COURSE TITLE: SOFTWARE QUALITY ENGINEERING (2019-2023)

Project: Mnist Handwritten Digit Classification



TO

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MNIST Handwritten Digit Recognition

Introduction

Handwritten digits recognition could be a well-researched subarea among the sphere that's involved with learning models to differentiate pre-segmented written digits. it's one among the foremost necessary problems in knowledge mining, machine learning, pattern recognition together with several different disciplines of computer science.

The main application of machine learning strategies over the last decade has determined efficacious in conformist decisive systems that are competitor to human performance and which accomplish so much improved than manually written classical artificial intelligence systems employed in the beginnings of optical character recognition technology. However, not all options of these specific models are antecedently inspected. An excellent try of researcher in machine learning and data processing has been contrived to realize economical approaches for approximation of recognition from data.

In 21st century written digit communication has its own normal and most of the days in standard of living are being employed as means that of voice communication and recording the knowledge to be shared with individuals. One among the challenges in handwritten characters recognition entirely lies within the variation and distortion of handwritten listing as a result of distinct community could use various type of handwriting, and management to draw the similar pattern of the characters of their recognized script. Identification of digit from wherever best discriminating options are often extracted is one among the main tasks within the space of digit recognition system. To find such regions totally different quite region sampling techniques are employed in pattern recognition.

The challenge in written character recognition is principally caused by the big variation of individual writing styles. Hence, strong feature extraction is extremely important to boost the performance of a handwritten character recognition system. These days handwritten digit recognition has obtained heap of concentration in the area of pattern recognition system sowing to its application in various fields. In next days, character recognition system may function as a cornerstone to initiate paperless surroundings by digitizing and process existing paper documents.

MNIST Dataset

The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems. The database is also widely used for training and testing in the field of machine learning. It was created by "re-mixing" the samples from NIST's original datasets. The creators felt that since NIST's training dataset was taken from American Census Bureau employees, while the testing dataset was taken from American high school students, it was not well-suited for machine learning experiments. Furthermore, the black and white images from NIST were normalized to fit into a 28x28 pixel bounding box and anti-aliased, which introduced grayscale levels.

The MNIST database contains 60,000 training images and 10,000 testing images. Half of the

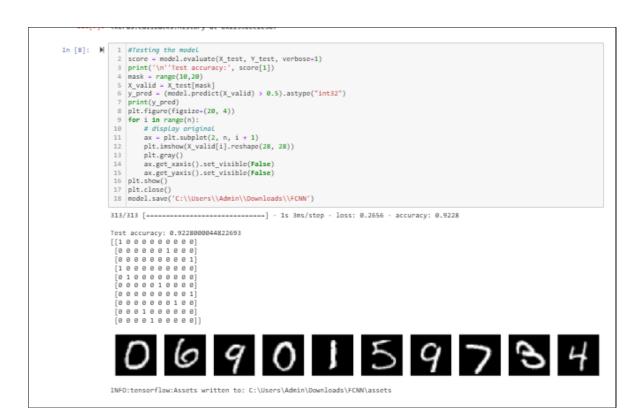
training set and half of the test set were taken from NIST's training dataset, while the other half of the training set and the other half of the test set were taken from NIST's testing dataset.

