In [1]:

```
import numpy as np
import cv2
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import tensorflow as tf
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
!unzip drive/MyDrive/train_data.zip
```

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 [14]:

```
# 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'images/{i+1:05d}.png'
    imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)
# load the labels
clean_labels = np.genfromtxt('clean_labels.csv', delimiter=',', dtype="int8")
noisy_labels = np.genfromtxt('noisy_labels.csv', delimiter=',', dtype="int8")
```

In [5]:

```
# [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
```

In [6]:

```
def preprocess(image,label):
  image2 = tf.cast(image,dtype=tf.float64)/225.0
  return image2,label
```

In [7]:

```
img_train_noisy,img_vali_noisy,labels_train_noisy, labels_vali_noisy= train_test
_split(imgs,noisy_labels,test_size = 0.2,random_state=4)
noisy_train_dataset= tf.data.Dataset.from_tensor_slices((img_train_noisy, labels
_train_noisy))
noisy_vali_dataset = tf.data.Dataset.from_tensor_slices((img_vali_noisy, labels_
vali_noisy))
noisy_train_set =noisy_train_dataset.map(preprocess)
noisy_vali_set = noisy_vali_dataset.map(preprocess)
noisy_train_ds = noisy_train_set.cache().batch(4).prefetch(buffer_size=10)
noisy_vali_ds = noisy_vali_set.cache().batch(4).prefetch(buffer_size=10)
```

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 [8]:

```
# [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
es
    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 [9]:

```
# [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 [10]:

```
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)
```

In [11]:

```
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))
```

Model I

For model I, we treat noisy label as clean labels and ultilize the tranfer learning with a VGG16 model as pretrained model.The accuracy of prediction on clean labels only dataset is around 54%.

In [12]:

```
pre_model = tf.keras.Sequential()

pre_model= tf.keras.applications.VGG16(include_top=False,
                   input_shape=(32,32,3),
                   pooling='avg',
                   weights='imagenet')
pre_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=["accuracy"])
#pre_model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/kera
s-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.
h5
58889256/58889256 [==============================] - 0s 0us/step
```

In [ ]:

```
for layer in pre_model.layers:
        layer.trainable=False
VGG16_model = tf.keras.Sequential()
VGG16_model.add(pre_model)
VGG16_model.add(tf.keras.layers.Flatten())
VGG16_model.add(tf.keras.layers.Dense(10, activation='softmax'))
VGG16_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=["accuracy"])
model1_history = VGG16_model.fit(noisy_train_ds,epochs = 20,
          verbose=1,
          validation_data = noisy_vali_ds)
```

```
Epoch 1/20
10000/10000 [==============================] - 90s 8ms/step - loss:
2.2819 - accuracy: 0.1579 - val_loss: 2.2431 - val_accuracy: 0.2016
Epoch 2/20
10000/10000 [==============================] - 80s 8ms/step - loss:
2.2313 - accuracy: 0.2107 - val_loss: 2.2268 - val_accuracy: 0.2203
Epoch 3/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.2158 - accuracy: 0.2259 - val_loss: 2.2191 - val_accuracy: 0.2276
Epoch 4/20
10000/10000 [==============================] - 80s 8ms/step - loss:
2.2060 - accuracy: 0.2340 - val_loss: 2.2145 - val_accuracy: 0.2338
Epoch 5/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1988 - accuracy: 0.2396 - val_loss: 2.2115 - val_accuracy: 0.2380
Epoch 6/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1930 - accuracy: 0.2430 - val_loss: 2.2095 - val_accuracy: 0.2406
Epoch 7/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1883 - accuracy: 0.2452 - val_loss: 2.2080 - val_accuracy: 0.2420
Epoch 8/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1843 - accuracy: 0.2481 - val_loss: 2.2071 - val_accuracy: 0.2422
Epoch 9/20
10000/10000 [==============================] - 80s 8ms/step - loss:
2.1808 - accuracy: 0.2508 - val_loss: 2.2064 - val_accuracy: 0.2422
Epoch 10/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1778 - accuracy: 0.2525 - val_loss: 2.2060 - val_accuracy: 0.2431
Epoch 11/20
10000/10000 [==============================] - 78s 8ms/step - loss:
2.1751 - accuracy: 0.2539 - val_loss: 2.2058 - val_accuracy: 0.2436
Epoch 12/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1726 - accuracy: 0.2555 - val_loss: 2.2057 - val_accuracy: 0.2438
Epoch 13/20
10000/10000 [==============================] - 78s 8ms/step - loss:
2.1705 - accuracy: 0.2569 - val_loss: 2.2057 - val_accuracy: 0.2447
Epoch 14/20
10000/10000 [==============================] - 78s 8ms/step - loss:
2.1685 - accuracy: 0.2582 - val_loss: 2.2058 - val_accuracy: 0.2445
Epoch 15/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1667 - accuracy: 0.2583 - val_loss: 2.2060 - val_accuracy: 0.2441
Epoch 16/20
10000/10000 [==============================] - 78s 8ms/step - loss:
2.1650 - accuracy: 0.2591 - val_loss: 2.2063 - val_accuracy: 0.2442
Epoch 17/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1635 - accuracy: 0.2593 - val_loss: 2.2066 - val_accuracy: 0.2435
Epoch 18/20
10000/10000 [==============================] - 79s 8ms/step - loss:
2.1621 - accuracy: 0.2604 - val_loss: 2.2069 - val_accuracy: 0.2432
Epoch 19/20
10000/10000 [==============================] - 78s 8ms/step - loss:
2.1607 - accuracy: 0.2609 - val_loss: 2.2073 - val_accuracy: 0.2425
Epoch 20/20
 1726/10000 [====>.........................] - ETA: 55s - loss: 2.16
13 - accuracy: 0.2575
```

