# CAPTCHA Bypass


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### *Description*

CAPTCHA, or Completely Automated Public Turing Test to Tell Computers and Humans Apart, is a challenge-response test that determines whether a user is authentic (human) or inauthentic (machine). They require users to authenticate themselves by retyping a character sequence prior to completing a request. This notebook implements a CAPTCHA bypass using deep learning. The team aims to investigate weaknesses and vulnerabilities of the CAPTCHA system.

In [ ]:
```
%%shell
jupyter nbconvert --to html /content/captcha.ipynb
```

```
[NbConvertApp] Converting notebook /content/captcha.ipynb to html
[NbConvertApp] Writing 695383 bytes to /content/captcha.html
```

Out[ ]:

In [1]:
```
# Imports
import torch
import torch.nn as nn
import os
from skimage import io
from torch.utils.data import Dataset, DataLoader
import torch.utils.data
import torchvision
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import numpy as np
import time
import seaborn as sns
```

# Part 1. Data Processing

The dataset for this model is generated using the following library: [https://github.com/lepture/captcha (https://github.com/lepture/captcha)](https://github.com/lepture/captcha) and automated by the script `dataset_generator.py` .

The character space began as purely numeric (0-9) but has since expanded to become alphanumeric (0-9, A-Z). Alphabetical characters are capitalized. Characters are uniformly distributed in terms of occurrence in the dataset.

The generated dataset `alphanumeric_dataset.zip` is availiable on the private team Google Drive because it is too large for the Github repository. Upload `alphanumeric_dataset.zip` into the Colab Files and unzip.

In [1]:
```
# Unzip dataset
!unzip  -qq /content/alphanumeric_dataset.zip -d /content/
```

```
replace /content/alphanumeric_dataset/004HE.png? [y]es, [n]o, [A]ll, [N]one,
[r]ename:
```

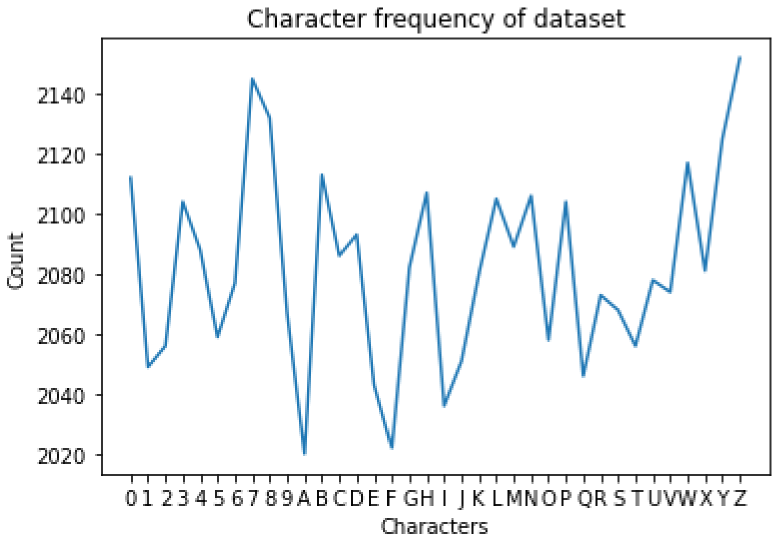
In [2]:
```
class CaptchaDataset(Dataset):
  """ Captcha Dataset """

  def __init__(self, directory):
    self.directory = directory
    self.captchas = os.listdir(directory)
    self.captchas.remove("metadata.txt")

    self.transform = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

    self.character_set = open(directory + "/metadata.txt", "r").readline().spl
it(',')
    self.characters_to_identifier = {}

    for i in range(len(self.character_set)):
      self.characters_to_identifier.update({ self.character_set[i]: i })

  def __len__(self):
    # Assumes each file in the dataset directory represents a data sample
    return len(self.captchas)

  def __getitem__(self, index):
    sample_name = self.captchas[index]
    sample_captcha_values = list(sample_name[0:-4]) # Slice s.t. remove png fi
le extension

    # Read the image and represent it as a tensor
    image = io.imread(self.directory + '/' + sample_name)
    image = self.transform(image)

    # Represent each character as an integer identifier
    label = []
    for char in sample_captcha_values:
      label.append(self.characters_to_identifier.get(char))

    return (image, torch.tensor(label))
```

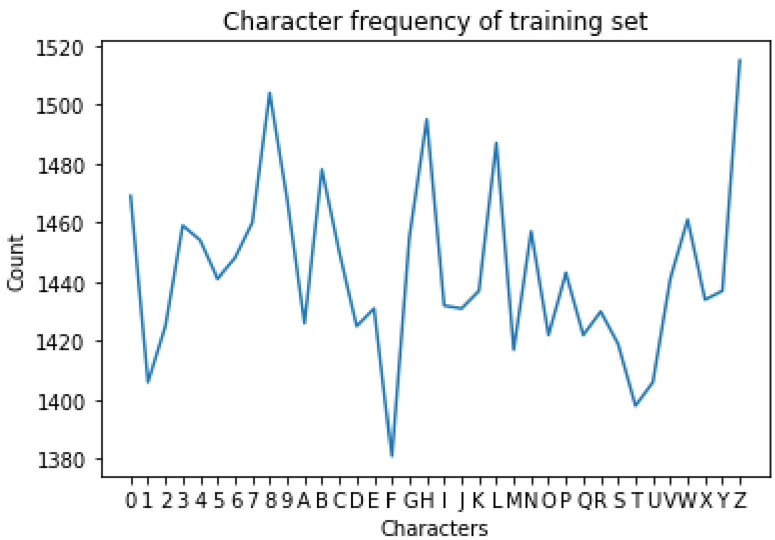
In [3]:
```
dataset_path = "/content/alphanumeric_dataset"

# Instantiate dataset
dataset = CaptchaDataset(dataset_path)
```

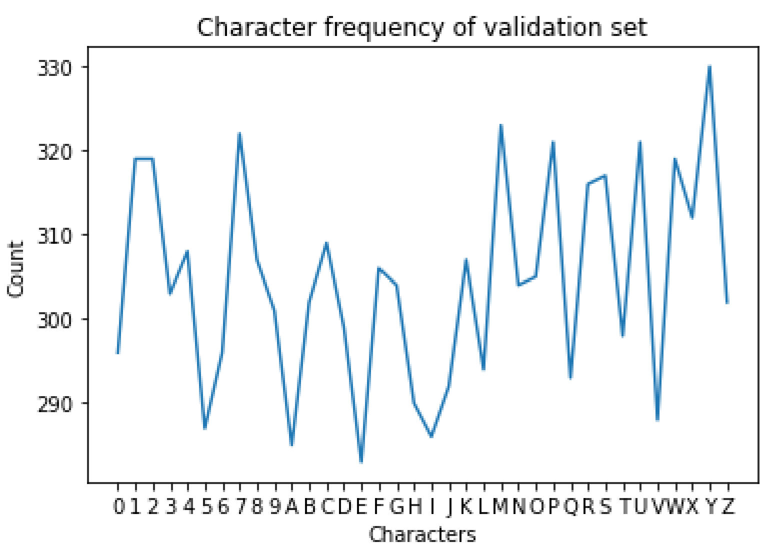
In [4]:
```
def visualize_character_frequency(dataloader, title):
  character_frequency = {} # Contains frequency information
  character_set = dataset.character_set

  # Populate character_frequency
  for _, labels in dataloader:
    for label in labels:
      for char_identifier in label:
        char = character_set[char_identifier.item()]
        current_value = character_frequency.get(char, None)

        if current_value is None:
          character_frequency.update({ char : 0 })
        else:
          character_frequency.update({ char : current_value + 1 })

  x_values = range(len(character_set))
  y_values = []

  for char in character_set:
    count = character_frequency.get(char)
    y_values.append(count)

  plt.title(title)
  plt.plot(x_values, y_values)
  plt.xlabel("Characters")
  plt.ylabel("Count")
  plt.xticks(x_values, character_set)
  plt.show()
```