Analysis of MNIST Data Set with FCN and CNN

The MNIST data set gives a maximum accuracy of 87% generally with algorithm including SVM, RF and Naïve Bayes. Two algorithms were tested with the dataset: Fully Convolutional Network and Convolutional Neural Network. The training and testing was done and CNN was found to have the highest accuracy of 98% approximately. Therefore it was used for the model. However, both were tested for results in GUI user based application as well. The detailed work is shown below:

```
IMPORT DATA SET AND PREPROCESSING
In [2]: M 1 ###1. Load Data and Splot Data
                        from tensorflow import keras
                        from keras.datasets import mnist
                        from keras.models import Sequential
                        from keras.layers.core import Dense, Activation
                    6 from keras.utils import np_utils
                   8 import numpy as np
9 from tensorflow import keras
                  18 from tensorflow.keras import layers
11 from keras.datasets import mnist
                   13 (X train, Y train), (X test, Y test) = mnist.load data()
In [3]: ⋈ 1 #preprocessing
                    1 #preprocessing
2 import matplotlib.pyplot as plt
3 n = 10 # how many digits we will display
4 plt.figure(figsize-(20, 4))
                       plt.figure(rigsize=(ze, +/)
for i in range(n):
    # display ariginal
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(X_test[i].reshape(28, 28))
                            plt.gray()
                             ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
                   12 plt.show(
                                                          1041495
 In [4]: M
                   1 print("Previous X train shape: {} \nPrevious Y train shape:{}".format(X train.shape, Y train.shape))
                       X_train = X_train.reshape(60000, 784)
X_test = X_test.reshape(10000, 784)
                       X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
                   7 X_test /= 255
8 classes = 10
                  9 Y_train = np_utils.to_categorical(Y_train, classes)
18 Y_test = np_utils.to_categorical(Y_test, classes)
11 print("New X_train shape: {} \nNew Y_train shape: {}".format(X_train.shape, Y_train.shape))
                 Previous X_train shape: (60000, 28, 28)
Previous Y_train shape:(60000,)
                 New X_train shape: (60000, 784)
New Y_train shape:(60000, 10)
In [5]: M 1 #Setting up parameters
2 input_size = 784
3 batch_size = 200
                    4 hidden1 = 400
5 hidden2 = 20
                   6 epochs = 2
```

```
Recognition Through Fully Covulutional Network Model.
                1 #Building FCN Model
2 ###4.Build the model
In [6]: M
                 3 model - Sequential()
                  4 model.add(Dense(hidden1, input_dim-input_size, activation-'relu'))
                 # output = relu (dot (W, input) + bias)
model.add(Dense(hidden2, activation='relu'))
model.add(Dense(classes, activation='softmax'))
                 9 # Compilation
                model.compile(loss='categorical_crossentropy',
metrics=['accuracy'], optimizer='sgd')
model.summary()
               Model: "sequential"
               Layer (type)
                                                   Output Shape
                                                                                    Param #
                                               (None, 400)
               dense (Dense)
                                                                                   314000
                                                  (None, 20)
               dense_1 (Dense)
                                                                                    8828
               dense_2 (Dense)
                                                   (None, 10)
                                                                                     210
               Total params: 322,230
               Trainable params: 322,230
               Non-trainable params: 0
In [7]: M 1 #Training the model
                 2 # Fitting on Data
                3 model.fit(X_train, Y_train, batch_size-batch_size, epochs-10, verbose-2)
4 ###5.Test
               Epoch 1/10
               300/300 - 5s - loss: 1.5074 - accuracy: 0.6038
Epoch 2/10
300/300 - 2s - loss: 0.7047 - accuracy: 0.8234
               Epoch 3/10
               300/300 - 2s - loss: 0.5072 - accuracy: 0.8679
Epoch 4/10
               380/380 - 2s - loss: 0.4235 - accuracy: 0.8858
Epoch 5/10
               300/300 - 2s - loss: 0.3772 - accuracy: 0.8948
               Se0/380 - 2s - loss: 0.3470 - accuracy: 0.9022
Epoch 7/10
               380/380 - 2s - loss: 0.3251 - accuracy: 0.9081
               See/380 - 25 - loss: 0.3251 - accuracy: 0.5061
Epoch 8/10
380/380 - 25 - loss: 0.3076 - accuracy: 0.9123
Epoch 9/10
380/380 - 25 - loss: 0.2931 - accuracy: 0.9164
               Epoch 10/10
               300/300 - 2s - loss: 0.2807 - accuracy: 0.9197
    Out[7]: <keras.callbacks.History at 0x22592ec2e50>
```