In [ ]:

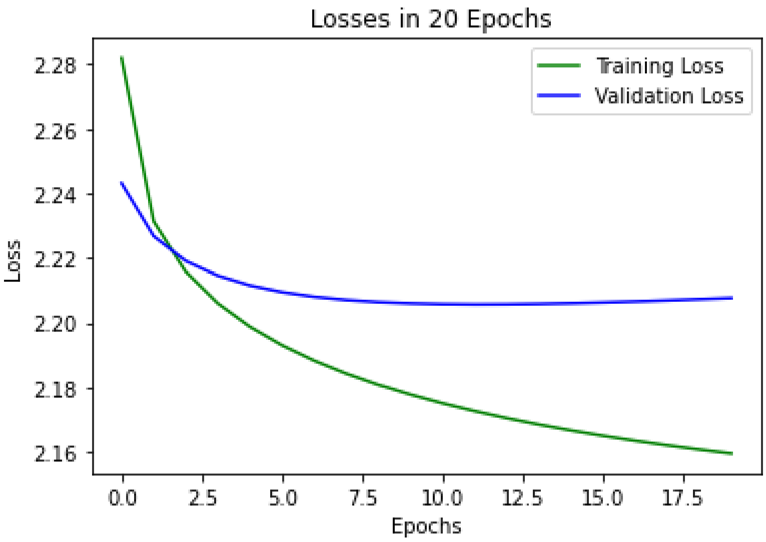
```
#VGG16_model.save("VGG16_model",save_format='h5')
```

In [14]:

```
training_losses = model1_history.history["loss"]
vali_losses = model1_history.history["val_loss"]
epochs = range(0,20)
plt.plot(epochs,training_losses,"g",label = "Training Loss")
plt.plot(epochs,vali_losses,"b",label = "Validation Loss")
plt.title(" Losses in 20 Epochs")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show
```