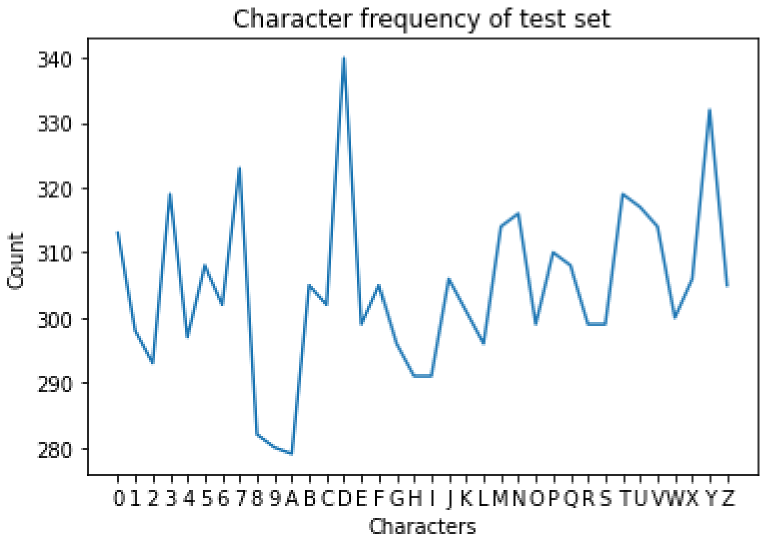
In [5]:
```
def get_data_loaders(dataset, batch_size, total_size=None):

  if total_size is None:
    total_size = len(dataset)

  training_ratio = 0.7
  validation_ratio = 0.15
  # test_ratio implied

  train_length = int(total_size * training_ratio)
  validation_length = int((total_size - train_length) * (validation_ratio / (
1 - training_ratio )))
  test_length = total_size - train_length - validation_length
  fill = len(dataset) - total_size

  train_set, valid_set, test_set, fill_set = torch.utils.data.random_split(dat
aset, [train_length, validation_length, test_length, fill], torch.Generator().
manual_seed(10))

  train_loader = torch.utils.data.DataLoader(train_set, batch_size=batch_size,
num_workers=1, drop_last=True, shuffle=True)
  valid_loader = torch.utils.data.DataLoader(valid_set, batch_size=batch_size,
num_workers=1, drop_last=True, shuffle=True)
  test_loader = torch.utils.data.DataLoader(test_set, batch_size=batch_size, n
um_workers=1, drop_last=True, shuffle=True)

  return train_loader, valid_loader, test_loader
```

In [6]:
```
# Dataset visualization
train, valid, test = get_data_loaders(dataset, 100)

visualize_character_frequency(torch.utils.data.DataLoader(dataset, num_workers
=1), title="Character frequency of dataset")
visualize_character_frequency(train, title="Character frequency of training se
t")
visualize_character_frequency(valid, title="Character frequency of validation
 set")
visualize_character_frequency(test, title="Character frequency of test set")
```


Character frequency of dataset
Count
2020
2040
2060
2080
2100
2120
2140
0 1 2 3 4 5 6 7 8 9 A B C D E F G H I J K L M N O P Q R S T U V W X Y Z
Characters


Character frequency of training set
Count
1380
1400
1420
1440
1460
1480
1500
1520
0 1 2 3 4 5 6 7 8 9 A B C D E F G H I J K L M N O P Q R S T U V W X Y Z
Characters


Character frequency of validation set
Count
290
300
310
320
330
0 1 2 3 4 5 6 7 8 9 A B C D E F G H I J K L M N O P Q R S T U V W X Y Z
Characters




## Part 2. Character Segmentation

Character segmentation must occur prior to character classification. This entails using `OpenCV.findContours()` to perform blob detection on a CAPTCHA image input. This will extract each individual character (5 total) for input to the model. This module has two implementations, one using deep-learning and another that does not. The deep learning implementation uses a model to predict good "slicing" points for overlapping characters.

The models used in the module are supplied as trained models `2Char.pth` and `3Char.pth` which can be found in the project GitHub repo. Make sure you upload these files to your local session before running the below cells.

In [7]:
```
import random
import cv2
import torchvision as tv
```

In [8]:
```
class Chars2(nn.Module):
    def __init__(self):
        super(Chars2, self).__init__()
        self.conv1 = nn.Conv2d(1,7,5,1,4)
        self.pool1 = nn.MaxPool2d(2, 2)

        self.conv2 = nn.Conv2d(7, 14, 5,1, 4)
        self.pool2 = nn.MaxPool2d(2,2)


        self.conv3 = nn.Conv2d(14, 28, 5,1, 4)
        self.pool3 = nn.MaxPool2d(2,2)

        self.conv4 = nn.Conv2d(28, 56, 5,1, 4)
        self.pool4 = nn.MaxPool2d(2,2)

        self.conv5 = nn.Conv2d(56, 70, 5,1, 4)
        self.pool5 = nn.MaxPool2d(2,2)

        self.conv6 = nn.Conv2d(70, 80, 5,1, 4)
        self.pool6 = nn.MaxPool2d(2,2)



        self.fc1 = nn.Linear(2000, 100)
        self.fc2 = nn.Linear(100, 1)

        self.lrelu=torch.nn.LeakyReLU(-0.001)

    def forward(self, img):
        x = self.pool1(self.lrelu(self.conv1(img)))
        x = self.pool2(self.lrelu(self.conv2(x)))
        x = self.pool3(self.lrelu(self.conv3(x)))
        x = self.pool4(self.lrelu(self.conv4(x)))
        #print(x.shape)
        x = self.pool5(self.lrelu(self.conv5(x)))
        #print(x.shape)
        x = self.pool6(self.lrelu(self.conv6(x)))
        #print(x.shape)
        x = x.view(-1, 2000)
        x = self.fc2(self.lrelu(self.fc1(x)))
        return x
```

In [9]:
```
class Chars3(nn.Module):
    def __init__(self):
        super(Chars3, self).__init__()
        self.conv1 = nn.Conv2d(1,7,5,1,4)
        self.pool1 = nn.MaxPool2d(2, 2)

        self.conv2 = nn.Conv2d(7, 14, 5,1, 4)
        self.pool2 = nn.MaxPool2d(2,2)

        self.conv3 = nn.Conv2d(14, 28, 5,1, 4)
        self.pool3 = nn.MaxPool2d(2,2)

        self.conv4 = nn.Conv2d(28, 56, 5,1, 4)
        self.pool4 = nn.MaxPool2d(2,2)

        self.conv5 = nn.Conv2d(56, 70, 5,1, 4)
        self.pool5 = nn.MaxPool2d(2,2)

        self.conv6 = nn.Conv2d(70, 80, 5,1, 4)
        self.pool6 = nn.MaxPool2d(2,2)



        self.fc1 = nn.Linear(2000, 130)
        self.fc2 = nn.Linear(130, 2)

        self.lrelu=torch.nn.LeakyReLU(-0.001)

    def forward(self, img):
        x = self.pool1(self.lrelu(self.conv1(img)))
        x = self.pool2(self.lrelu(self.conv2(x)))
        x = self.pool3(self.lrelu(self.conv3(x)))
        x = self.pool4(self.lrelu(self.conv4(x)))
        #print(x.shape)
        x = self.pool5(self.lrelu(self.conv5(x)))
        #print(x.shape)
        x = self.pool6(self.lrelu(self.conv6(x)))
        #print(x.shape)
        x = x.view(-1, 2000)
        x = self.fc2(self.lrelu(self.fc1(x)))
        return x
```

In [10]:
```
"""Load Previously saved model weights"""
modelChars2=Chars2()
modelChars2.load_state_dict(torch.load('2Char.pth'))
modelChars3=Chars3()
modelChars3.load_state_dict(torch.load('3Char.pth'))
```

Out[10]: <All keys matched successfully>

In [11]:
```
def processimage(image, thresh):
      #Format image type/ dimensions
      image=image.permute(1,2,0)
      image=image.numpy()
      imageorig=image

      #Modify image so contours/ borders can be easily found
      #Greyscale
      image = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
      #Binary Threshold
      NA, image = cv2.threshold(image, thresh, 1, cv2.THRESH_BINARY)
      #Erosion
      #kernel = np.ones((2,2),np.uint8)
      #image = cv2.dilate(image,kernel,iterations = 1)
      #Vertical Blur and Resharpen
      morpher = cv2.getStructuringElement(cv2.MORPH_RECT, (1,5))
      image = cv2.morphologyEx(image, cv2.MORPH_CLOSE, morpher)
      #Binary Threshold
      thresh, image = cv2.threshold(image,thresh, 1, cv2.THRESH_BINARY)
      #Expand Border
      image=cv2.copyMakeBorder(image, 5, 5, 5, 5,cv2.BORDER_CONSTANT,value=1)
      image = image.astype(np.uint8)

      return imageorig,image
```

