group86_other_algorithms

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1 COMP5318 - Machine Learning and Data Mining: Assignment 2

Group 86

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1.1 The notebook includes sections :

```
Section 0. Hardware and software specifications
Section 1. Library and general functions
Section 2. Data pre-processing
Section 3. Implement algorithms
    3.1 AdaBoost Classifier
    3.2 Convolutional Neural Network Classifier
    3.3 Support-Vector-Machine Classifier
Section 4. Compare result between algorithms in train dataset
Section 5: Best perfroming algorithms in testing data  (we will submit this in seperate notebo
```

1.2 CODE RUNNING INSTRUCTIONS:

```
Instruction:
Simply change the switches in **0.Switches** blocks and run all.

Dataset directory:
Same directory as the jupyter notebook, in the format of :
---[current dir]
   |----[This file]
   |----[dataset]
      |----test
      |----train


The default parameters will used the saved model to run simple tests,
and load confusion matrices, accuracies, etc. from disk and plot them
for display purpose.
```

1.2.1 Hardware and software specifcations

hardware: 1. CPU: Intel i7-8700K @ 3.70GHz 2. RAM: 64G DDR4 3000MHz 3. Graphics: NVidia GeForce GTX 1080Ti 4. Chipset: Z370

1.2.2 Software specifications

[1]:
```
import os, platform
print('OS name:', os.name, ', system:', platform.system(), ', release:',␣
↪platform.release())
import sys
print("Anaconda version:")
#!conda list anaconda
print("Python version: ", sys.version)
print("Python version info: ", sys.version_info)
import PIL
from PIL import Image
print("PIL version: ", PIL.__version__)
import matplotlib
import matplotlib.pyplot as plt
print("Matplotlib version: ", matplotlib.__version__)
#import tensorflow as tf
#print("Keras version:", tf.keras.__version__)
import cv2
print("OpenCV version: ", cv2.__version__)
import numpy as np
print("nump version: ", np.__version__)
```

```
OS name: nt , system: Windows , release: 10
Anaconda version:
Python version:  3.8.3 (default, Jul  2 2020, 17:30:36) [MSC v.1916 64 bit
(AMD64)]
Python version info:  sys.version_info(major=3, minor=8, micro=3,
releaselevel='final', serial=0)
PIL version:  7.2.0
Matplotlib version:  3.2.2
OpenCV version:  4.4.0
nump version:  1.18.5
```

1.3 Section 0. Switches (Default settings is great for demo purpose)

Load saved model or run training?

[2]:
```
load_saved_model = True
```

Run preprocessing benchmark or not?

[3]:
```
run_preprocessing_benchmark = True
```

Run test code for 3 classifiers?

[4]:
```
run_test_code_for_classifiers = True
```

number of threads when preprocessing images

[5]:
```
g_thread_num = 6
```

Run hyper parameter tuning? (Slow if turned on!)

[6]:
```
# Caution: Slow if turned on.
do_hyper_parameter_tuning = False
```

Run 10-fold cross validation? (Slow if turned on)

[7]:
```
# Caution: Slow if turned on.
run_ten_fold = False
```

1.4 Section 1. Library and general functions

[8]:
```
#  Go to anaconda prompt to install package imblearn
# anaconda: conda install -c glemaitre imbalanced-learn
#pip install kmeans-smote

from skimage import io, transform
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

import cv2

import time
```