Out[14]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```

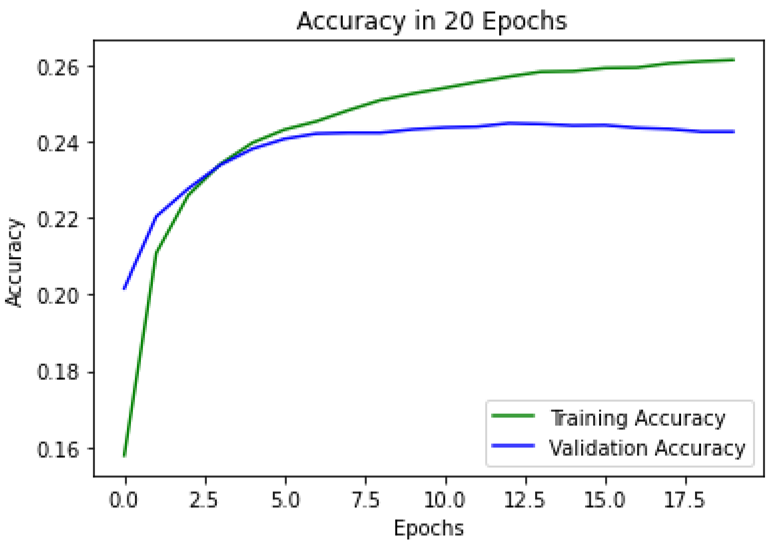


In [15]:

```
training_accuracy = model1_history.history["accuracy"]
vali_accuracy = model1_history.history["val_accuracy"]
epochs = range(0,20)
plt.plot(epochs,training_accuracy,"g",label = "Training Accuracy")
plt.plot(epochs,vali_accuracy,"b",label = "Validation Accuracy")
plt.title(" Accuracy in 20 Epochs")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show
```

Out[15]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [16]:

```
clean_dataset = tf.data.Dataset.from_tensor_slices((imgs[:10000], clean_labels))
clean_set =clean_dataset.map(preprocess)
clean_ds = clean_set.cache().batch(4).prefetch(buffer_size=10)
VGG16_model.evaluate(clean_ds)
```

```
2500/2500 [==============================] - 17s 7ms/step - loss: 1.
7499 - accuracy: 0.5482
```

Out[16]:

```
[1.7499467134475708, 0.5482000112533569]
```

2500/2500 [==============================] - 17s 7ms/step - loss: 1.7499 - accuracy: 0.5482
[1.7499467134475708, 0.5482000112533569]

In [17]:

```
def model_I(image):
    '''
    This function should takes in the image of dimension 32*32*3 as input and re
turns a label prediction
    '''
    classes_hat = VGG16_model.predict(np.array([image/225,]))
    y_pred=np.argmax(classes_hat,axis=1)
    return(y_pred)
```

In [ ]:

```
evaluation(model_I, clean_labels, imgs[:10000])
```

precision recall f1-score support

```
           0       0.65      0.60      0.62      1005
           1       0.50      0.66      0.57       974
           2       0.51      0.45      0.48      1032
           3       0.41      0.40      0.40      1016
           4       0.50      0.54      0.52       999
           5       0.48      0.44      0.46       937
           6       0.63      0.58      0.61      1030
           7       0.60      0.58      0.59      1001
           8       0.65      0.66      0.65      1025
           9       0.56      0.57      0.57       981

    accuracy                           0.55     10000
    macro avg       0.55      0.55      0.55      10000
    weighted avg       0.55      0.55      0.55      1000
```