In [12]:
```
def segmentimage(image,narrow):
    #Return list of borderlines in image
    contours, hierarchy = cv2.findContours(image, cv2.RETR_TREE, cv2.CHAIN_APP
ROX_SIMPLE)
    #imagecont=cv2.drawContours(image, contours, -1, (0, 0.5, 0), 1)

    #Creates boxes for every large object
    boxes=[]
    for contour in contours:
        [x,y,w,h]=cv2.boundingRect(contour)
        if(w>8 and w<120 and h>22):
          boxes.append([x,y,w,h])
    boxes.sort(key=lambda x: x[0])

    #Eliminates boxes that are contained whithin other boxes (subparts of a le
tter)
    i=1
    while (i<len(boxes)):
      box=boxes[i]
      boxprev=boxes[i-1]
      if (box[0]>boxprev[0] and box[1]>boxprev[1] and (box[0]+box[2])<(boxprev
[0]+boxprev[2]) and (box[1]+box[3])<(boxprev[1]+boxprev[3])):
        boxes.pop(i)
        i-=1
      i+=1

    #If boxes are too wide they may contain multiple boxes
    #They are split vertically into 2 or 3 subboxes (even width splits)
    i=0
    """while (i<len(boxes)):
      box=boxes[i]
      if (box[2]>box[3]*(0.95-narrow)):
        x,y,w,h=boxes.pop(i)
        boxes.insert(i,[x+int((2*w)/3),y,int(w/3),h])
        boxes.insert(i,[x+int((w)/3),y,int(w/3),h])
        boxes.insert(i,[x,y,int(w/3),h])
      elif (box[2]>box[3]*(0.6-narrow)):
        x,y,w,h=boxes.pop(i)
        boxes.insert(i,[x+int(w/2),y,int(w/2),h])
        boxes.insert(i,[x,y,int(w/2),h])
      if (i>=len(boxes)-1):
        break
      i+=1"""

    return boxes
```

In [13]:
```
#Resizes an image according to the given dimensions. No distortion applied
def resizeimage(image,dheight,dwidth):
  height=image.shape[0]
  width=image.shape[1]
  if (width>height):
    topbuffer=int ((width-height)/2)
    topbufferoverwidth=float(topbuffer)/width
    sidebufferoverwidth=0
    image=cv2.copyMakeBorder(image,topbuffer,topbuffer, 0, 0,cv2.BORDER_CONSTA
NT,value=1)
  else:
    sidebuffer=int ((height-width)/2)
    sidebufferoverwidth=float(sidebuffer)/height
    topbufferoverwidth=0
    image=cv2.copyMakeBorder(image,0,0, int ((height-width)/2), int ((height-w
idth)/2),cv2.BORDER_CONSTANT,value=1)
  image = cv2.resize(image, dsize=(dwidth, dheight), interpolation=cv2.INTER_C
UBIC)
  return image,topbufferoverwidth,sidebufferoverwidth
```

In [14]:
```
def getcharacterimages(images,dheight=80,dwidth=80, showsegments=False, deeple
arning=False ):
  characters=[]
  for i in range (0,len(images)):
    imageraw = images[i]

    """CAPTCHA image pre-processed, custom function called"""
    # Rectangle Borders of each character obtained, custom function called
    # Binary Threshold is adaptably adjusted until image is seen
    thresh, narrow = 0.6,0
    for x in range(0,5):
      imageorig, image=processimage(imageraw,thresh)
      imageboxes = np.copy(image)
      boxes=segmentimage(image,narrow)
      if (len(boxes)<=1):
        thresh+=x*0.1
      else:
        break

    """Estimating Characters per box"""
    # We estimate this number by the ratio of height to width
    # The ratio is adaptably adjusted until we meet 5 characters
    narrow=0
    for x in range (0,200):
      numchars=[]
      narrow+=x*0.005
      for i in range(0,len(boxes)):
        box=boxes[i]
        if (box[2]>box[3]*(0.95-narrow)):
          numchars.append(3)
        elif (box[2]>box[3]*(0.6-narrow)):
          numchars.append(2)
        else:
          numchars.append(1)
      # Only break if 5 characters are estimated
      sum=0
      for j in range(0,len(numchars)):
        sum+=numchars[j]
      if (sum>=5):
        break

    #Add 0 estimates, if there are still less than 5 numchar estimates
    while (len(numchars)<5):
      numchars.append(0)

    """If deeplearning off, cut boxes"""
    if (deeplearning==False):
      boxnum=0
      for i in range(0,len(boxes)):
          #boxnum tracks boxes, i tracks numchars prediction
          box=boxes[boxnum]
          if (numchars[i]==3):
            x,y,w,h=boxes.pop(boxnum)
            boxes.insert(boxnum,[x+int((2*w)/3),y,int(w/3),h])
            boxes.insert(boxnum,[x+int((w)/3),y,int(w/3),h])
            boxes.insert(boxnum,[x,y,int(w/3),h])
```

```
            boxnum+=3
          elif (numchars[i]==2):
            x,y,w,h=boxes.pop(boxnum)
            boxes.insert(boxnum,[x+int(w/2),y,int(w/2),h])
            boxes.insert(boxnum,[x,y,int(w/2),h])
            boxnum+=2
          else:
            boxnum+=1


    #Filter bad segmentation cases
    #Update: Feature no longer possible
    #if filterBadSegmentation and len(boxes) < 5:
      #continue

    """Cutting out Box Images from CAPTCHA"""
    charactersset=[]
    for i in range(0,5):
      # If insufficient letters obtainable, add an empty image
      if (i<len(boxes)):
        box=boxes[i]
      else:
        box=[0,0,1,1]

      [x,y,w,h]=box
      char=image[y:y+h,x:x+w]
      height=char.shape[0]
      width=char.shape[1]
      # cv2.copyMakeBorder(soruce, top, bottom, left, right, borderType, valu
e)

      #Resizing Image
      char,topbufferoverwidth,sidebufferoverwidth=resizeimage(char,80,80)


      """If deeplearning = True, use models to split images"""
      if (deeplearning==False):
        charactersset.append(char)
      else:
        if (numchars[i]==2):
          input=torch.Tensor(char).unsqueeze(0).unsqueeze(0)
          #Splitting Estimate from Model
          horsplit=round(modelChars2(input).item())
          if (topbufferoverwidth!=0):
            #Cut off excess top, split according to model prediction, resize
            char1=char[round(topbufferoverwidth*80):round(80-80*topbufferoverw
idth),0:horsplit]
            char2=char[round(topbufferoverwidth*80):round(80-80*topbufferoverw
idth),horsplit:]
            char1=resizeimage(char1,80,80)[0]
            char2=resizeimage(char2,80,80)[0]
            charactersset.append(char1)
            charactersset.append(char2)
          else:
            #Cut off excess sides, split according to model prediction, resize
            char1=char[:,round(sidebufferoverwidth*80):horsplit]
            char2=char[:,horsplit:round(80-sidebufferoverwidth*80)]
```

```
            char1=resizeimage(char1,80,80)[0]
            char2=resizeimage(char2,80,80)[0]
            charactersset.append(char1)
            charactersset.append(char2)
        elif (numchars[i]==3):
          input=torch.Tensor(char).unsqueeze(0).unsqueeze(0)
          #Splitting Estimate from Model
          output=modelChars3(input).squeeze()
          horsplit=round(output[0].item()),round(output[1].item())
          if (topbufferoverwidth!=0):
            #Cut off excess top, split according to model prediction, resize
            char1=char[round(topbufferoverwidth*80):round(80-80*topbufferoverw
idth),0:horsplit[0]]
            char2=char[round(topbufferoverwidth*80):round(80-80*topbufferoverw
idth),horsplit[0]:horsplit[1]]
            char3=char[round(topbufferoverwidth*80):round(80-80*topbufferoverw
idth),horsplit[1]:]
            char1=resizeimage(char1,80,80)[0]
            char2=resizeimage(char2,80,80)[0]
            char3=resizeimage(char3,80,80)[0]
            charactersset.append(char1)
            charactersset.append(char2)
            charactersset.append(char3)
          else:
            #Cut off excess sides, split according to model prediction, resize
            char1=char[:,round(sidebufferoverwidth*80):horsplit[0]]
            char2=char[:,horsplit[0]:horsplit[1]]
            char3=char[:,horsplit[1]:round(80-sidebufferoverwidth*80)]
            char1=resizeimage(char1,80,80)[0]
            char2=resizeimage(char2,80,80)[0]
            char3=resizeimage(char3,80,80)[0]
            charactersset.append(char1)
            charactersset.append(char2)
            charactersset.append(char3)
        else:
          charactersset.append(char)


      #Draw Boxes
      cv2.rectangle(imageboxes,(x,y),(x+w,y+h),0,1)

    """Resizes Images accoring to the given dimensions"""
    for i in range(0,5):
      nchar=resizeimage(charactersset[i],dheight,dwidth)[0]
      charactersset[i]=torch.Tensor(nchar)

    charactersset=torch.stack(charactersset[0:5])
    characters.append(charactersset)



    """ShowSegments = True: Visualization of the entire process"""
    if (showsegments==True):
      plt.imshow(imageorig)
      plt.show()
      plt.imshow(imageboxes, cmap='gray', vmin = 0, vmax = 1)
      plt.show()
```

```
      print("      ",end="")
      for j in range(0,len(numchars)):
        print(numchars[j],end="        ")
      print("",end="")

      for i in range(0,len(charactersset)):
        plt.subplot(1,5,i+1)
        plt.imshow(charactersset[i], cmap='gray', vmin = 0, vmax = 1)
      plt.show()

  return torch.stack(characters)
```

