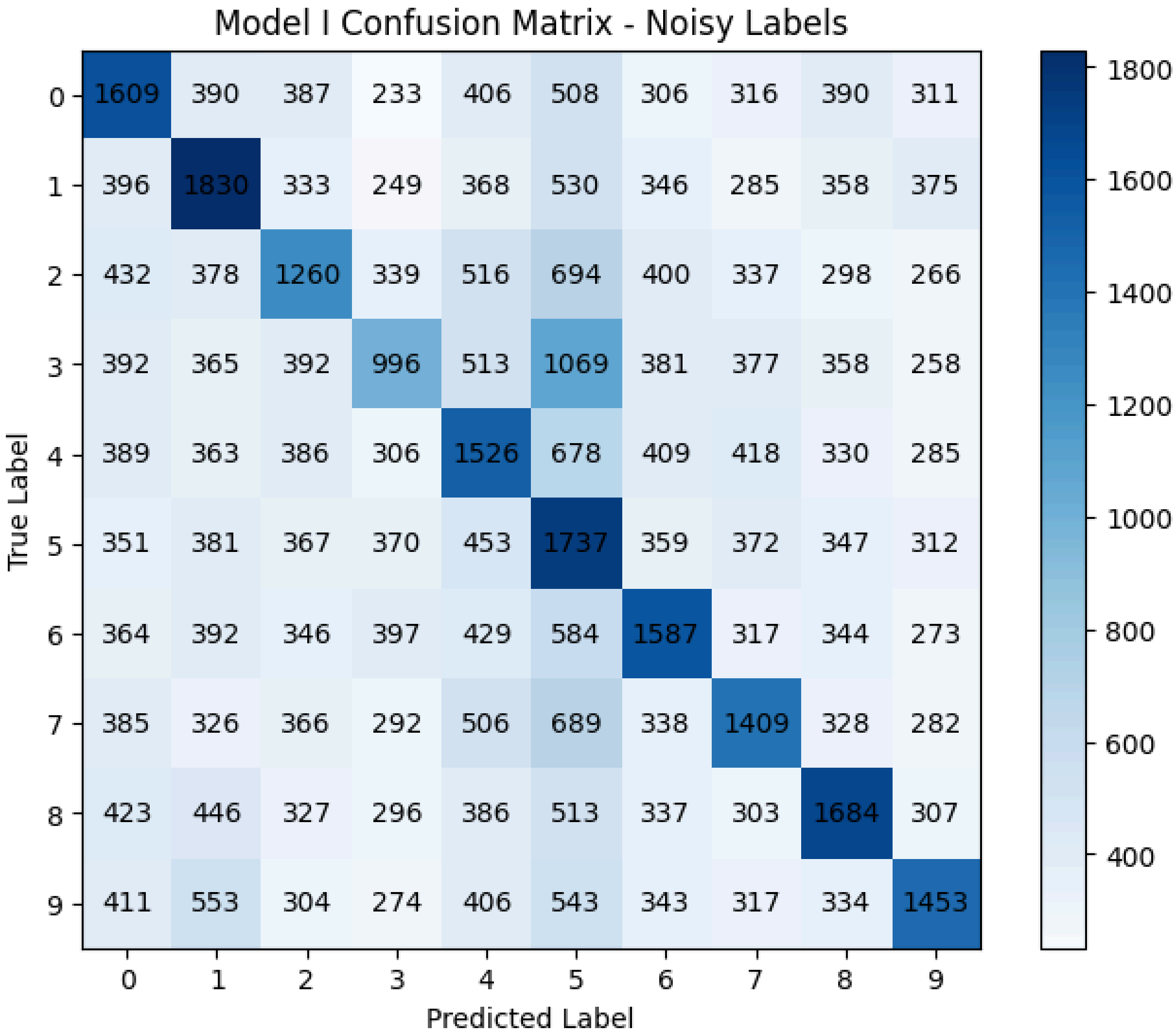
Actual: frog
Predicted: deer

Actual: dog
Predicted: car

See the confusion matrices below to visualize the performance of model I on noisy data and clean data.

In [131…

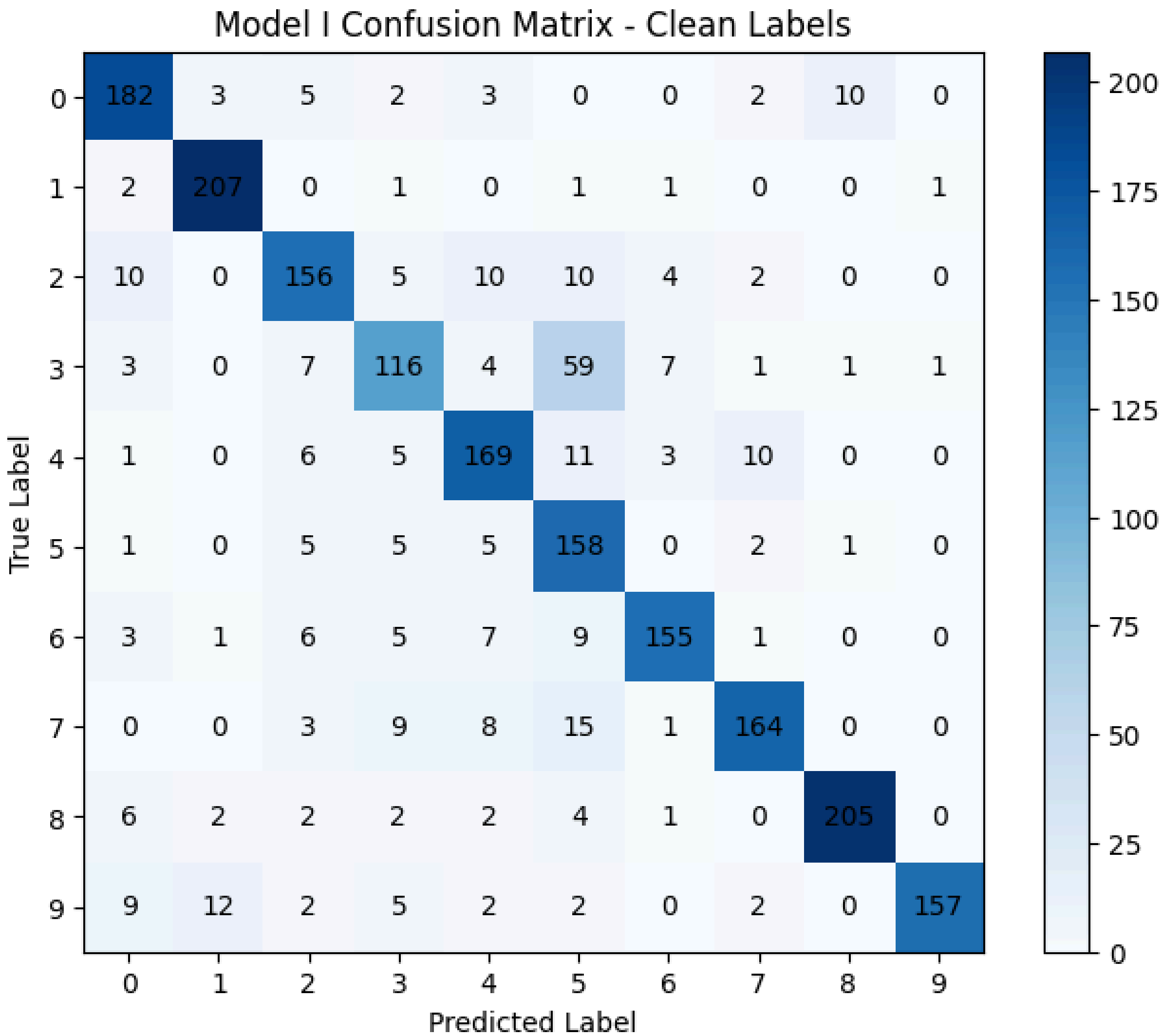
```
from sklearn.metrics import confusion_matrix
import numpy as np

true_labels = []
predicted_labels = []

model.eval()
with torch.no_grad():
    for inputs, labels in noisy_loader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        true_labels.extend(labels.numpy())
        predicted_labels.extend(predicted.numpy())

true_labels = np.array(true_labels)
predicted_labels = np.array(predicted_labels)
cm = confusion_matrix(true_labels, predicted_labels)

plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Model I Confusion Matrix - Noisy Labels')
plt.colorbar()
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, str(cm[i, j]), horizontalalignment='center', verticalalig
plt.xticks(np.arange(10), np.arange(10))
plt.yticks(np.arange(10), np.arange(10))
plt.show()
```