2.3 Model II

In [6]:

```
pre_model = tf.keras.Sequential()

pre_model= tf.keras.applications.VGG16(include_top=False,
                    input_shape=(32,32,3),
                    pooling='avg',
                    weights='imagenet')
pre_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
               loss=tf.keras.losses.SparseCategoricalCrossentropy(),
               metrics=["accuracy"])
fcHead = pre_model.output
# Add flatten layer
fcHead = tf.keras.layers.BatchNormalization(name='BN')(fcHead)
fcHead = tf.keras.layers.Flatten(name='flatten')(fcHead)
# Add FC
fcHead = tf.keras.layers.Dense(128, activation='relu')(fcHead)
fcHead = tf.keras.layers.Dropout(0.5)(fcHead)
# Output layer with softmax activation
fcHead = tf.keras.layers.Dense(10, activation='softmax')(fcHead)

VGG16_model2 = tf.keras.Model(inputs=pre_model.input, outputs=fcHead)

VGG16_model2.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
               loss=tf.keras.losses.SparseCategoricalCrossentropy(),
               metrics=["accuracy"])
stage1_history = VGG16_model2.fit(imgs[:10000], clean_labels,epochs = 20,verbose
=1, validation_split=0.2)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/kera
s-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.
h5
58889256/58889256 [==============================] - 2s 0us/step
Epoch 1/20
250/250 [==============================] - 19s 32ms/step - loss: 1.9
879 - accuracy: 0.3036 - val_loss: 1.7159 - val_accuracy: 0.3950
Epoch 2/20
250/250 [==============================] - 7s 29ms/step - loss: 1.40
01 - accuracy: 0.5281 - val_loss: 1.2758 - val_accuracy: 0.5730
Epoch 3/20
250/250 [==============================] - 7s 30ms/step - loss: 1.01
20 - accuracy: 0.6671 - val_loss: 1.1503 - val_accuracy: 0.6355
Epoch 4/20
250/250 [==============================] - 7s 30ms/step - loss: 0.94
40 - accuracy: 0.6977 - val_loss: 2.2398 - val_accuracy: 0.4120
Epoch 5/20
250/250 [==============================] - 7s 30ms/step - loss: 0.74
93 - accuracy: 0.7630 - val_loss: 0.9851 - val_accuracy: 0.6830
Epoch 6/20
250/250 [==============================] - 7s 30ms/step - loss: 0.59
28 - accuracy: 0.8069 - val_loss: 0.9044 - val_accuracy: 0.7075
Epoch 7/20
250/250 [==============================] - 8s 30ms/step - loss: 0.41
54 - accuracy: 0.8746 - val_loss: 0.7560 - val_accuracy: 0.7625
Epoch 8/20
250/250 [==============================] - 8s 33ms/step - loss: 0.33
08 - accuracy: 0.9010 - val_loss: 0.7265 - val_accuracy: 0.7750
Epoch 9/20
250/250 [==============================] - 8s 30ms/step - loss: 0.21
42 - accuracy: 0.9379 - val_loss: 0.8482 - val_accuracy: 0.7590
Epoch 10/20
250/250 [==============================] - 8s 30ms/step - loss: 0.18
04 - accuracy: 0.9467 - val_loss: 0.8107 - val_accuracy: 0.7795
Epoch 11/20
250/250 [==============================] - 8s 30ms/step - loss: 0.13
37 - accuracy: 0.9610 - val_loss: 0.8608 - val_accuracy: 0.7755
Epoch 12/20
250/250 [==============================] - 8s 31ms/step - loss: 0.12
57 - accuracy: 0.9641 - val_loss: 0.9745 - val_accuracy: 0.7500
Epoch 13/20
250/250 [==============================] - 8s 31ms/step - loss: 0.13
38 - accuracy: 0.9603 - val_loss: 1.5794 - val_accuracy: 0.6850
Epoch 14/20
250/250 [==============================] - 8s 30ms/step - loss: 0.12
37 - accuracy: 0.9610 - val_loss: 1.0568 - val_accuracy: 0.7680
Epoch 15/20
250/250 [==============================] - 8s 31ms/step - loss: 0.08
94 - accuracy: 0.9721 - val_loss: 0.9124 - val_accuracy: 0.7925
Epoch 16/20
250/250 [==============================] - 8s 30ms/step - loss: 0.06
04 - accuracy: 0.9834 - val_loss: 0.9960 - val_accuracy: 0.7705
Epoch 17/20
250/250 [==============================] - 8s 32ms/step - loss: 0.06
30 - accuracy: 0.9825 - val_loss: 1.1149 - val_accuracy: 0.7640
Epoch 18/20
250/250 [==============================] - 8s 30ms/step - loss: 0.04
75 - accuracy: 0.9869 - val_loss: 0.8902 - val_accuracy: 0.8045
Epoch 19/20
250/250 [==============================] - 8s 30ms/step - loss: 0.05
35 - accuracy: 0.9851 - val_loss: 1.2104 - val_accuracy: 0.7625
```

```
Epoch 20/20
250/250 [==============================] - 8s 30ms/step - loss: 0.08
44 - accuracy: 0.9766 - val_loss: 1.0626 - val_accuracy: 0.7730
```

In [7]:

```
corrected_labels = np.argmax(VGG16_model2.predict(imgs), axis=1)
```

```
1563/1563 [==============================] - 13s 8ms/step
```

In [8]:

```
corrected_labels[:10000]= clean_labels[:10000]
```

In [15]:

```
final_model = tf.keras.applications.VGG16(include_top=False,
                    input_shape=(32,32,3),
                    pooling='avg',
                    weights='imagenet')
final_model = tf.keras.Sequential([
                            final_model,
                            tf.keras.layers.Dense(128, activation='relu'),
                            tf.keras.layers.Dense(10, activation = 'softmax')
                            ])

#compile
final_model.compile(optimizer="adam",loss="sparse_categorical_crossentropy",metr
ics=["accuracy"])

#train
model2_final_history = final_model.fit(imgs,corrected_labels, epochs = 10, valid
ation_split=0.2, batch_size=16, verbose=1)
```