In [15]:

```
"""
How To Use - getcharacterimages(images, showsegments=False)

Input = tensor(batchsize,numchannels,height,width) (see below)
Output = tensor(batchsize, numcharacters = 5, height = 80, width = 80 )

Set `showsegments` to `True`to visualize segmentation
"""
train, valid, test = get_data_loaders(dataset, 100)

for images, labels in valid:
  characters = getcharacterimages(images, showsegments=False, deeplearning=Tru
e)
```

# Part 3. Base Model

The base model is a non-deep learning method. The base model leverages the previous character segmentation module (the non-deep learning implementation) and an SVM architecture is used for character classification.

The base model is to serve as a baseline of comparison for the primary model.

In [16]:

```
from sklearn import svm
import numpy as np
```

In [17]:
```
class BaseModel:

  def __init__(self):
    self.classifier = svm.SVC()

  def fit_classifier(self, dataloader):

    # Preprocessing to make our PyTorch data in acceptable format

    input_acc = []
    labels_acc = []

    for images, labels in dataloader:

      segmented_captchas = getcharacterimages(images, dheight=28, dwidth=28)

      # Iterate over each captcha
      for i in range(len(segmented_captchas)):
        captcha = segmented_captchas[i]

        # Iterate over each character
        for j in range(len(captcha)):
          input_acc.append(captcha[j].detach().numpy().reshape(-1))
          labels_acc.append(labels[i][j].detach().numpy())

    input_acc = np.array(input_acc)
    labels_acc = np.array(labels_acc)

    # Train character classification

    self.classifier.fit(input_acc, labels_acc)

  def predict(self, images):
    segmented_captchas = getcharacterimages(images, dheight=28, dwidth=28)

    output = []
    for captcha in segmented_captchas:

      out_captcha = []

      for character in captcha:
        numpy_char = character.detach().numpy().reshape((1, -1)) # Reshape to
 acceptable input for SVM predict()
        out_char = self.classifier.predict(numpy_char)
        out_captcha.append(out_char.item())

      output.append(out_captcha)

    return torch.tensor(output)
```

In [18]:
```
base_model = BaseModel()
train_small, valid_small, test_small = get_data_loaders(dataset, 100, 3000)

base_model.fit_classifier(train_small)
```

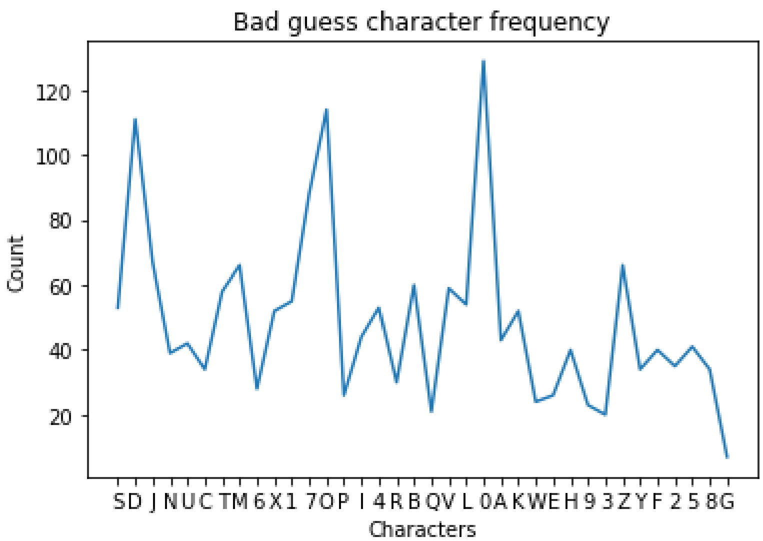
In [19]:
```
def evaluate_base_model(model, dataloader):

  total_character_guesses = 0
  total_captcha_guesses = 0

  incorrect_character_guesses = 0
  incorrect_captcha_guesses = 0

  failed_guess_frequency = {}

  for images, labels in dataloader:
    out = model.predict(images)

    # Iterate through each sample captcha in batch
    for i in range(len(labels)):
      bad_guess = False

      # Iterate through each character of captcha
      for j in range(len(labels[i])):

        total_character_guesses = total_character_guesses + 1
        guess = out[i][j]
        expected = labels[i][j]

        if (guess != expected):
          incorrect_character_guesses = incorrect_character_guesses + 1

          # Track per character bad guesses
          current_failed_guess_count = failed_guess_frequency.get(dataset.char
acter_set[guess], 0)
          failed_guess_frequency.update({ dataset.character_set[guess]: curren
t_failed_guess_count + 1 })

          bad_guess = True

      if bad_guess:
        incorrect_captcha_guesses = incorrect_captcha_guesses + 1

      total_captcha_guesses = total_captcha_guesses + 1

  # Overall accuracy information

  character_guess_accuracy = (total_character_guesses - incorrect_character_gu
esses) / total_character_guesses
  captcha_guess_accuracy = (total_captcha_guesses - incorrect_captcha_guesses)
/ total_captcha_guesses

  print(f"Character Accuracy: {character_guess_accuracy}")
  print(f"Captcha Accuracy: {captcha_guess_accuracy}")

  # Plot incorrect character guess frequency

  bad_guess_character_set = failed_guess_frequency.keys()

  x_values = range(len(bad_guess_character_set))
  y_values = []
```

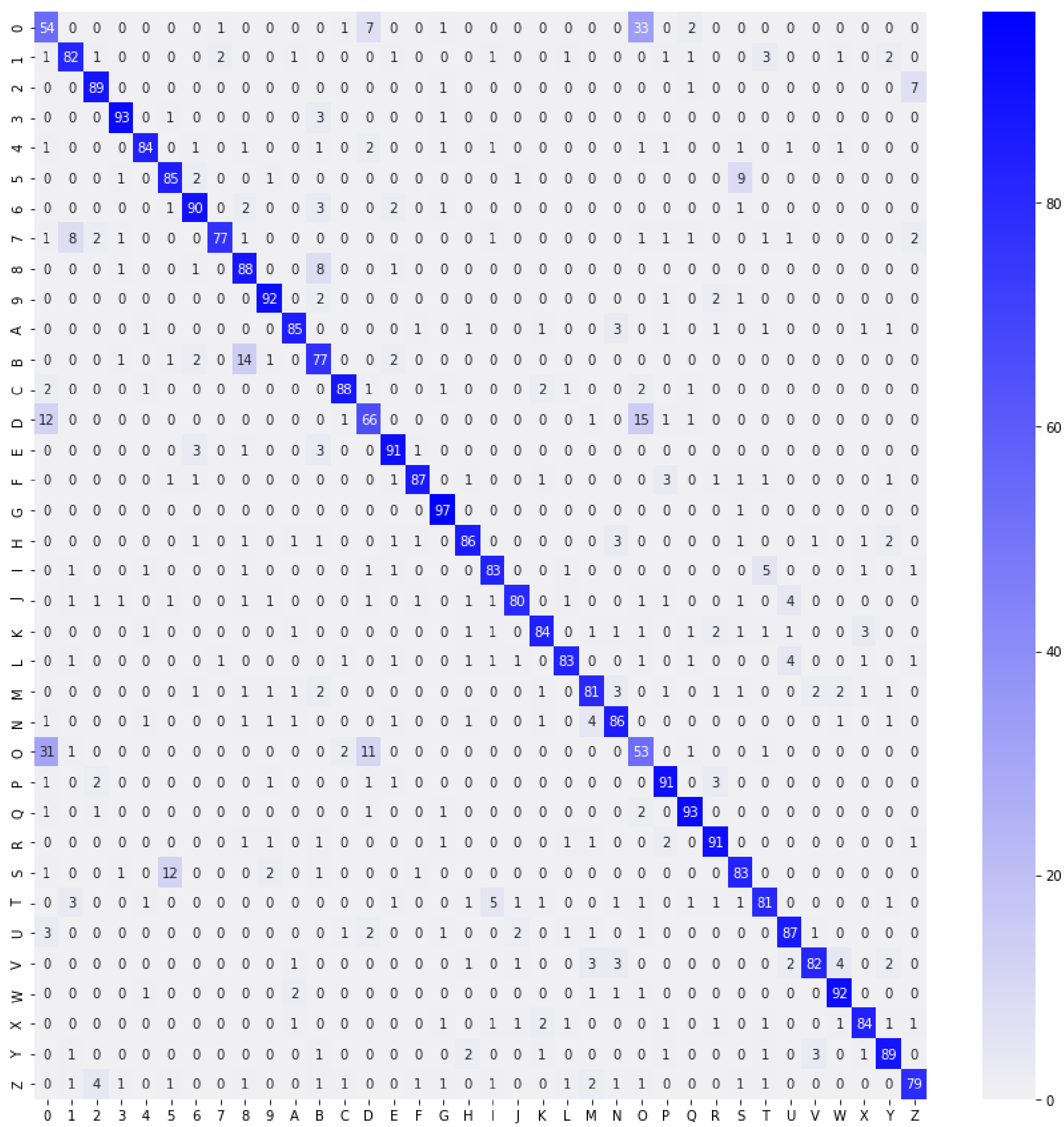
```
  for char in bad_guess_character_set:
    count = failed_guess_frequency.get(char)
    y_values.append(count)

  plt.title("Bad guess character frequency")
  plt.plot(x_values, y_values)
  plt.xlabel("Characters")
  plt.ylabel("Count")
  plt.xticks(x_values, bad_guess_character_set)
  plt.show()
```