Recognition Through Convulational Neural Network Model.

```
In [9]: M 1 #CWN
                       #Prepare the data
# Model / data parameters
num_classes = 18
input_shape = (28, 28, 1)
                       6
7 # the data, split between train and test sets
                       8 (x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()
                     9
18 # Scale images to the [8, 1] range
11 x_train = x_train.astype("float32") / 255
12 x_test = x_test.astype("float32") / 255
13 # Make sure images have shape (28, 28, 1)
14 x_train = np.expand_dims(x_train, -1)
15 x_test = np.expand_dims(x_test, -1)
16 print(x_train.shape:", x_train.shape)
17 print(x_train.shape[8], "train.smaples")
18 print(x_train.shape[8], "test samples")
19
19
                     20 # convert class vectors to binary class matrices
21 y train - keras.utils.to_categorical(y_train, num_classes)
22 y test - keras.utils.to_categorical(y_test, num_classes)
                    x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
In [18]: M 1 #Build Model CNW 2 model = keras.Sequential(
                              12
13 )
                      14
15 model.summary()
                     Model: "sequential_1"
                     Layer (type)
                                                                 Output Shape
                                                                                                           Param #
                                                                (None, 26, 26, 32)
                     conv2d (Conv2D)
                                                                                                          320
                     max_pooling2d (MaxPooling2D) (None, 13, 13, 32)
                     conv2d_1 (Conv2D) (None, 11, 11, 64)
                                                                                                           18496
                     max_pooling2d_1 (MaxPooling2 (None, 5, 5, 64)
                     flatten (Flatten)
                                                                (None, 1600)
                     dropout (Dropout)
                     dense_3 (Dense)
                                                                 (None, 10)
                                                                                                           16010
                      Total params: 34,826
                     Trainable params: 34,826
Non-trainable params: 0
```

```
In [11]: M
        1 #Train Model
         batch_size = 128
          model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
        7 model.fit(x_train, y_train, batch_size-batch_size, epochs-epochs, validation_split=0.1)
       Epoch 1/15
       422/422 [--
                    cy: 0.9795
       Epoch 2/15
                  422/422 [ --
       cy: 0.9842
       Enoch 3/15
       422/422 [--
                     cy: 0.9898
       Epoch 4/15
       422/422 [--
                   -----] - 55s 130ms/step - loss: 0.0697 - accuracy: 0.9782 - val_loss: 0.0409 - val_accura
       cv: 0.9898
       Epoch 5/15
       422/422 [--
                  -----] - 50s 118ms/step - loss: 0.0617 - accuracy: 0.9809 - val loss: 0.0413 - val accura
       cy: 0.9898
       Epoch 6/15
       422/422 [-----
                 cy: 0.9888
       Epoch 7/15
       422/422 [=-
                   -----] - 45s 106ms/step - loss: 0.0516 - accuracy: 0.9840 - val_loss: 0.0371 - val_accura
       cy: 0.9897
       Epoch 8/15
       422/422 [--
                    cy: 0.9917
       Epoch 9/15
       422/422 [ ---
                    cy: 0.9920
       Epoch 10/15
       422/422 [---
                    cy: 0.9907
Epoch 11/15
       422/422 [--
                   -----] - 43s 103ms/step - loss: 0.0412 - accuracy: 0.9865 - val_loss: 0.0318 - val_accura
       cy: 0.9922
       Epoch 12/15
       422/422 [ ---
                    cv: 0.9923
       Epoch 13/15
       422/422 [---
                 cy: 0.9918
       Epoch 14/15
422/422 [---
                     cy: 0.9928
       Epoch 15/15
       422/422 [--
                  cy: 0.9913
  Out[11]: ckeras.callbacks.History at 0x2258eda9840>
In [12]: N 1 #Test model -Evaluate
        2 score = model.evaluate(x_test, y_test, verbose=0)
         print("Test loss:", score[0])
        4 print("Test accuracy:", score[1])
       Test loss: 0.025686144828796387
       Test accuracy: 0.9912999868392944
In [13]: M 1 model.save('C:\\Users\\Admin\\Downloads\\CNN')
       INFO:tensorflow:Assets written to: C:\Users\Admin\Downloads\CNN\assets
```

Testing models through GUI Application

```
1 #GUI
2 from keras.models import load_model
In [17]: M
                3 from tkinter import
                4 import tkinter as tk
                5 import win32gui
                6 from PIL import ImageGrab, Image
                7 import numpy as np
                8 model = load_model('C:\\Users\\Admin\\Downloads\\CNN')
                9 def predict_digit(img):
                     #resize image to 28x28 pixels
                       img = img.resize((28,28))
                      #convert rgb to grayscale
img = img.convert('L')
                12
                13
                14
                       img = np.array(img)
                       #reshaping to support our model input and normalizing
                15
                       img = img.reshape(1,28,28,1)
                16
                      img = img/255.0
                17
                       #predicting the class
                18
                       res = model.predict([img])[0]
                19
                28
                       return np.argmax(res), max(res)
                21 class App(tk.Tk):
                      def __init__(self):
    tk.Tk.__init__(self)
                23
                24
                            self.x = self.y = 0
                            # Creating elements
                25
                           self.canvas = tk.Canvas(self, width=300, height=300, bg = "white", cursor="cross")
                26
                           self.label = tk.Label(self, text="Thinking..", font-("Helvetica", 48))
self.classify_btn = tk.Button(self, text = "Recognise", command = self.self.button_clear = tk.Button(self, text = "Clear", command = self.clear_all)
                27
                28
                                                                                                                  self.classify_handwriting)
                29
                38
                            # Grid structure
                31
                            self.canvas.grid(row-0, column-0, pady-2, sticky-W, )
                            self.label.grid(row-0, column=1,pady=2, padx=2)
                33
                             self.classify_btn.grid(row=1, column=1, pady=2, padx=2)
                            self.button_clear.grid(row=1, column=0, pady=2)
#self.canvas.bind("<Motion>", self.start_pos)
self.canvas.bind("<81-Motion>", self.draw_lines)
                34
                35
                36
                37
                      def clear all(self):
                38
                            self.canvas.delete("all")
                39
                       def classify handwriting(self):
                         HWND - self.canvas.winfo_id() # get the handle of the canvas
                48
                41
                            rect = win32gui.GetWindowRect(HWND) # get the coordinate of the canvas
                42
                             im = ImageGrab.grab(rect)
                43
                            digit, acc = predict_digit(im)
                             self.label.configure(text= str(digit)+', '+ str(int(acc*100))+'%')
               44
                       def draw_lines(self, event):
               45
                46
                           self.x = event.x
                47
                             self.y = event.y
               48
                            r-8
                49
                            self.canvas.create oval(self.x-r, self.y-r, self.x + r, self.y + r, fill='black')
                58 app - App()
                51 mainloop()
```