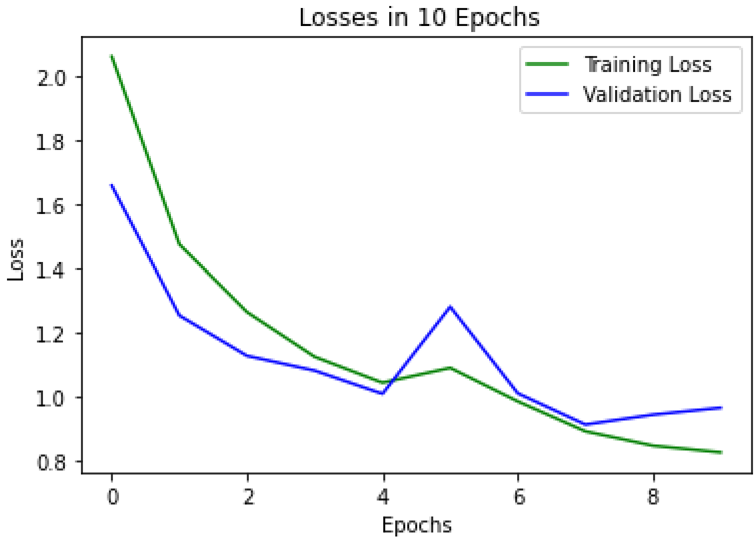
```
Epoch 1/10
2500/2500 [==============================] - 60s 24ms/step - loss:
2.0600 - accuracy: 0.2605 - val_loss: 1.6572 - val_accuracy: 0.3648
Epoch 2/10
2500/2500 [==============================] - 58s 23ms/step - loss:
1.4740 - accuracy: 0.4500 - val_loss: 1.2527 - val_accuracy: 0.5387
Epoch 3/10
2500/2500 [==============================] - 58s 23ms/step - loss:
1.2634 - accuracy: 0.5449 - val_loss: 1.1268 - val_accuracy: 0.6035
Epoch 4/10
2500/2500 [==============================] - 58s 23ms/step - loss:
1.1239 - accuracy: 0.6023 - val_loss: 1.0807 - val_accuracy: 0.6228
Epoch 5/10
2500/2500 [==============================] - 56s 22ms/step - loss:
1.0431 - accuracy: 0.6335 - val_loss: 1.0085 - val_accuracy: 0.6457
Epoch 6/10
2500/2500 [==============================] - 56s 23ms/step - loss:
1.0891 - accuracy: 0.6282 - val_loss: 1.2800 - val_accuracy: 0.5507
Epoch 7/10
2500/2500 [==============================] - 58s 23ms/step - loss:
0.9844 - accuracy: 0.6544 - val_loss: 1.0097 - val_accuracy: 0.6502
Epoch 8/10
2500/2500 [==============================] - 57s 23ms/step - loss:
0.8910 - accuracy: 0.6893 - val_loss: 0.9122 - val_accuracy: 0.6832
Epoch 9/10
2500/2500 [==============================] - 58s 23ms/step - loss:
0.8462 - accuracy: 0.7055 - val_loss: 0.9430 - val_accuracy: 0.6789
Epoch 10/10
2500/2500 [==============================] - 58s 23ms/step - loss:
0.8254 - accuracy: 0.7167 - val_loss: 0.9645 - val_accuracy: 0.6843
```

In [16]:

```
training_losses = model2_final_history.history["loss"]
vali_losses = model2_final_history.history["val_loss"]
epochs = range(0,10)
plt.plot(epochs,training_losses,"g",label = "Training Loss")
plt.plot(epochs,vali_losses,"b",label = "Validation Loss")
plt.title(" Losses in 10 Epochs")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show
```