In [132…

```
true_labels = []
predicted_labels = []

model.eval()
with torch.no_grad():
    for inputs, labels in val_loader:
        outputs = model(inputs)
        _, predicted = torch.max(outputs, 1)
        true_labels.extend(labels.numpy())
        predicted_labels.extend(predicted.numpy())

true_labels = np.array(true_labels)
predicted_labels = np.array(predicted_labels)
cm = confusion_matrix(true_labels, predicted_labels)

plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Model I Confusion Matrix - Clean Labels')
plt.colorbar()
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, str(cm[i, j]), horizontalalignment='center', verticalalig
plt.xticks(np.arange(10), np.arange(10))
```

```
plt.yticks(np.arange(10), np.arange(10))
plt.show()
```



2.3. Model II (InceptionV3 for Label Noise Correction and Prediction)

- In this model, we enhance the data by scaling the images to a resolution of 75 x 75 x 3, which allows for a more detailed and feature-rich representation. This is done to improve the spatial resolution. The resulting collection of images, named 'imgs_load', is stored in 'img_load.py' and divided using a ratio of 75% for training and 25% for testing.

In [83]:
```
imgs_load = np.empty((n_img,75,75,3))
for i in range(n_img):
    img_fn = f'../data/images/{i+1:05d}.png'
    imgs_load[i,:,:,:]=cv2.resize(cv2.imread(img_fn),(75,75),interpolation=cv2.I

# Save the array to a numpy file
np.save('imgs_load.npy', imgs_load)
#Re-load the imgs_load.npy under imgs_load
imgs_load = np.load('imgs_load.npy')
```

In [92]:
```
# Function to resize an image to the target size
def resize_image(img):
    resized_img = cv2.resize(img, (75, 75), interpolation=cv2.INTER_CUBIC)
    return resized_img

# Resize images
imgs_resized = np.array([resize_image(img) for img in imgs_load])

# Preprocess images for InceptionV3
imgs_inception = inception_v3.preprocess_input(imgs_load)

# Split data into training and testing sets
imgs_inception_train, imgs_inception_test, noisy_labels_train, noisy_labels_test
    imgs_inception, noisy_labels, test_size=0.25, random_state=42)

# Check the shape of the resized training images
print("Shape of resized imgs_inception_train:", imgs_inception_train.shape)
```

```
Shape of resized imgs_inception_train: (37500, 75, 75, 3)
```

In [93]:
```
# loading the inception_v3 model
def create_model_inception(input_shape, n_classes, optimizer, fine_tune):

    # Path to the locally saved weights file
    local_weight_file = 'inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h

    conv_base = inception_v3.InceptionV3(include_top=False,
                        weights=None,input_shape=input_shape)
    conv_base.load_weights(local_weight_file)

    if fine_tune > 0:
        for layer in conv_base.layers[:-fine_tune]:
            layer.trainable = False
    else:
        for layer in conv_base.layers:
            layer.trainable = False

    # Building the top model (fully-connected layers)
    top_model = conv_base.output
    top_model = Flatten()(top_model)
    top_model = Dense(n_classes * 8, activation='relu')(top_model)
    top_model = Dense(n_classes * 4, activation='relu')(top_model)
    top_model = Dropout(0.2)(top_model)
    output_layer = Dense(n_classes, activation='softmax')(top_model)

    # Creating and compiling the complete model
    model = Model(inputs=conv_base.input, outputs=output_layer)
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=

    return model

# Model parameters
input_shape = (75, 75, 3)
n_classes = 10
optim = Adam(learning_rate=0.001)

# Create the model with the local InceptionV3 weights
inception_model = create_model_inception(input_shape, n_classes, optim, fine_tur
```