1.4.1 global variables

[9]:
```
# choose one of below two line depend file location******

g_dataset_dir = "./dataset/"
#g_dataset_dir = "../dataset/"


a_random_file = "./dataset/train/1b1B1b2-2pK2q1-4p1rB-7k-8-8-3B4-3rb3.jpeg"
#a_random_file = "../dataset/train/1b1B1b2-2pK2q1-4p1rB-7k-8-8-3B4-3rb3.jpeg"

saved_model_path = "./saved_model/"
abc_model_file = saved_model_path + "abc_dump.pkl"
svc_model_file = saved_model_path + "svc_dump.pkl"
cnn_model_file = saved_model_path + "cnn_weights"
```

```python
ten_fold_result_path = "./ten_fold_results/"


# define global variable

g_train_dir = g_dataset_dir + "/train/"
g_test_dir = g_dataset_dir + "/test/"

g_image_size = 400

g_grid_row = 8
g_grid_col = 8

g_grid_num = g_grid_row * g_grid_col
g_grid_size = int(g_image_size / g_grid_row)


#Processing 1 - scale down
g_down_sampled_size = 200
g_down_sampled_grid_size = int(g_grid_size / (g_image_size /␣
 ↪g_down_sampled_size))

# global instance of mapping of char vs chess pieces
# reference: Forsyth-Edwards Notation, https://en.wikipedia.org/wiki/
 ↪Forsyth%E2%80%93Edwards_Notation
#
# pawn = "P", knight = "N", bishop = "B", rook = "R", queen = "Q" and king = "K"
# White pieces are designated using upper-case letters ("PNBRQK") while black␣
 ↪pieces use lowercase ("pnbrqk")
# we use 0 to note an empty grid.
# 13 items in total.

g_piece_mapping = {
    "P" : "pawn",
    "N" : "knight",
    "B" : "bishop",
    "R" : "rook",
    "Q" : "queen",
    "K" : "king",

    "p" : "pawn",
    "n" : "knight",
    "b" : "bishop",
    "r" : "rook",
    "q" : "queen",
    "k" : "king",
```

```
    "0" : "empty_grid"
}

g_num_labels = len(g_piece_mapping)

g_labels = ["P",
"N",
"B",
"R",
"Q",
"K",
"p",
"n",
"b",
"r",
"q",
"k",
"0"]
```

1.4.2 Helper codes for label & board

[10]:
```
#DataHelper.py

import os

import cv2
from skimage import io
import numpy as np

import glob
import h5py

# get clean name by a path, where in our case this gets the FEN conviniently
def GetCleanNameByPath(file_name):
    return os.path.splitext(os.path.basename(file_name))[0]

# get full paths to the files in a directory.
def GetFileNamesInDir(path_name, extension="*", num_return = 0):
    if num_return == 0:
        return glob.glob(path_name + "/*." + extension)
    else:
        return glob.glob(path_name + "/*." + extension)[:num_return]

# get name list
def GetCleanNamesInDir(path_name, extension = "*", num_return = 0):
    names = GetFileNamesInDir(path_name, extension)
```

```python
    offset = len(extension) + 1
    clean_names = [os.path.basename(x)[:-offset] for x in names]
    if num_return == 0:
        return clean_names
    else:
        return clean_names[:num_return]

# read dataset
def ReadImages(file_names, path = "", format = cv2.IMREAD_COLOR):
    if path == "":
        return [cv2.imread(f, format) for f in file_names]
    else:
        return [cv2.imread(path + "/" + f, format) for f in file_names]

# read image by name
def ReadImage(file_name, gray = False):
    return io.imread(file_name, as_gray = gray)


# h5py functions

# read h5py file
# we assume the labels and
def ReadH5pyFile(file_name, data_name):
    h5_buffer = h5py.File(file_name)
    return h5_buffer[data_name].copy()

# write h5py file
def WriteH5pyFile(file_name, mat, data_name = "dataset"):
    with h5py.File(file_name, 'w') as f:
        f.create_dataset(data_name, data = mat)
```