In [20]:
```
def get_confusion_matrix_base_model(model, dataloader):

  matrix = np.zeros((len(dataset.character_set), len(dataset.character_set)))
  character_frequency = np.zeros(len(dataset.character_set))

  for images, labels in dataloader:
    out = model.predict(images)

    # Iterate through each sample captcha in batch
    for i in range(len(labels)):
      # Iterate through each character of captcha
      for j in range(len(labels[i])):
        guess = int(out[i][j])
        expected = int(labels[i][j])

        character_frequency[guess] = character_frequency[guess] + 1
        matrix[guess][expected] = matrix[guess][expected] + 1

  # Normalize to percentages
  for i in range(len(matrix)):
    for j in range(len(matrix)):
      matrix[i][j] = (matrix[i][j] / character_frequency[i] * 100).round()

  plt.subplots(figsize=(15,15))
  labels = dataset.character_set
  sns.heatmap(matrix, annot=True, cmap=sns.color_palette("light:b", as_cmap=True), xticklabels=labels, yticklabels=labels)
```

In [21]:
```
evaluate_base_model(base_model, valid)
get_confusion_matrix_base_model(base_model, valid)
```

```
Character Accuracy: 0.8392727272727273
Captcha Accuracy: 0.5104545454545455
```



## Part 4: Primary Model

The primary model is a standard CNN with two convolutional layers and three fully-connected layers. Each convolutional layer is coupled with a max pooling layer (stride 2). Dropout is used for the FC network to help reduce overfitting. The CNN takes an entire CAPTCHA image as input, however, learns to classify each character individually. The previous segmentation module is leveraged, specifically the deep-learning implementation.

In [22]:
```
import torch.nn.functional as F
import torch.optim as optim
import pandas as pd
```

In [23]:
```
class CaptchaLargeCNN(nn.Module):
    def __init__(self):
        super(CaptchaLargeCNN, self).__init__()
        self.name = "CaptchaLargeCNN"

        self.conv1 = nn.Conv2d(1, 5, 5)
        self.pool1 = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(5, 10, 7)
        self.pool2 = nn.MaxPool2d(2,2)

        self.fc1 = nn.Linear(2560, 1000)
        self.fc2 = nn.Linear(1000, 250)
        self.fc3 = nn.Linear(250, 36)

        self.dropout = nn.Dropout(p=0.5)

    def forward(self, img, preprocessed=False):
        if not preprocessed:
          x = getcharacterimages(img, dheight=80, dwidth=80, deeplearning=True
)
        else:
          x = img

        x = x.reshape(-1, 1, 80, 80)
        x = self.pool1(F.relu(self.conv1(x)))
        x = self.pool2(F.relu(self.conv2(x)))
        x = x.view(-1, 2560)
        x = self.dropout(F.relu(self.fc1(x)))
        x = self.dropout(F.relu(self.fc2(x)))
        return self.fc3(x)
```

In [24]:
```
def plot(title, xlabel, ylabel, data1, data1_label, data2, data2_label, epochs
):
    plt.title(title)
    plt.plot(epochs, data1, label=data1_label)
    if data2 is not None:
      plt.plot(epochs, data2, label=data2_label)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.legend(loc='best')
    plt.show()
```

In [25]:
```
def get_accuracy(model, data_loader):
  total = 0
  correct = 0
  char_correct = 0
  captcha_length = 5
  for imgs, labels in data_loader:
      if use_cuda and torch.cuda.is_available():
          imgs = imgs.cuda()
          labels = labels.cuda()

      for i in range(batch_size):
        output = model(imgs[i].unsqueeze(dim=0), preprocessed=True)
        pred = output.max(1, keepdim=True)[1] # get the index of the max logit
        num_correct = 0
        for j in range(captcha_length):
          # print(labels[i][j])
          # print(pred[j])
          if labels[i][j] == pred[j].squeeze(0):
            num_correct += 1
            char_correct += 1
          # print(num_correct)
        if num_correct == 5:
          correct += 1
        total += 1
  return correct / total, char_correct / (5 * total)
```

In [26]:
```
def get_confusion_matrix(model, dataloader):

  matrix = np.zeros((len(dataset.character_set), len(dataset.character_set)))
  character_frequency = np.zeros(len(dataset.character_set))

  for images, labels in dataloader:

    if use_cuda and torch.cuda.is_available():
        images = images.cuda()
        labels = labels.cuda()

    out = model(images, preprocessed=True)
    out = out.max(1, keepdim=True)[1]
    out = out.reshape(-1, 5)  # Shape back into per captcha

    # Iterate through each sample captcha in batch
    for i in range(len(labels)):
      # Iterate through each character of captcha
      for j in range(len(labels[i])):
        guess = int(out[i][j])
        expected = int(labels[i][j])

        character_frequency[guess] = character_frequency[guess] + 1
        matrix[guess][expected] = matrix[guess][expected] + 1

  # Normalize to percentages
  for i in range(len(matrix)):
    for j in range(len(matrix)):
      matrix[i][j] = (matrix[i][j] / character_frequency[i] * 100).round()

  plt.subplots(figsize=(15,15))
  labels = dataset.character_set
  sns.heatmap(matrix, annot=True, cmap=sns.color_palette("light:b", as_cmap=True), xticklabels=labels, yticklabels=labels)
```

In [27]:
```
def get_model_name(name, epoch, learning_rate=1e-4):
  """
  Generate a name for the model consisting of all the hyperparameter values
  """
  path="model_{0}_lr{1}_epoch{2}".format(
      name, learning_rate, epoch)
  return path
```

In [28]:
```
def train_cnn(model, x, y, num_epochs=20, learning_rate=0.001):
    torch.manual_seed(360)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=
0.0001)

    train_loader = x
    valid_loader = y

    iters = []
    losses = []
    train_acc = []
    valid_acc = []

    epoch = 0

    for epoch in range(num_epochs):

        random.shuffle(train_loader)

        for imgs, labels in train_loader:
            labels = labels.reshape(-1)

            if use_cuda and torch.cuda.is_available():
                imgs = imgs.cuda()
                labels = labels.cuda()

            out = model(imgs, preprocessed=True) # forward pass
            loss = criterion(out, labels) # compute the total loss
            loss.backward()  # backward pass (compute parameter updates)
            optimizer.step()  # make the updates for each parameter
            optimizer.zero_grad()  # a clean up step for PyTorch

        # Save the current model (checkpoint) to a file
        model_path = get_model_name(model.name, epoch, learning_rate=learning_
rate)
        torch.save(model.state_dict(), model_path)

        # save the current training information
        iters.append(epoch)
        losses.append(float(loss))  # compute *average* loss
        captcha_acc, char_acc = get_accuracy(model, train_loader)
        train_acc.append(captcha_acc)  # compute training accuracy
        if y != None:
            valid_acc.append(
                get_accuracy(model, valid_loader)[0]
            )  # compute validation accuracy
        if y != None:
            print(
                (
                    "Epoch {}: Character accuracy: {}, Training accuracy: {},
 " + "Validation accuracy: {}"
                ).format(epoch + 1, char_acc, train_acc[epoch], valid_acc[epoc
h])
            )
```