In [95]:
```
inception_checkpoint = ModelCheckpoint('inception.weights.best.hdf5', save_best_
early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=

# Splitting the data with K-Fold cross-validation
n_split = 5
kf = KFold(n_splits=n_split)

# Training loop
start_time = time.time()

for fold, (train_index, test_index) in enumerate(kf.split(imgs_inception_train),
    print(f"Training on fold {fold}/{n_split}")
    x_train, x_test = imgs_inception_train[train_index], imgs_inception_train[te
    y_train, y_test = noisy_labels_train[train_index], noisy_labels_train[test_i

    # Train the model
    history = inception_model.fit(x_train, tf.one_hot(y_train, n_classes),
                                  validation_data=(x_test, tf.one_hot(y_test, n_
                                  batch_size=64,
                                  epochs=10,
                                  callbacks=[inception_checkpoint, early_stop],
                                  verbose=1)

    # Evaluate the model on the current fold
    print(f"Evaluation on fold {fold}")
    inception_model.evaluate(x_test, tf.one_hot(y_test, n_classes))
```

```
Training on fold 1/5
Epoch 1/10
469/469 [==============================] - ETA: 0s - loss: 3.0392 - accuracy: 0.
1383
Epoch 1: val_loss improved from inf to 2.39120, saving model to inception.weight
s.best.hdf5
469/469 [==============================] - 24s 51ms/step - loss: 3.0392 - accura
cy: 0.1383 - val_loss: 2.3912 - val_accuracy: 0.1505
Epoch 2/10
469/469 [==============================] - ETA: 0s - loss: 2.5501 - accuracy: 0.
1421
Epoch 2: val_loss improved from 2.39120 to 2.31141, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 25s 52ms/step - loss: 2.5501 - accura
cy: 0.1421 - val_loss: 2.3114 - val_accuracy: 0.1687
Epoch 3/10
469/469 [==============================] - ETA: 0s - loss: 2.3850 - accuracy: 0.
1519
Epoch 3: val_loss improved from 2.31141 to 2.30109, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 24s 51ms/step - loss: 2.3850 - accura
cy: 0.1519 - val_loss: 2.3011 - val_accuracy: 0.1561
Epoch 4/10
469/469 [==============================] - ETA: 0s - loss: 2.3198 - accuracy: 0.
1689
Epoch 4: val_loss improved from 2.30109 to 2.28453, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 24s 52ms/step - loss: 2.3198 - accura
cy: 0.1689 - val_loss: 2.2845 - val_accuracy: 0.1884
Epoch 5/10
469/469 [==============================] - ETA: 0s - loss: 2.2856 - accuracy: 0.
1868
Epoch 5: val_loss improved from 2.28453 to 2.28076, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 24s 51ms/step - loss: 2.2856 - accura
```

```
cy: 0.1868 - val_loss: 2.2808 - val_accuracy: 0.1892
Epoch 6/10
469/469 [==============================] - ETA: 0s - loss: 2.2702 - accuracy: 0.
1988
Epoch 6: val_loss improved from 2.28076 to 2.26792, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 24s 51ms/step - loss: 2.2702 - accura
cy: 0.1988 - val_loss: 2.2679 - val_accuracy: 0.1968
Epoch 7/10
469/469 [==============================] - ETA: 0s - loss: 2.2559 - accuracy: 0.
2107
Epoch 7: val_loss did not improve from 2.26792
469/469 [==============================] - 23s 50ms/step - loss: 2.2559 - accura
cy: 0.2107 - val_loss: 2.2837 - val_accuracy: 0.2092
Epoch 8/10
468/469 [============================>.] - ETA: 0s - loss: 2.2681 - accuracy: 0.
2170
Epoch 8: val_loss did not improve from 2.26792
469/469 [==============================] - 23s 50ms/step - loss: 2.2681 - accura
cy: 0.2170 - val_loss: 2.2687 - val_accuracy: 0.2113
Epoch 9/10
468/469 [============================>.] - ETA: 0s - loss: 2.2639 - accuracy: 0.
2212
Epoch 9: val_loss did not improve from 2.26792
469/469 [==============================] - 24s 51ms/step - loss: 2.2643 - accura
cy: 0.2213 - val_loss: 2.3710 - val_accuracy: 0.2019
Epoch 10/10
469/469 [==============================] - ETA: 0s - loss: 2.2671 - accuracy: 0.
2268
Epoch 10: val_loss did not improve from 2.26792
469/469 [==============================] - 30s 65ms/step - loss: 2.2671 - accura
cy: 0.2268 - val_loss: 2.3253 - val_accuracy: 0.2068
Evaluation on fold 1
235/235 [==============================] - 12s 46ms/step - loss: 2.3253 - accura
cy: 0.2068
Training on fold 2/5
Epoch 1/10
469/469 [==============================] - ETA: 0s - loss: 2.2861 - accuracy: 0.
2214
Epoch 1: val_loss improved from 2.26792 to 2.26473, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 31s 65ms/step - loss: 2.2861 - accura
cy: 0.2214 - val_loss: 2.2647 - val_accuracy: 0.2279
Epoch 2/10
469/469 [==============================] - ETA: 0s - loss: 2.2970 - accuracy: 0.
2213
Epoch 2: val_loss improved from 2.26473 to 2.25683, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 29s 61ms/step - loss: 2.2970 - accura
cy: 0.2213 - val_loss: 2.2568 - val_accuracy: 0.2269
Epoch 3/10
469/469 [==============================] - ETA: 0s - loss: 2.2948 - accuracy: 0.
2246
Epoch 3: val_loss did not improve from 2.25683
469/469 [==============================] - 28s 60ms/step - loss: 2.2948 - accura
cy: 0.2246 - val_loss: 2.2823 - val_accuracy: 0.2353
Epoch 4/10
469/469 [==============================] - ETA: 0s - loss: 2.3108 - accuracy: 0.
2258
Epoch 4: val_loss did not improve from 2.25683
469/469 [==============================] - 28s 60ms/step - loss: 2.3108 - accura
cy: 0.2258 - val_loss: 2.3160 - val_accuracy: 0.2131
Epoch 5/10
469/469 [==============================] - ETA: 0s - loss: 2.3016 - accuracy: 0.
2293
```

```
Epoch 5: val_loss did not improve from 2.25683
469/469 [==============================] - 28s 60ms/step - loss: 2.3016 - accura
cy: 0.2293 - val_loss: 2.2582 - val_accuracy: 0.2332
Epoch 6/10
469/469 [==============================] - ETA: 0s - loss: 2.3233 - accuracy: 0.
2266
Epoch 6: val_loss did not improve from 2.25683
469/469 [==============================] - 28s 60ms/step - loss: 2.3233 - accura
cy: 0.2266 - val_loss: 2.3683 - val_accuracy: 0.2151
Epoch 7/10
469/469 [==============================] - ETA: 0s - loss: 2.3427 - accuracy: 0.
2293
Epoch 7: val_loss did not improve from 2.25683
469/469 [==============================] - 28s 59ms/step - loss: 2.3427 - accura
cy: 0.2293 - val_loss: 2.2587 - val_accuracy: 0.2379
Evaluation on fold 2
235/235 [==============================] - 10s 44ms/step - loss: 2.2568 - accura
cy: 0.2269
Training on fold 3/5
Epoch 1/10
469/469 [==============================] - ETA: 0s - loss: 2.2679 - accuracy: 0.
2341
Epoch 1: val_loss improved from 2.25683 to 2.22219, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 28s 60ms/step - loss: 2.2679 - accura
cy: 0.2341 - val_loss: 2.2222 - val_accuracy: 0.2411
Epoch 2/10
469/469 [==============================] - ETA: 0s - loss: 2.2833 - accuracy: 0.
2309
Epoch 2: val_loss improved from 2.22219 to 2.21599, saving model to inception.we
ights.best.hdf5
469/469 [==============================] - 29s 62ms/step - loss: 2.2833 - accura
cy: 0.2309 - val_loss: 2.2160 - val_accuracy: 0.2411
Epoch 3/10
469/469 [==============================] - ETA: 0s - loss: 2.3009 - accuracy: 0.
2294
Epoch 3: val_loss did not improve from 2.21599
469/469 [==============================] - 29s 61ms/step - loss: 2.3009 - accura
cy: 0.2294 - val_loss: 2.2268 - val_accuracy: 0.2384
Epoch 4/10
469/469 [==============================] - ETA: 0s - loss: 2.3372 - accuracy: 0.
2269
Epoch 4: val_loss did not improve from 2.21599
469/469 [==============================] - 30s 65ms/step - loss: 2.3372 - accura
cy: 0.2269 - val_loss: 2.3845 - val_accuracy: 0.2028
Epoch 5/10
469/469 [==============================] - ETA: 0s - loss: 2.3549 - accuracy: 0.
2204
Epoch 5: val_loss did not improve from 2.21599
469/469 [==============================] - 29s 62ms/step - loss: 2.3549 - accura
cy: 0.2204 - val_loss: 2.3097 - val_accuracy: 0.2311
Epoch 6/10
469/469 [==============================] - ETA: 0s - loss: 2.3613 - accuracy: 0.
2249
Epoch 6: val_loss did not improve from 2.21599
469/469 [==============================] - 29s 62ms/step - loss: 2.3613 - accura
cy: 0.2249 - val_loss: 2.3326 - val_accuracy: 0.2241
Epoch 7/10
469/469 [==============================] - ETA: 0s - loss: 2.3779 - accuracy: 0.
2232
Epoch 7: val_loss did not improve from 2.21599
469/469 [==============================] - 30s 63ms/step - loss: 2.3779 - accura
cy: 0.2232 - val_loss: 2.4417 - val_accuracy: 0.1965
Evaluation on fold 3
235/235 [==============================] - 12s 51ms/step - loss: 2.2160 - accura
```

```
cy: 0.2411
Training on fold 4/5
Epoch 1/10
469/469 [==============================] - ETA: 0s - loss: 2.2644 - accuracy: 0.
2346
Epoch 1: val_loss did not improve from 2.21599
469/469 [==============================] - 29s 62ms/step - loss: 2.2644 - accura
cy: 0.2346 - val_loss: 2.2443 - val_accuracy: 0.2355
Epoch 2/10
469/469 [==============================] - ETA: 0s - loss: 2.3181 - accuracy: 0.
2310
Epoch 2: val_loss did not improve from 2.21599
469/469 [==============================] - 28s 61ms/step - loss: 2.3181 - accura
cy: 0.2310 - val_loss: 2.3669 - val_accuracy: 0.2041
Epoch 3/10
469/469 [==============================] - ETA: 0s - loss: 2.3381 - accuracy: 0.
2272
Epoch 3: val_loss did not improve from 2.21599
469/469 [==============================] - 31s 66ms/step - loss: 2.3381 - accura
cy: 0.2272 - val_loss: 2.3266 - val_accuracy: 0.2128
Epoch 4/10
469/469 [==============================] - ETA: 0s - loss: 2.3662 - accuracy: 0.
2234
Epoch 4: val_loss did not improve from 2.21599
469/469 [==============================] - 29s 62ms/step - loss: 2.3662 - accura
cy: 0.2234 - val_loss: 2.3168 - val_accuracy: 0.2244
Epoch 5/10
468/469 [============================>.] - ETA: 0s - loss: 2.3677 - accuracy: 0.
2265
Epoch 5: val_loss did not improve from 2.21599
469/469 [==============================] - 28s 59ms/step - loss: 2.3676 - accura
cy: 0.2265 - val_loss: 2.3900 - val_accuracy: 0.2155
Epoch 6/10
469/469 [==============================] - ETA: 0s - loss: 2.3852 - accuracy: 0.
2269
Epoch 6: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 59ms/step - loss: 2.3852 - accura
cy: 0.2269 - val_loss: 2.2982 - val_accuracy: 0.2272
Evaluation on fold 4
235/235 [==============================] - 10s 44ms/step - loss: 2.2443 - accura
cy: 0.2355
Training on fold 5/5
Epoch 1/10
469/469 [==============================] - ETA: 0s - loss: 2.2871 - accuracy: 0.
2304
Epoch 1: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 58ms/step - loss: 2.2871 - accura
cy: 0.2304 - val_loss: 2.2852 - val_accuracy: 0.2555
Epoch 2/10
469/469 [==============================] - ETA: 0s - loss: 2.3239 - accuracy: 0.
2289
Epoch 2: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 58ms/step - loss: 2.3239 - accura
cy: 0.2289 - val_loss: 2.3263 - val_accuracy: 0.2193
Epoch 3/10
469/469 [==============================] - ETA: 0s - loss: 2.3697 - accuracy: 0.
2238
Epoch 3: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 57ms/step - loss: 2.3697 - accura
cy: 0.2238 - val_loss: 2.3712 - val_accuracy: 0.2164
Epoch 4/10
469/469 [==============================] - ETA: 0s - loss: 2.3735 - accuracy: 0.
2222
Epoch 4: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 58ms/step - loss: 2.3735 - accura
```

```
cy: 0.2222 - val_loss: 2.4273 - val_accuracy: 0.2152
Epoch 5/10
469/469 [==============================] - ETA: 0s - loss: 2.3844 - accuracy: 0.
2231
Epoch 5: val_loss did not improve from 2.21599
469/469 [==============================] - 26s 56ms/step - loss: 2.3844 - accura
cy: 0.2231 - val_loss: 2.2855 - val_accuracy: 0.2284
Epoch 6/10
469/469 [==============================] - ETA: 0s - loss: 2.3847 - accuracy: 0.
2219
Epoch 6: val_loss did not improve from 2.21599
469/469 [==============================] - 27s 57ms/step - loss: 2.3847 - accura
cy: 0.2219 - val_loss: 2.3815 - val_accuracy: 0.2169
Evaluation on fold 5
235/235 [==============================] - 10s 42ms/step - loss: 2.2852 - accura
cy: 0.2555
```