Out[16]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```

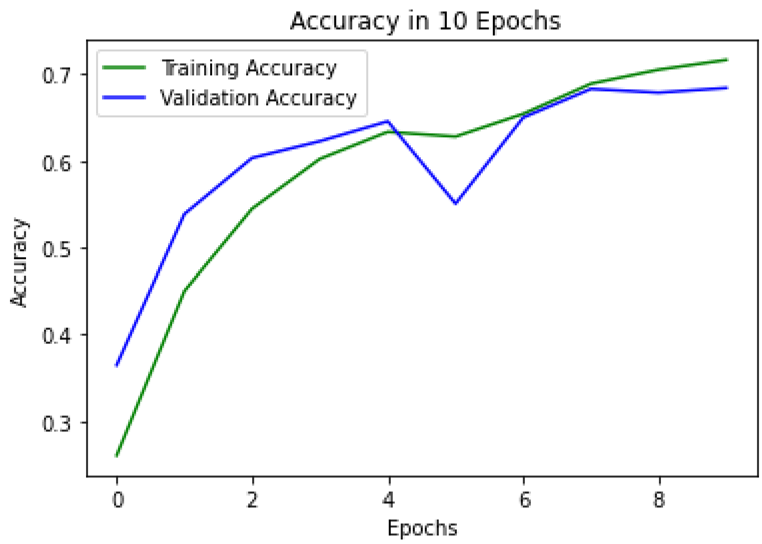


In [17]:

```
training_accuracy = model2_final_history.history["accuracy"]
vali_accuracy = model2_final_history.history["val_accuracy"]
epochs = range(0,10)
plt.plot(epochs,training_accuracy,"g",label = "Training Accuracy")
plt.plot(epochs,vali_accuracy,"b",label = "Validation Accuracy")
plt.title(" Accuracy in 10 Epochs")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show
```

Out[17]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [18]:

```
def model_II(image):
    '''
    This function should takes in the image of dimension 32*32*3 as input and re
turns a label prediction
    '''
    # write your code here...
    return np.argmax(final_model.predict(np.array([image,]), verbose=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.

In [19]:

```
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 [27]:

```
n_test = 10000
test_labels = np.genfromtxt('../data/test_labels.csv', delimiter=',', dtype="int
8")
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)
```

```
---------------------------------------------------------------------
-------
OSError                                   Traceback (most recent cal
l last)
<ipython-input-27-971764389230> in <module>
      1 n_test = 10000
----> 2 test_labels = np.genfromtxt('../data/test_labels.csv', delim
iter=',', dtype="int8")
      3 test_imgs = np.empty((n_test,32,32,3))
      4 for i in range(n_test):
      5     img_fn = f'../data/test_images/test{i+1:05d}.png'

/usr/local/lib/python3.7/dist-packages/numpy/lib/npyio.py in genfrom
txt(fname, dtype, comments, delimiter, skip_header, skip_footer, con
verters, missing_values, filling_values, usecols, names, excludelis
t, deletechars, replace_space, autostrip, case_sensitive, defaultfm
t, unpack, usemask, loose, invalid_raise, max_rows, encoding, like)
   1791             fname = os_fspath(fname)
   1792         if isinstance(fname, str):
-> 1793             fid = np.lib._datasource.open(fname, 'rt', encod
ing=encoding)
   1794             fid_ctx = contextlib.closing(fid)
   1795         else:

/usr/local/lib/python3.7/dist-packages/numpy/lib/_datasource.py in o
pen(path, mode, destpath, encoding, newline)
    191
    192     ds = DataSource(destpath)
--> 193     return ds.open(path, mode, encoding=encoding, newline=ne
wline)
    194
    195

/usr/local/lib/python3.7/dist-packages/numpy/lib/_datasource.py in o
pen(self, path, mode, encoding, newline)
    531                                       encoding=encoding, new
line=newline)
    532         else:
--> 533             raise IOError("%s not found." % path)
    534
    535

OSError: ../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.

In [20]:

```
evaluation(model_II, clean_labels[:1000], imgs[:1000])
```

```
              precision    recall  f1-score   support

           0       0.76      0.74      0.75       102
           1       0.88      0.92      0.90       112
           2       0.57      0.61      0.59        99
           3       0.52      0.15      0.24        92
           4       0.79      0.71      0.74        99
           5       0.47      0.87      0.61        85
           6       0.72      0.79      0.75       107
           7       0.83      0.84      0.84       102
           8       0.94      0.68      0.79        99
           9       0.84      0.92      0.88       103

    accuracy                           0.73      1000
   macro avg       0.73      0.72      0.71      1000
weighted avg       0.74      0.73      0.72      1000
```

In [29]:

```
evaluation(baseline_model, clean_labels[:1000], imgs[:1000])
```

```
              precision    recall  f1-score   support

           0       0.32      0.45      0.37       102
           1       0.18      0.25      0.21       112
           2       0.24      0.05      0.08        99
           3       0.23      0.15      0.18        92
           4       0.26      0.52      0.34        99
           5       0.18      0.12      0.14        85
           6       0.28      0.36      0.31       107
           7       0.55      0.06      0.11       102
           8       0.27      0.44      0.34        99
           9       0.23      0.12      0.15       103

    accuracy                           0.25      1000
   macro avg       0.27      0.25      0.22      1000
weighted avg       0.27      0.25      0.23      1000
```