[11]:
```python
#BoardHelper.py

import re
import string
from collections import OrderedDict

import numpy as np
import skimage.util
from skimage.util.shape import view_as_blocks

#from ChessGlobalDefs import *

#FEN TO LABELS OF SQUARES
def FENtoL(fen):
    rules = {
```

```python
        r"-": r"",
        r"1": r"0",
        r"2": r"00",
        r"3": r"000",
        r"4": r"0000",
        r"5": r"00000",
        r"6": r"000000",
        r"7": r"0000000",
        r"8": r"00000000",
    }

    for key in rules.keys():
        fen = re.sub(key, rules[key], fen)

    return list(fen)


# Label array to char list:
def LabelArrayToL(arr):
    rules = {
        0 : "P",
        1 : "N",
        2 : "B",
        3 : "R",
        4 : "Q",
        5 : "K",

        6 : "p",
        7 : "n",
        8 : "b",
        9 : "r",
       10 : "q",
       11 : "k",

       12 : "0"
    }

    flattened = arr.flatten(order = "C")

    L = []

    for x in flattened:
        L.append(rules[x])

    return L

# char list to FEN
```

```python
def LtoFEN(L):

    FEN = ""

    for y in range(8):
        counter = 0
        for x in range(8):
            idx = x + y * 8
            char = L[idx]

            if char == "0":
                counter += 1
                if x == 7:
                    FEN += str(counter)
            else:
                if counter:
                    FEN += str(counter)
                    counter = 0

                FEN += char
        if y != 7:
            FEN += "-"


    return FEN



# FEN to one-hot encoding, in our case, it returns an 64 by 13 array, with each
 ↪row as a one-hot to a grid.
def FENtoOneHot(fen):

    # this rule is in the same format as g_piece_mapping
    #rules = {
    #    "P" : np.array([1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]),
    #    "N" : np.array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]),
    #    "B" : np.array([0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]),
    #    "R" : np.array([0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]),
    #    "Q" : np.array([0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0]),
    #    "K" : np.array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]),
    #
    #    "p" : np.array([0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0]),
    #    "n" : np.array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0]),
    #    "b" : np.array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0]),
    #    "r" : np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0]),
    #    "q" : np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0]),
    #    "k" : np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0]),
```

```
    #
    #    "O" : np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1])
    #}
    rules = {
        "P" : 0,
        "N" : 1,
        "B" : 2,
        "R" : 3,
        "Q" : 4,
        "K" : 5,

        "p" : 6,
        "n" : 7,
        "b" : 8,
        "r" : 9,
        "q" : 10,
        "k" : 11,

        "0" : 12
    }

    L = FENtoL(fen)
    one_hot_array = np.zeros((g_grid_num, g_num_labels), dtype = np.int32) # 64␣
 ↪by 13
    for i, c in enumerate(L):
        one_hot_array[i, rules[c]] = 1

    return one_hot_array

# get 8*8 char matrix
def LtoCharMat(l):
    if type(l) == list:
        return np.array(l).reshape((8,8))
    if type(l) == str:
        return np.array([l]).reshape((8,8))

def GetBoardCell(board_image, row = 0, col = 0, size = 50):
    return np.array(board_image)[row*size:(row+1)*size,col*size:(col+1)*size]

# get grids of image
def ImageToGrids(image, grid_size_x, grid_size_y):
    return skimage.util.shape.view_as_blocks(image, block_shape = (grid_size_y,␣
 ↪grid_size_x, 3)).squeeze(axis = 2)

# get grids of image
def ImageToGrids_grey(image, grid_size_x, grid_size_y):
```

```
    return skimage.util.shape.view_as_blocks(image, block_shape = (grid_size_y,␣
↪grid_size_x, 1)).squeeze(axis = 2)
```

1.5 Section 2. Data pre-processing

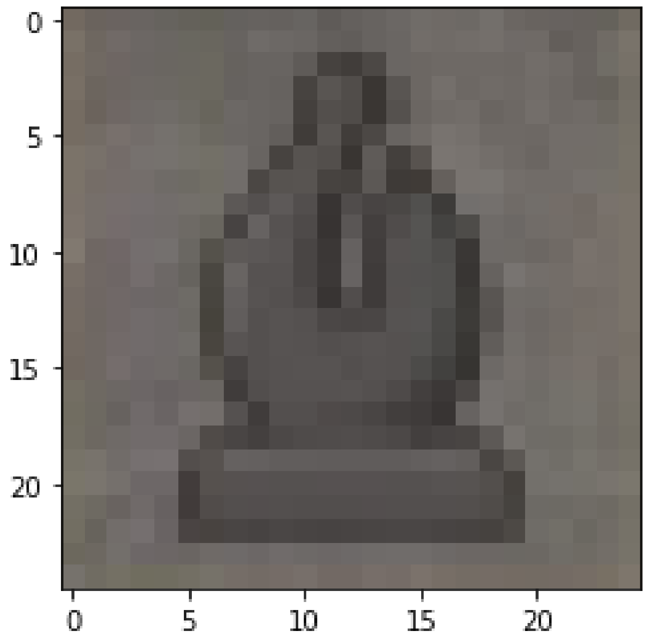
1.5.1 Pre-processing - generic

[12]:
```
# split into 64 small square from 1 board
# image resized to 400x 400 to 200x 200. 64 square at 25x 25 each

def PreprocessImage(image):
    image = transform.resize(image, (g_down_sampled_size, g_down_sampled_size),␣
↪mode='constant')

    # 1st and 2nd dim is 8
    grids = ImageToGrids(image, g_down_sampled_grid_size,␣
↪g_down_sampled_grid_size)

    return grids.reshape(g_grid_row * g_grid_col, g_down_sampled_grid_size,␣
↪g_down_sampled_grid_size, 3)

# split into 64 small square from 1 board -
# output of x: number of image x 64 x 25 x 25 x 3 , y: number of image x 64 x 13
def func_generator(train_file_names):
    x = []
    y = []
    for image_file_name in train_file_names:
        img = ReadImage(image_file_name)
        x.append(PreprocessImage(img))
        y.append(np.array(FENtoOneHot(GetCleanNameByPath(image_file_name))))

    return np.array(x), np.array(y)
```