In [88]:
```
import os
os.environ['CUDA_VISIBLE_DEVICES'] = ''
```

In [97]:
```
inception_new = inception_v3.InceptionV3(include_top=False,
                            weights=None,input_shape=(75,75,3))
```

In [102…
```
inception_new.load_weights('inception.weights.best.hdf5', by_name=True)
inception_new_train_output = inception_new.predict(imgs_inception)

# Save array as .npy file
np.save('inception_new_train_output.npy', inception_new_train_output)
```

```
2024-03-20 14:46:27.234443: I tensorflow/core/grappler/optimizers/custom_graph_o
ptimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
1563/1563 [==============================] - 47s 29ms/step
```

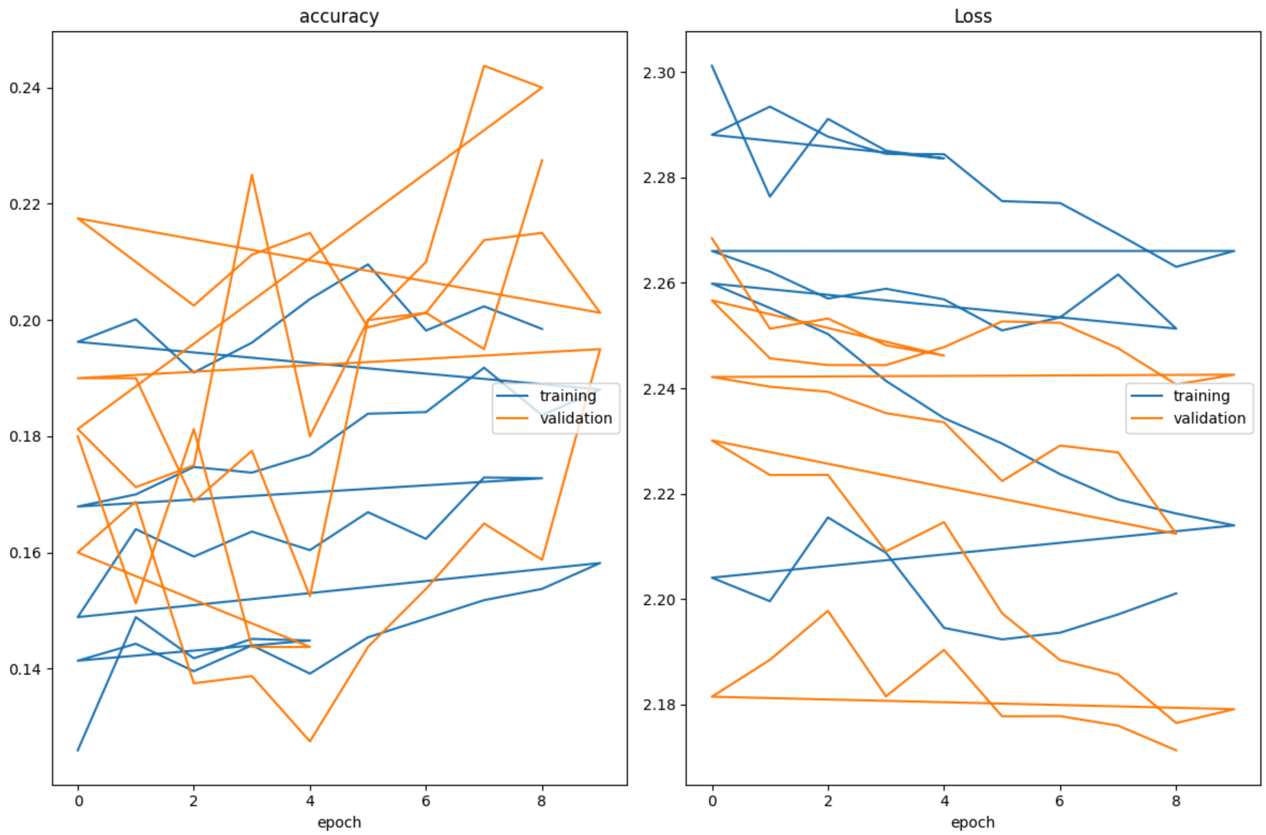
In [103…
```
# the first 10,000 labels
x_train1 = inception_new_train_output[:n_clean_noisy] #labels based on above inc
x_train2 = noisy_labels[:n_clean_noisy] #labels based on noisy labels
y_train = tf.one_hot(clean_labels,10) #labels based on clean label
```