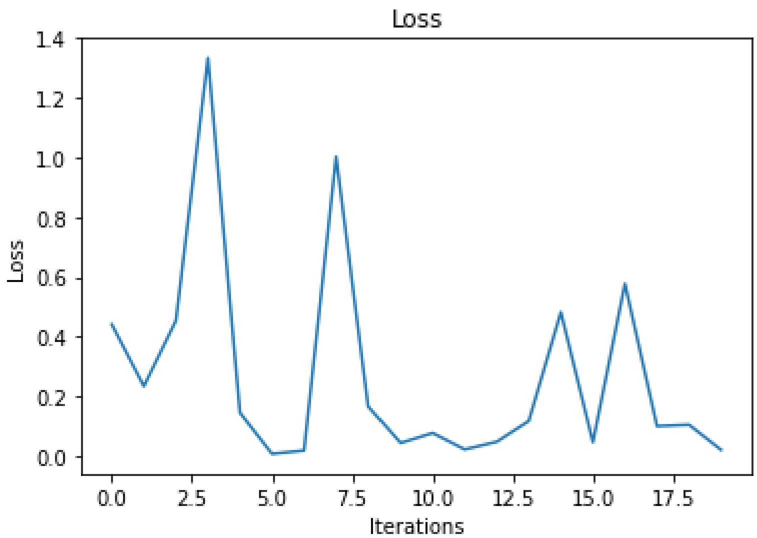
```
        else:
            print(
                ("Epoch {}: Character accuracy: {}, Training accuracy: {}").fo
rmat(epoch + 1, char_acc, train_acc[epoch])
            )
        epoch += 1

    plt.title("Loss")
    plt.plot(iters, losses, label="Train")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Accuracy")
    plt.plot(iters, train_acc, label="Train")
    if y != None:
        plt.plot(iters, valid_acc, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Accuracy")
    plt.legend(loc="best")
    plt.show()

    if y != None:
        return losses, train_acc, valid_acc
    return losses, train_acc
```

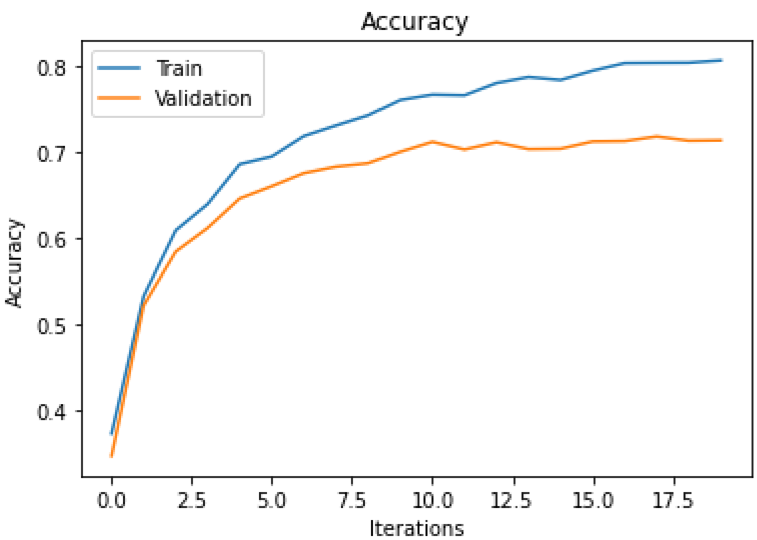
In [29]:

```
# Preprocess segmentation on dataset to improve training times

cnn_train, cnn_valid = [], []
batch_size = 4

train, valid, test = get_data_loaders(dataset, batch_size)

for images, labels in train:
    cnn_train.append((getcharacterimages(images, dwidth=80, dheight=80, deeple
arning=True), labels))

for images, labels in valid:
    cnn_valid.append((getcharacterimages(images, dwidth=80, dheight=80, deeple
arning=True), labels))
```

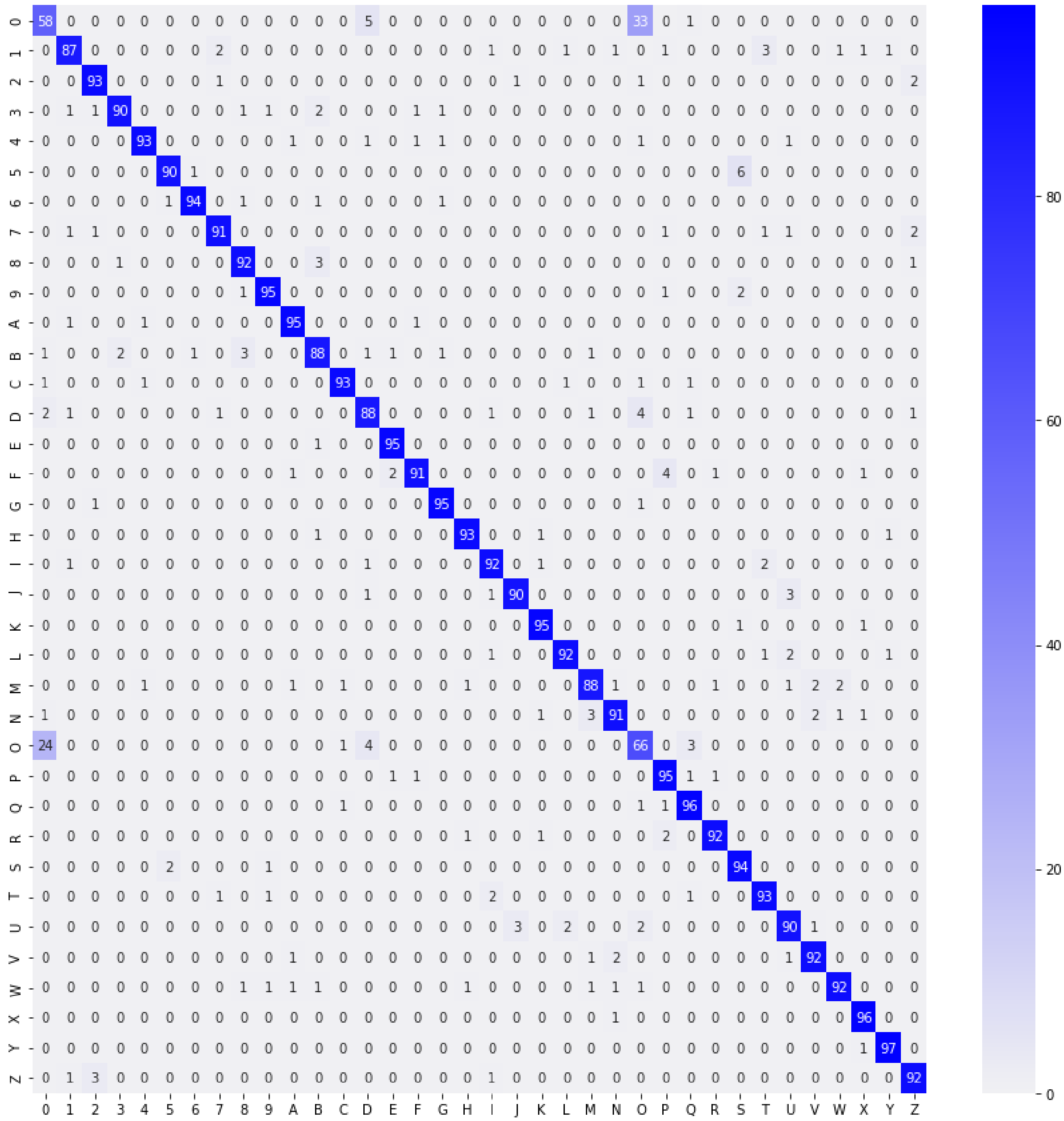
In [30]:
```
use_cuda = True
model = CaptchaLargeCNN()

if use_cuda and torch.cuda.is_available():
  model.cuda()

losses, train_acc, valid_acc = train_cnn(model, cnn_train, cnn_valid, 20, 0.00
01)
```

```
Epoch 1: Character accuracy: 0.7870998475609756, Training accuracy: 0.3726181
4024390244, Validation accuracy: 0.34653024911032027
Epoch 2: Character accuracy: 0.8495998475609756, Training accuracy: 0.5322027
43902439, Validation accuracy: 0.5213523131672598
Epoch 3: Character accuracy: 0.8753048780487804, Training accuracy: 0.6082317
073170732, Validation accuracy: 0.5836298932384342
Epoch 4: Character accuracy: 0.886280487804878, Training accuracy: 0.63900533
53658537, Validation accuracy: 0.6112099644128114
Epoch 5: Character accuracy: 0.8986661585365854, Training accuracy: 0.6853086
890243902, Validation accuracy: 0.6454626334519573
Epoch 6: Character accuracy: 0.9028391768292683, Training accuracy: 0.6942644
81707317, Validation accuracy: 0.6596975088967971
Epoch 7: Character accuracy: 0.9098513719512196, Training accuracy: 0.7179878
048780488, Validation accuracy: 0.6748220640569395
Epoch 8: Character accuracy: 0.9138528963414634, Training accuracy: 0.7302782
012195121, Validation accuracy: 0.6823843416370107
Epoch 9: Character accuracy: 0.9169588414634147, Training accuracy: 0.7420922
256097561, Validation accuracy: 0.6863879003558719
Epoch 10: Character accuracy: 0.9233803353658536, Training accuracy: 0.760003
8109756098, Validation accuracy: 0.6997330960854092
Epoch 11: Character accuracy: 0.92578125, Training accuracy: 0.76619664634146
34, Validation accuracy: 0.7112989323843416
Epoch 12: Character accuracy: 0.9248666158536586, Training accuracy: 0.765434
4512195121, Validation accuracy: 0.7024021352313167
Epoch 13: Character accuracy: 0.9300685975609756, Training accuracy: 0.779725
6097560976, Validation accuracy: 0.7108540925266904
Epoch 14: Character accuracy: 0.932545731707317, Training accuracy: 0.7866806
402439024, Validation accuracy: 0.702846975088968
Epoch 15: Character accuracy: 0.932374237804878, Training accuracy: 0.7832507
621951219, Validation accuracy: 0.7032918149466192
Epoch 16: Character accuracy: 0.9350228658536586, Training accuracy: 0.794112
0426829268, Validation accuracy: 0.7117437722419929
Epoch 17: Character accuracy: 0.9384717987804878, Training accuracy: 0.802877
2865853658, Validation accuracy: 0.7121886120996441
Epoch 18: Character accuracy: 0.9398246951219512, Training accuracy: 0.803163
1097560976, Validation accuracy: 0.7175266903914591
Epoch 19: Character accuracy: 0.9404344512195122, Training accuracy: 0.803353
6585365854, Validation accuracy: 0.7126334519572953
Epoch 20: Character accuracy: 0.9415205792682927, Training accuracy: 0.806021
3414634146, Validation accuracy: 0.7130782918149466
```