Testing models through GUI Application

```
from keras.models import load_model
from tkinter import *
      4 import tkinter as tk
5 import win32gui
 5 import win32gui
6 from PIL import ImageGrab, Image
7 import numpy as np
8 model = load_model('C:\\Users\\Admin\\Downloads\\FCNN')
9 def predict_digit(img):
10 #restre image to 28x28 pixels
11 img = img.resize((28,28))
12 #convert rgb to grayscale
13 img = img.convert('L')
14 img = np.array(img)
15 #reshaping to support our model input and normalizin
16 #reshaping to support our model input and normalizin
17 #reshaping to support our model input and normalizin
18 #reshaping to support our model input and normalizin
19 #reshaping to support our model input and normalizin
10 #reshaping to support our model input and normalizin
11 #reshaping to support our model input and normalizin
12 #reshaping to support our model input and normalizin
13 #reshaping to support our model input and normalizin
14 #reshaping to support our model input and normalizin
15 #reshaping to support our model input and normalizin
16 #reshaping to support number our model input and normalizin
17 #reshaping to support number our number our number our number of number
                                             #reshaping to support our mod
img = img.reshape(1,28,28,1)
                                                                                                                                                                                             our model input and normalizing
                                           ing = img/255.0

#predicting the class

res = model.predict([img])[0]

return np.argmax(res), max(res)
 21 class App(tk.Tk):
                                        def __init__(self):
    tk.Tk.__init__(self)
    self.x = self.y = 0
    # Creating elements
 24
                                                                     self.canvas = tk.Canvas(self, width=300, height=300, bg = "white", cursor="cross")
self.label = tk.Label(self, text="Thinking..", font-("Welvetica", 40))
self.classify_btn = tk.Button(self, text = "Recognise", command = self.clas
self.button_clear = tk.Button(self, text = "Clear", command = self.clear_all)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                self.classify_handwriting)
 28
 29
38
31
32
33
34
                                     # Grid structure
self.canvas.grid(row-0, column-0, pady-2, sticky-M,)
self.label.grid(row-0, column-1, pady-2, padx-2)
self.classify_btn.grid(row-1, column-1, pady-2, padx-2)
self.button_clear.grid(row-1, column-0, pady-2)
#self.canvas.bind("Motton", self.stort_pos)
self.canvas.bind("Kelf-Motion", self.stort_pos)
self.canvas.delete("all")

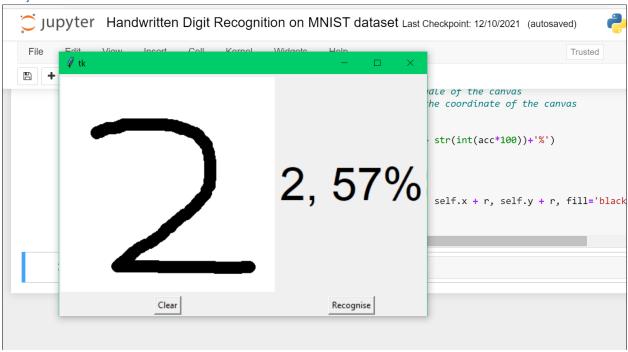
def clear_all(self):
self.canvas.delete("all")

def classify_handwriting(self):
HWND = self.canvas.winfo_id() # get the handle of the canvas
rect = win3/gui.detkindowRect(HWND) # get the coordinate of the canvas
im = ImageGrab.grab(rect)
digit, acc = predict_digit(im)
self.label.configure(text- str(digit)+', '+ str(int(acc*100))+'%')

def draw_lines(self, event):
self.x = event.x
                                                                        # Grid structure
 35
36
37
48
41
42
43
44
 46
                                                                           self.y = event.y
 48
                                                                        r-8
                                                                        self.canvas.create_oval(self.x-r, self.y-r, self.x + r, self.y + r, fill='black')
```

GUI TESTING

Fully Convolutional Network



Convolutional Neural Network