In [104…
```
# create array from previous prediction by transposing the matrix to 2x2 dimensi
label_cleaning_input = np.concatenate((inception_new_train_output.reshape(n_img,
```

In [105…
```
np.save('label_cleaning_input.npy', label_cleaning_input)
```

In [107…
```
# Design dense layers and architecture with basic CNN

label_cleaning_model = tf.keras.Sequential([
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation = 'relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(10, activation='softmax')
])

label_cleaning_model.compile(optimizer='adam',
                             loss='categorical_crossentropy',
                             metrics=['accuracy'])


inception_checkpoint2 = ModelCheckpoint('labelcorrection.weights.best.hdf5', sav
early_stop2 = EarlyStopping(monitor='loss', patience=3, restore_best_weights=Tru
```

```
plot_loss2 = PlotLossesCallback()

n_split=5

y_noisy1 = noisy_labels[:n_clean_noisy]

#train the model with inputs of image matrix from the prediction with clean labe

for train_index,test_index in KFold(n_split).split(label_cleaning_input[:n_clean
  x_train,x_test=label_cleaning_input[train_index],label_cleaning_input[test_inc
  y_train,y_test=clean_labels[train_index],clean_labels[test_index]

  lcn_fit = label_cleaning_model.fit(x_train,
                          tf.one_hot(y_train,10),
                          batch_size=64,
                          epochs=10,
                          validation_split=0.1,
                          callbacks=[inception_checkpoint2, early_stop2, plot_
                          verbose=1)


  print('Model evaluation ',label_cleaning_model.evaluate(x_test,tf.one_hot(y_te
```




```
accuracy
	training           (min:    0.126, max:    0.210, cur:    0.198)
	validation         (min:    0.127, max:    0.244, cur:    0.228)
Loss
	training           (min:    2.192, max:    2.301, cur:    2.201)
	validation         (min:    2.171, max:    2.268, cur:    2.171)
113/113 [==============================] - 2s 17ms/step - loss: 2.2011 - accurac
y: 0.1985 - val_loss: 2.1713 - val_accuracy: 0.2275
63/63 [==============================] - 1s 10ms/step - loss: 2.1764 - accuracy:
0.2085
Model evaluation  [2.176377773284912, 0.2084999978542328]
```

In [108…

```
import tensorflow as tf
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from sklearn.model_selection import KFold
import numpy as np
import matplotlib.pyplot as plt

# Your existing model definition
label_cleaning_model = tf.keras.Sequential([
     tf.keras.layers.Dense(128, activation='relu'),
     tf.keras.layers.Dense(64, activation = 'relu'),
     tf.keras.layers.Dropout(0.5),
     tf.keras.layers.Dense(10, activation='softmax')
])

label_cleaning_model.compile(optimizer='adam',
                             loss='categorical_crossentropy',
                             metrics=['accuracy'])

# Callbacks
inception_checkpoint2 = ModelCheckpoint('labelcorrection.weights.best.hdf5', sav
early_stop2 = EarlyStopping(monitor='loss', patience=3, restore_best_weights=Tru

# K-Fold Cross-Validation
n_split = 5
fold_losses = []
fold_accuracies = []

y_noisy1 = noisy_labels[:n_clean_noisy]

for train_index, test_index in KFold(n_split).split(label_cleaning_input[:n_clea
    x_train, x_test = label_cleaning_input[train_index], label_cleaning_input[te
    y_train, y_test = clean_labels[train_index], clean_labels[test_index]

    label_cleaning_model.fit(x_train,
                             tf.one_hot(y_train, 10),
                             batch_size=64,
                             epochs=10,
                             validation_split=0.1,
                             callbacks=[inception_checkpoint2, early_stop2],
                             verbose=1)

    # Evaluate the model
    scores = label_cleaning_model.evaluate(x_test, tf.one_hot(y_test, 10), verbo
    fold_losses.append(scores[0])
    fold_accuracies.append(scores[1])

# Calculate average metrics
average_loss = np.mean(fold_losses)
average_accuracy = np.mean(fold_accuracies)

# Plotting the results
plt.figure(figsize=(12, 5))

# Plot for average loss
plt.subplot(1, 2, 1)
plt.plot(range(1, n_split + 1), fold_losses, marker='o', color='r')
plt.title('Loss per Fold')
plt.xlabel('Fold')
plt.ylabel('Loss')
```

```
plt.xticks(range(1, n_split + 1))
plt.axhline(y=average_loss, color='b', linestyle='--', label=f'Average Loss: {av
plt.legend()

# Plot for average accuracy
plt.subplot(1, 2, 2)
plt.plot(range(1, n_split + 1), fold_accuracies, marker='o', color='g')
plt.title('Accuracy per Fold')
plt.xlabel('Fold')
plt.ylabel('Accuracy')
plt.xticks(range(1, n_split + 1))
plt.axhline(y=average_accuracy, color='b', linestyle='--', label=f'Average Accur
plt.legend()

plt.tight_layout()
plt.show()
```