Loss
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Loss
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Iterations


Accuracy
Train
Validation
0.8
0.7
0.6
0.5
0.4
Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Iterations

In [31]:
```
get_confusion_matrix(model, cnn_valid)
```




## Part 5: AlexNet Transfer Learning

The pretrained AlexNet model was imported as a backup to the primary model if the CNN architecture yielded subpar results. Similar to the primary model, the AlexNet model was coupled with the character segmentation module.

In [32]:
```
import torchvision.models
alexnet = torchvision.models.alexnet(pretrained=True)

AlexNet_train, AlexNet_valid = [], []

train, valid, test = get_data_loaders(dataset, 100)

for images, labels in train:
    AlexNet_train.append((getcharacterimages(images, dwidth=80, dheight=80, de
eplearning=True), labels))

for images, labels in valid:
    AlexNet_valid.append((getcharacterimages(images, dwidth=80, dheight=80, de
eplearning=True), labels))
```

In [33]:
```
imgs_train, labels_train = [], []
imgs_valid, labels_valid = [], []

for img, label in AlexNet_train:
    img_grey = img.reshape(-1, 1, 80, 80)
    label = label.reshape(-1)
    img_color = img_grey.repeat(1,3,1,1)
    features = torch.from_numpy(alexnet.features(img_color).detach().numpy())
    imgs_train.append(features)
    labels_train.append(label)

for img, label in AlexNet_valid:
    img = img.reshape(-1, 1, 80, 80)
    label = label.reshape(-1)
    img_color = img.repeat(1,3,1,1)
    features = torch.from_numpy(alexnet.features(img_color).detach().numpy())
    imgs_valid.append(features)
    labels_valid.append(label)

AlexNet_train = list(zip(imgs_train, labels_train))
AlexNet_valid = list(zip(imgs_valid, labels_valid))
```

In [34]:
```
def get_accuracy_alexnet(model, data_loader):
  total = 0
  correct = 0
  char_correct = 0
  captcha_length = 5
  for imgs, labels in data_loader:
      if torch.cuda.is_available():
          imgs = imgs.cuda()
          labels = labels.cuda()
      output = model(imgs)
      pred = output.max(1, keepdim=True)[1].squeeze(1) # get the index of the
 max logit
      for i in range(0, len(output), captcha_length):
        num_correct = 0
        for j in range(captcha_length):
          if labels[i+j] == pred[i+j]:
            num_correct += 1
            char_correct += 1
        if num_correct == 5:
          correct += 1
        total += 1
  return correct / total, char_correct / (5 * total)

def train_alexnet(model, x, y, batch_size=128, num_epochs=20, learning_rate=0.
001):
    torch.manual_seed(360)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    train_loader = x
    valid_loader = y

    iters = []
    losses = []
    train_acc = []
    valid_acc = []

    epoch = 0

    for epoch in range(num_epochs):
        for img, label in train_loader:
            if use_cuda and torch.cuda.is_available():
                img = img.cuda()
                label = label.cuda()
            out = model(img) # forward pass
            loss = criterion(out, label) # compute the total loss
            loss.backward()  # backward pass (compute parameter updates)
            optimizer.step()  # make the updates for each parameter
            optimizer.zero_grad()  # a clean up step for PyTorch

        # Save the current model (checkpoint) to a file
        model_path = get_model_name(model.name, epoch, learning_rate=learning_
rate)
        torch.save(model.state_dict(), model_path)
```

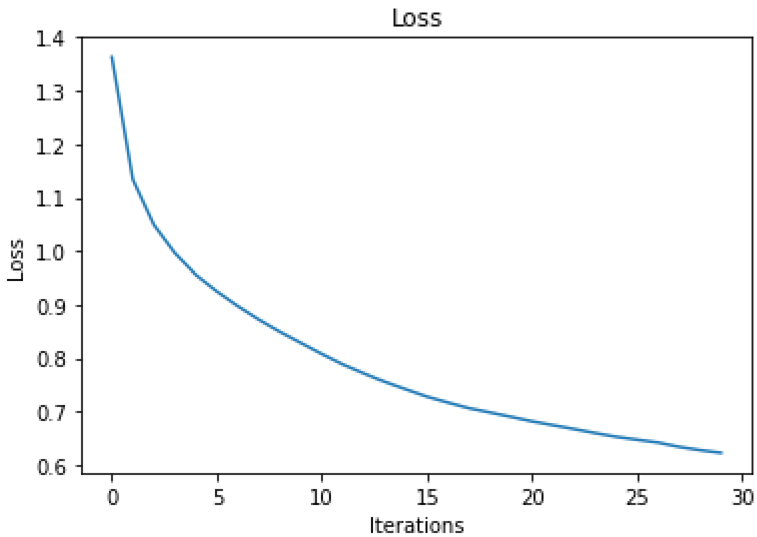
```
        # save the current training information
        iters.append(epoch)
        losses.append(float(loss))  # compute *average* loss
        captcha_acc, char_acc = get_accuracy_alexnet(model, train_loader)
        train_acc.append(captcha_acc)  # compute training accuracy
        if y != None:
            captcha_acc, char_acc = get_accuracy_alexnet(model, valid_loader)
# compute validation accuracy
            valid_acc.append(captcha_acc)
        if y != None:
            print(
                (
                    "Epoch {}: Character accuracy: {}, Training accuracy: {},
 " + "Validation accuracy: {}"
                ).format(epoch + 1, char_acc, train_acc[epoch], valid_acc[epoc
h])
            )
        else:
            print(
                ("Epoch {}: Character accuracy: {}, Training accuracy: {}").fo
rmat(epoch + 1, char_acc, train_acc[epoch])
            )
        epoch += 1

        # model_path = get_model_name(model.name, batch_size, learning_rate, e
poch)
        # torch.save(model.state_dict(), model_path)
    plt.title("Loss")
    plt.plot(iters, losses, label="Train")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Accuracy")
    plt.plot(iters, train_acc, label="Train")
    if y != None:
        plt.plot(iters, valid_acc, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Accuracy")
    plt.legend(loc="best")
    plt.show()

    if y != None:
        return losses, train_acc, valid_acc
    return losses, train_acc
```