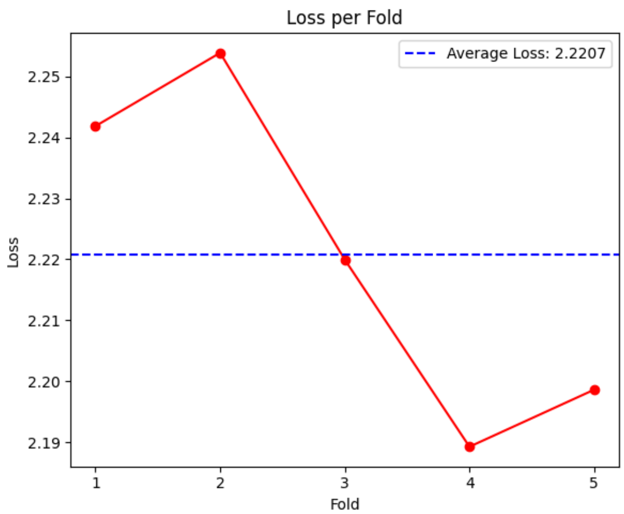
```
Epoch 1/10
  1/113 [..............................] - ETA: 37s - loss: 2.3022 - accuracy:
0.1250
2024-03-20 14:52:39.174957: I tensorflow/core/grappler/optimizers/custom_graph_o
ptimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
113/113 [==============================] - ETA: 0s - loss: 2.3101 - accuracy: 0.
1226
Epoch 1: val_loss improved from inf to 2.27257, saving model to labelcorrection.
weights.best.hdf5
2024-03-20 14:52:41.217442: I tensorflow/core/grappler/optimizers/custom_graph_o
ptimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
113/113 [==============================] - 2s 19ms/step - loss: 2.3101 - accurac
y: 0.1226 - val_loss: 2.2726 - val_accuracy: 0.1700
Epoch 2/10
111/113 [============================>.] - ETA: 0s - loss: 2.3063 - accuracy: 0.
1441
Epoch 2: val_loss improved from 2.27257 to 2.25145, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.3071 - accurac
y: 0.1431 - val_loss: 2.2515 - val_accuracy: 0.1488
Epoch 3/10
111/113 [============================>.] - ETA: 0s - loss: 2.3096 - accuracy: 0.
1467
Epoch 3: val_loss improved from 2.25145 to 2.24604, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.3090 - accurac
y: 0.1472 - val_loss: 2.2460 - val_accuracy: 0.1713
Epoch 4/10
110/113 [============================>.] - ETA: 0s - loss: 2.3081 - accuracy: 0.
1440
Epoch 4: val_loss did not improve from 2.24604
113/113 [==============================] - 2s 14ms/step - loss: 2.3097 - accurac
y: 0.1437 - val_loss: 2.2469 - val_accuracy: 0.1550
Epoch 5/10
110/113 [============================>.] - ETA: 0s - loss: 2.2916 - accuracy: 0.
1440
Epoch 5: val_loss improved from 2.24604 to 2.24590, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.2911 - accurac
y: 0.1444 - val_loss: 2.2459 - val_accuracy: 0.1363
Epoch 6/10
112/113 [============================>.] - ETA: 0s - loss: 2.2967 - accuracy: 0.
1405
Epoch 6: val_loss did not improve from 2.24590
113/113 [==============================] - 2s 16ms/step - loss: 2.2969 - accurac
y: 0.1406 - val_loss: 2.2467 - val_accuracy: 0.1375
```

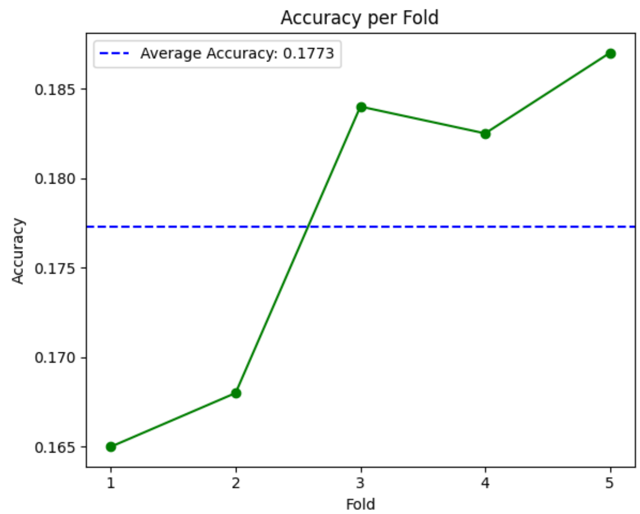
```
Epoch 7/10
110/113 [===========================>.] - ETA: 0s - loss: 2.2920 - accuracy: 0.
1428
Epoch 7: val_loss did not improve from 2.24590
113/113 [==============================] - 2s 15ms/step - loss: 2.2918 - accurac
y: 0.1418 - val_loss: 2.2508 - val_accuracy: 0.1513
Epoch 8/10
113/113 [==============================] - ETA: 0s - loss: 2.2858 - accuracy: 0.
1426
Epoch 8: val_loss did not improve from 2.24590
113/113 [==============================] - 2s 15ms/step - loss: 2.2858 - accurac
y: 0.1426 - val_loss: 2.2524 - val_accuracy: 0.1338
Epoch 9/10
113/113 [==============================] - ETA: 0s - loss: 2.2852 - accuracy: 0.
1476
Epoch 9: val_loss did not improve from 2.24590
113/113 [==============================] - 2s 16ms/step - loss: 2.2852 - accurac
y: 0.1476 - val_loss: 2.2484 - val_accuracy: 0.1625
Epoch 10/10
113/113 [==============================] - ETA: 0s - loss: 2.2843 - accuracy: 0.
1499
Epoch 10: val_loss improved from 2.24590 to 2.24533, saving model to labelcorrec
tion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.2843 - accurac
y: 0.1499 - val_loss: 2.2453 - val_accuracy: 0.1787
Epoch 1/10
113/113 [==============================] - ETA: 0s - loss: 2.2769 - accuracy: 0.
1525
Epoch 1: val_loss improved from 2.24533 to 2.24491, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 16ms/step - loss: 2.2769 - accurac
y: 0.1525 - val_loss: 2.2449 - val_accuracy: 0.1425
Epoch 2/10
110/113 [===========================>.] - ETA: 0s - loss: 2.2704 - accuracy: 0.
1548
Epoch 2: val_loss did not improve from 2.24491
113/113 [==============================] - 2s 16ms/step - loss: 2.2703 - accurac
y: 0.1551 - val_loss: 2.2548 - val_accuracy: 0.1650
Epoch 3/10
112/113 [============================>.] - ETA: 0s - loss: 2.2774 - accuracy: 0.
1514
Epoch 3: val_loss did not improve from 2.24491
113/113 [==============================] - 2s 16ms/step - loss: 2.2775 - accurac
y: 0.1514 - val_loss: 2.2517 - val_accuracy: 0.1412
Epoch 4/10
110/113 [===========================>.] - ETA: 0s - loss: 2.2774 - accuracy: 0.
1467
Epoch 4: val_loss did not improve from 2.24491
113/113 [==============================] - 2s 15ms/step - loss: 2.2774 - accurac
y: 0.1458 - val_loss: 2.2483 - val_accuracy: 0.1700
Epoch 5/10
113/113 [==============================] - ETA: 0s - loss: 2.2686 - accuracy: 0.
1624
Epoch 5: val_loss improved from 2.24491 to 2.24174, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 16ms/step - loss: 2.2686 - accurac
y: 0.1624 - val_loss: 2.2417 - val_accuracy: 0.1912
Epoch 6/10
113/113 [==============================] - ETA: 0s - loss: 2.2747 - accuracy: 0.
1542
Epoch 6: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 14ms/step - loss: 2.2747 - accurac
y: 0.1542 - val_loss: 2.2493 - val_accuracy: 0.1400
Epoch 7/10
111/113 [===========================>.] - ETA: 0s - loss: 2.2745 - accuracy: 0.
```

```
1512
Epoch 7: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 14ms/step - loss: 2.2739 - accurac
y: 0.1506 - val_loss: 2.2439 - val_accuracy: 0.1813
Epoch 8/10
112/113 [============================>.] - ETA: 0s - loss: 2.2714 - accuracy: 0.
1564
Epoch 8: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 16ms/step - loss: 2.2720 - accurac
y: 0.1562 - val_loss: 2.2485 - val_accuracy: 0.1725
Epoch 1/10
113/113 [==============================] - ETA: 0s - loss: 2.2732 - accuracy: 0.
1572
Epoch 1: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 15ms/step - loss: 2.2732 - accurac
y: 0.1572 - val_loss: 2.2462 - val_accuracy: 0.1488
Epoch 2/10
111/113 [============================>.] - ETA: 0s - loss: 2.2677 - accuracy: 0.
1554
Epoch 2: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 15ms/step - loss: 2.2684 - accurac
y: 0.1554 - val_loss: 2.2424 - val_accuracy: 0.1587
Epoch 3/10
112/113 [============================>.] - ETA: 0s - loss: 2.2692 - accuracy: 0.
1567
Epoch 3: val_loss did not improve from 2.24174
113/113 [==============================] - 2s 16ms/step - loss: 2.2691 - accurac
y: 0.1565 - val_loss: 2.2487 - val_accuracy: 0.1525
Epoch 4/10
110/113 [============================>.] - ETA: 0s - loss: 2.2655 - accuracy: 0.
1582
Epoch 4: val_loss improved from 2.24174 to 2.23656, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.2656 - accurac
y: 0.1571 - val_loss: 2.2366 - val_accuracy: 0.2212
Epoch 5/10
110/113 [============================>.] - ETA: 0s - loss: 2.2773 - accuracy: 0.
1553
Epoch 5: val_loss did not improve from 2.23656
113/113 [==============================] - 2s 16ms/step - loss: 2.2787 - accurac
y: 0.1547 - val_loss: 2.2428 - val_accuracy: 0.1875
Epoch 6/10
113/113 [==============================] - ETA: 0s - loss: 2.2742 - accuracy: 0.
1607
Epoch 6: val_loss improved from 2.23656 to 2.22678, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 17ms/step - loss: 2.2742 - accurac
y: 0.1607 - val_loss: 2.2268 - val_accuracy: 0.1675
Epoch 7/10
112/113 [============================>.] - ETA: 0s - loss: 2.2589 - accuracy: 0.
1648
Epoch 7: val_loss improved from 2.22678 to 2.22659, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 14ms/step - loss: 2.2587 - accurac
y: 0.1643 - val_loss: 2.2266 - val_accuracy: 0.1750
Epoch 8/10
111/113 [============================>.] - ETA: 0s - loss: 2.2517 - accuracy: 0.
1672
Epoch 8: val_loss improved from 2.22659 to 2.22040, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.2519 - accurac
y: 0.1678 - val_loss: 2.2204 - val_accuracy: 0.1937
Epoch 9/10
111/113 [============================>.] - ETA: 0s - loss: 2.2484 - accuracy: 0.
1729
```

```
Epoch 9: val_loss improved from 2.22040 to 2.20776, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 14ms/step - loss: 2.2479 - accurac
y: 0.1735 - val_loss: 2.2078 - val_accuracy: 0.2225
Epoch 10/10
112/113 [============================>.] - ETA: 0s - loss: 2.2415 - accuracy: 0.
1687
Epoch 10: val_loss did not improve from 2.20776
113/113 [==============================] - 2s 14ms/step - loss: 2.2414 - accurac
y: 0.1686 - val_loss: 2.2188 - val_accuracy: 0.1900
Epoch 1/10
109/113 [===========================>..] - ETA: 0s - loss: 2.2389 - accuracy: 0.
1805
Epoch 1: val_loss improved from 2.20776 to 2.20130, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 14ms/step - loss: 2.2397 - accurac
y: 0.1804 - val_loss: 2.2013 - val_accuracy: 0.2050
Epoch 2/10
112/113 [============================>.] - ETA: 0s - loss: 2.2347 - accuracy: 0.
1755
Epoch 2: val_loss improved from 2.20130 to 2.18779, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 14ms/step - loss: 2.2343 - accurac
y: 0.1758 - val_loss: 2.1878 - val_accuracy: 0.2250
Epoch 3/10
112/113 [============================>.] - ETA: 0s - loss: 2.2261 - accuracy: 0.
1780
Epoch 3: val_loss improved from 2.18779 to 2.18770, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 15ms/step - loss: 2.2258 - accurac
y: 0.1783 - val_loss: 2.1877 - val_accuracy: 0.2062
Epoch 4/10
113/113 [==============================] - ETA: 0s - loss: 2.2270 - accuracy: 0.
1789
Epoch 4: val_loss improved from 2.18770 to 2.18551, saving model to labelcorrect
ion.weights.best.hdf5
113/113 [==============================] - 2s 14ms/step - loss: 2.2270 - accurac
y: 0.1789 - val_loss: 2.1855 - val_accuracy: 0.2250
Epoch 5/10
109/113 [===========================>..] - ETA: 0s - loss: 2.2272 - accuracy: 0.
1839
Epoch 5: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 15ms/step - loss: 2.2273 - accurac
y: 0.1839 - val_loss: 2.1929 - val_accuracy: 0.2000
Epoch 6/10
113/113 [==============================] - ETA: 0s - loss: 2.2330 - accuracy: 0.
1818
Epoch 6: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 15ms/step - loss: 2.2330 - accurac
y: 0.1818 - val_loss: 2.1935 - val_accuracy: 0.2000
Epoch 1/10
111/113 [============================>.] - ETA: 0s - loss: 2.2278 - accuracy: 0.
1829
Epoch 1: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 14ms/step - loss: 2.2281 - accurac
y: 0.1826 - val_loss: 2.1956 - val_accuracy: 0.2000
Epoch 2/10
110/113 [============================>.] - ETA: 0s - loss: 2.2225 - accuracy: 0.
1903
Epoch 2: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 14ms/step - loss: 2.2227 - accurac
y: 0.1897 - val_loss: 2.1938 - val_accuracy: 0.2013
Epoch 3/10
113/113 [==============================] - ETA: 0s - loss: 2.2283 - accuracy: 0.
1797
```

```
Epoch 3: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 15ms/step - loss: 2.2283 - accurac
y: 0.1797 - val_loss: 2.1918 - val_accuracy: 0.2000
Epoch 4/10
113/113 [==============================] - ETA: 0s - loss: 2.2237 - accuracy: 0.
1793
Epoch 4: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 14ms/step - loss: 2.2237 - accurac
y: 0.1793 - val_loss: 2.2013 - val_accuracy: 0.2212
Epoch 5/10
110/113 [============================>.] - ETA: 0s - loss: 2.2262 - accuracy: 0.
1845
Epoch 5: val_loss did not improve from 2.18551
113/113 [==============================] - 2s 14ms/step - loss: 2.2272 - accurac
y: 0.1839 - val_loss: 2.2101 - val_accuracy: 0.1988
```





In [109…

```
# Predict the 10,000 clean label with label cleaning network
pred_clean_labels = label_cleaning_model.predict(label_cleaning_input[n_clean_nc
pred_clean_labels = pred_clean_labels.argmax(axis=-1)
new_labels = np.append(clean_labels, pred_clean_labels)
new_labels_oh = tf.one_hot(new_labels,depth=10)
```

```
  76/1250 [>.............................] - ETA: 2s
2024-03-20 14:54:26.263070: I tensorflow/core/grappler/optimizers/custom_graph_o
ptimizer_registry.cc:114] Plugin optimizer for device_type GPU is enabled.
1250/1250 [==============================] - 2s 2ms/step
```