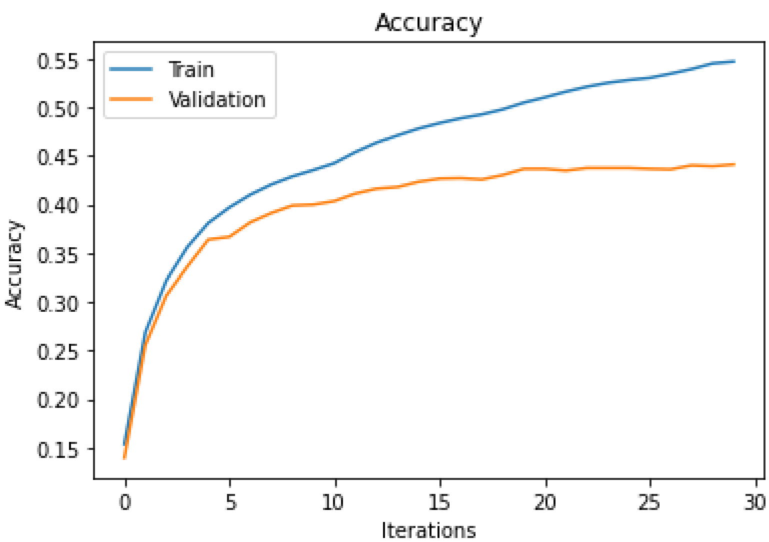
In [35]:
```
class AlexNetANNClassifier(nn.Module):
    def __init__(self):
        super(AlexNetANNClassifier, self).__init__()
        self.name = "AlexNetANNClassifier"
        self.fc1 = nn.Linear(256, 128)
        self.fc2 = nn.Linear(128, 64)
        self.fc3 = nn.Linear(64, 36)

    def forward(self, img):
        x = img.view(-1, 256)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        x = F.relu(x)
        x = self.fc3(x)
        return x
```

In [36]:
```
model = AlexNetANNClassifier()
if torch.cuda.is_available():
    model.cuda()

losses, train_acc, valid_acc = train_alexnet(model, AlexNet_train, AlexNet_val
id, 32, 30, 0.001)
```

```
Epoch 1: Character accuracy: 0.6531818181818182, Training accuracy: 0.1536538
4615384614, Validation accuracy: 0.13954545454545456
Epoch 2: Character accuracy: 0.7330909090909091, Training accuracy: 0.2686538
4615384613, Validation accuracy: 0.25545454545454543
Epoch 3: Character accuracy: 0.7601818181818182, Training accuracy: 0.3218269
2307692307, Validation accuracy: 0.30636363636363634
Epoch 4: Character accuracy: 0.7754545454545455, Training accuracy: 0.3558653
8461538464, Validation accuracy: 0.33590909090909093
Epoch 5: Character accuracy: 0.7846363636363637, Training accuracy: 0.3806730
7692307695, Validation accuracy: 0.36363636363636365
Epoch 6: Character accuracy: 0.7883636363636364, Training accuracy: 0.3966346
1538461536, Validation accuracy: 0.3663636363636364
Epoch 7: Character accuracy: 0.7942727272727272, Training accuracy: 0.4098076
923076923, Validation accuracy: 0.38136363636363635
Epoch 8: Character accuracy: 0.7974545454545454, Training accuracy: 0.4202884
6153846156, Validation accuracy: 0.39090909090909093
Epoch 9: Character accuracy: 0.8002727272727272, Training accuracy: 0.4285576
923076923, Validation accuracy: 0.3986363636363636
Epoch 10: Character accuracy: 0.8031818181818182, Training accuracy: 0.435096
15384615385, Validation accuracy: 0.39954545454545454
Epoch 11: Character accuracy: 0.8060909090909091, Training accuracy: 0.442211
5384615385, Validation accuracy: 0.4031818181818182
Epoch 12: Character accuracy: 0.8086363636363636, Training accuracy: 0.453557
69230769233, Validation accuracy: 0.4109090909090909
Epoch 13: Character accuracy: 0.8102727272727273, Training accuracy: 0.463173
0769230769, Validation accuracy: 0.4159090909090909
Epoch 14: Character accuracy: 0.8109090909090909, Training accuracy: 0.470961
5384615385, Validation accuracy: 0.4177272727272727
Epoch 15: Character accuracy: 0.8131818181818182, Training accuracy: 0.477980
7692307692, Validation accuracy: 0.42318181818181816
Epoch 16: Character accuracy: 0.8143636363636364, Training accuracy: 0.483557
6923076923, Validation accuracy: 0.4263636363636364
Epoch 17: Character accuracy: 0.8147272727272727, Training accuracy: 0.488461
53846153845, Validation accuracy: 0.4268181818181818
Epoch 18: Character accuracy: 0.8141818181818182, Training accuracy: 0.492403
84615384614, Validation accuracy: 0.4254545454545455
Epoch 19: Character accuracy: 0.8154545454545454, Training accuracy: 0.497596
15384615385, Validation accuracy: 0.43
Epoch 20: Character accuracy: 0.8178181818181818, Training accuracy: 0.504519
2307692308, Validation accuracy: 0.43636363636363634
Epoch 21: Character accuracy: 0.8177272727272727, Training accuracy: 0.509903
8461538462, Validation accuracy: 0.43636363636363634
Epoch 22: Character accuracy: 0.8176363636363636, Training accuracy: 0.515769
2307692308, Validation accuracy: 0.43454545454545457
Epoch 23: Character accuracy: 0.8185454545454546, Training accuracy: 0.520865
3846153846, Validation accuracy: 0.43727272727272726
Epoch 24: Character accuracy: 0.8193636363636364, Training accuracy: 0.524903
8461538461, Validation accuracy: 0.43727272727272726
Epoch 25: Character accuracy: 0.8193636363636364, Training accuracy: 0.527788
4615384615, Validation accuracy: 0.43727272727272726
Epoch 26: Character accuracy: 0.8189090909090909, Training accuracy: 0.53, Va
lidation accuracy: 0.43636363636363634
Epoch 27: Character accuracy: 0.8191818181818182, Training accuracy: 0.534326
9230769231, Validation accuracy: 0.4359090909090909
Epoch 28: Character accuracy: 0.8195454545454546, Training accuracy: 0.539038
4615384616, Validation accuracy: 0.44
Epoch 29: Character accuracy: 0.8198181818181818, Training accuracy: 0.544903
```

```
8461538461, Validation accuracy: 0.4390909090909091
Epoch 30: Character accuracy: 0.8197272727272727, Training accuracy: 0.546826
923076923, Validation accuracy: 0.4409090909090909
```




# Part 6: End-to-End System

The end-to-end system takes in a single CAPTCHA image and attempts to decode it. Currently, the end-to-end system performs character classification using the "best" CNN model from training as it yielded the highest accuracies without overfitting. The end-to-end system outputs its prediction of each character (5 total) and the input itself for comparison.

In [37]:
```
def decodeCharacter (encodedValue):
  if (encodedValue < 10):
    return str(encodedValue)
  else:
    return chr(encodedValue + 55)
```

In [38]:
```
def e2emodel (imgs):
  model = CaptchaLargeCNN()
  model.load_state_dict(torch.load(get_model_name(model.name, epoch=19, learni
ng_rate=0.0001)))

  # Prediction
  out = model(imgs)
  pred = out.max(1, keepdim=True)[1].squeeze(1).tolist()[:5]
  CAPTCHA_prediction = list(map(decodeCharacter, pred))
  print(f"Predicted output = {CAPTCHA_prediction}")

  # Plot batch of images
  plt.imshow(imgs[0][0])
```

In [43]:
```
imgs, labels = next(iter(test))
e2emodel(imgs)
```

```
Predicted output = ['V', '5', 'W', '9', '5']
```