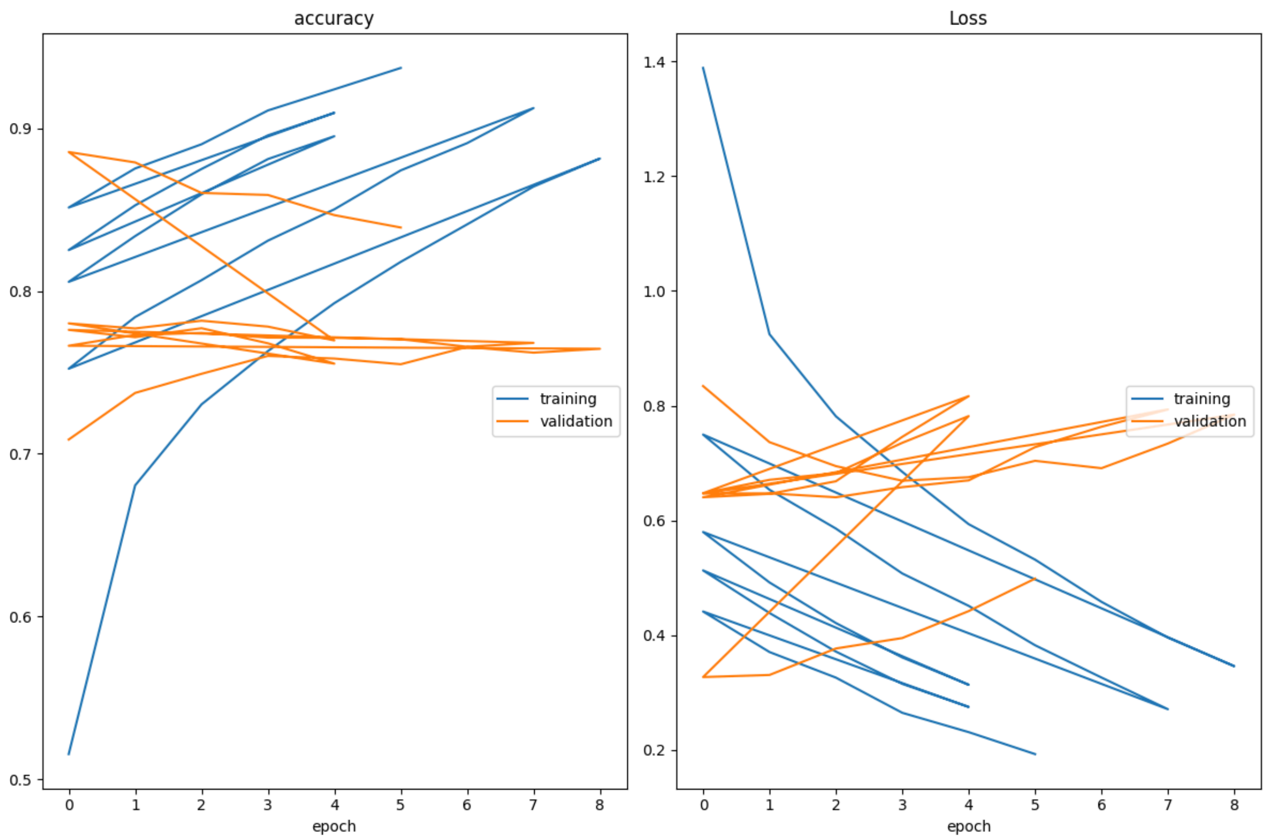
In [110…

```
# Create basic CNN fully connected layers architecture
img_class_model = tf.keras.Sequential([
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(10, activation='softmax')
])

img_class_model.compile(optimizer='adam',
                             loss='categorical_crossentropy',
                             metrics=['accuracy'])
```

In [101…

```
# Train the Model
start = time.time()
inception_checkpoint1 = ModelCheckpoint('inceptionclean.weights.best.keras', sav
early_stop1 = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights
plot_loss1 = PlotLossesCallback()
```

```
for train_index,test_index in KFold(n_split).split(inception_new_train_output):
  x_train,x_test=inception_new_train_output[train_index],inception_new_train_out
  y_train,y_test=new_labels[train_index],new_labels[test_index]

  img_class_fit = img_class_model.fit(x_train,
                              tf.one_hot(y_train,10),
                              batch_size=130,
                              epochs=10,
                              validation_split=0.2,
                              callbacks=[inception_checkpoint1,early_stop1, plot_l
                              verbose=1)
  print('Model evaluation ',img_class_model.evaluate(x_test,tf.one_hot(y_test,10

print('Model Training Time:', round((time.time() - start)/60, 2), 'mins')
```




```
accuracy
	training             (min:    0.516, max:    0.937, cur:    0.937)
	validation           (min:    0.709, max:    0.885, cur:    0.839)
Loss
	training             (min:    0.193, max:    1.389, cur:    0.193)
	validation           (min:    0.327, max:    0.834, cur:    0.498)
247/247 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9378 - loss: 0.1857 - val
_accuracy: 0.8390 - val_loss: 0.4984
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 525us/step - accuracy: 0.8455 - loss: 0.4710
Model evaluation  [0.60166996717453, 0.8036999702453613]
Model Training Time: 0.66 mins
```

In [112…

```
img_class_model.compile(optimizer='adam',
                        loss='categorical_crossentropy',
                        metrics=['accuracy'])

# Load the weights
img_class_model.load_weights('inceptionclean.weights.best.keras')
```

```
# Make predictions on test data
start = time.time()
inceptionclean_ii_preds = img_class_model.predict(x_test)
inceptionclean_ii_preds_classes = np.argmax(inceptionclean_ii_preds, axis=1)
prediction_time = time.time() - start

# Evaluate model accuracy
inception1_acc = accuracy_score(y_test, inceptionclean_ii_preds_classes)

# Print results
print('Prediction Time:', round(prediction_time, 2), 'seconds')
print("Inception Model Accuracy: {:.2f}%".format(inception1_acc * 100))
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 549us/step
Prediction Time: 0.28 seconds
Inception Model Accuracy: 80.37%
```

In [114…

```
def model_II(image):
    inception_preds = inception_new.predict([np.expand_dims(image, axis=0)],verb
    inception_pred_classes = np.argmax(img_class_model.predict(inception_preds,v
    return int(inception_pred_classes[0])
```

In [115…

```
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(' '.join('%5s' % classes[clean_labels[j]] for j in range(8)))
print('Predicted baseline labels:')
print(' '.join('%5s' % classes[model_II(imgs_inception[j])] for j in range(8)))
```

```
Clean labels:
 frog truck truck  deer   car   car  bird horse
Predicted baseline labels:
 frog truck plane  deer   car   car  bird horse
```

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.

In [9]:
```
# [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))
```

In [10]:
```
# [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="int
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)
```

```
              precision    recall  f1-score   support

           0       0.33      0.46      0.38      1000
           1       0.21      0.31      0.25      1000
           2       0.20      0.04      0.07      1000
           3       0.19      0.12      0.14      1000
           4       0.24      0.48      0.32      1000
```

```
           5       0.20      0.11      0.14      1000
           6       0.24      0.34      0.28      1000
           7       0.31      0.04      0.08      1000
           8       0.27      0.43      0.33      1000
           9       0.20      0.12      0.15      1000

    accuracy                           0.24     10000
   macro avg       0.24      0.24      0.21     10000
weighted avg       0.24      0.24      0.21     10000
```

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.