[13]:
```
# Example output for a file - generic
num_train = 1
train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg",num_return␣
↪= num_train)

x, y = func_generator(train_file_names)

print("x type :", type(x))
print("x shape:", x.shape)
print("y type :", type(y))
print("y shape:", y.shape)
print()
plt.imshow(x[0][1])
```

```
x type : <class 'numpy.ndarray'>
x shape: (1, 64, 25, 25, 3)
y type : <class 'numpy.ndarray'>
y shape: (1, 64, 13)
```

[13]: <matplotlib.image.AxesImage at 0x1e80c167910>



1.5.2 Pre-processing - canny

[14]:
```python
# Processing image with canny
import cv2

def PreprocessImage_canny(image):
    image = cv2.Canny(image,100,200)
    image = transform.resize(image, (g_down_sampled_size, g_down_sampled_size),␣
 ↪mode='constant')
    # 1st and 2nd dim is 8
    image = image[..., np.newaxis]
    grids = ImageToGrids_grey(image, g_down_sampled_grid_size,␣
 ↪g_down_sampled_grid_size)
    return grids.reshape(g_grid_row * g_grid_col, g_down_sampled_grid_size,␣
 ↪g_down_sampled_grid_size)

# atomic func:
def func_canny(file_name):
```

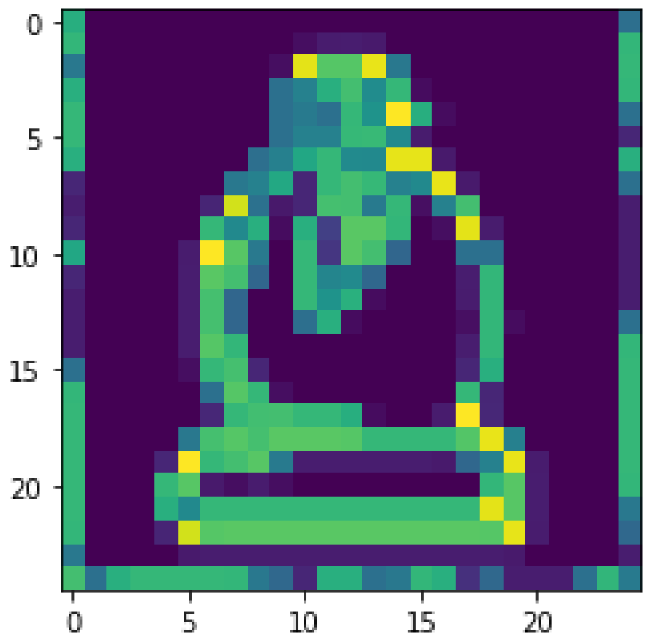
```
    img = ReadImage(file_name)
    x = PreprocessImage_canny(img)
    y = np.array(FENtoL(GetCleanNameByPath(file_name)))
    return x, y

# split into 64 small square from 1 - output of x: number of image x64 x 25 x25␣
 ↪, y:number of image x 64
def func_generator_canny(image_file_names):
    xs = []
    ys = []
    for image_file_name in image_file_names:
        x, y = func_canny(image_file_name)
        xs.append(x)
        ys.append(y)

    return xs, ys
```

[15]:

```
# Example output for a file - canny

num_train = 1
train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg",num_return␣
 ↪= num_train)

x, y = func_generator_canny(train_file_names)

print("x type    :", type(x))
print("x[0] type :", type(x[0]))
print("x[0] shape:", x[0].shape)
print("y type    :", type(y))
print("y[0] type :", type(y[0]))
print("y[0] shape:", y[0].shape)

plt.imshow(x[0][1])
```

```
x type    : <class 'list'>
x[0] type : <class 'numpy.ndarray'>
x[0] shape: (64, 25, 25)
y type    : <class 'list'>
y[0] type : <class 'numpy.ndarray'>
y[0] shape: (64,)
```

[15]: <matplotlib.image.AxesImage at 0x1e80c2465b0>



1.5.3 Pre-processing - SIFT

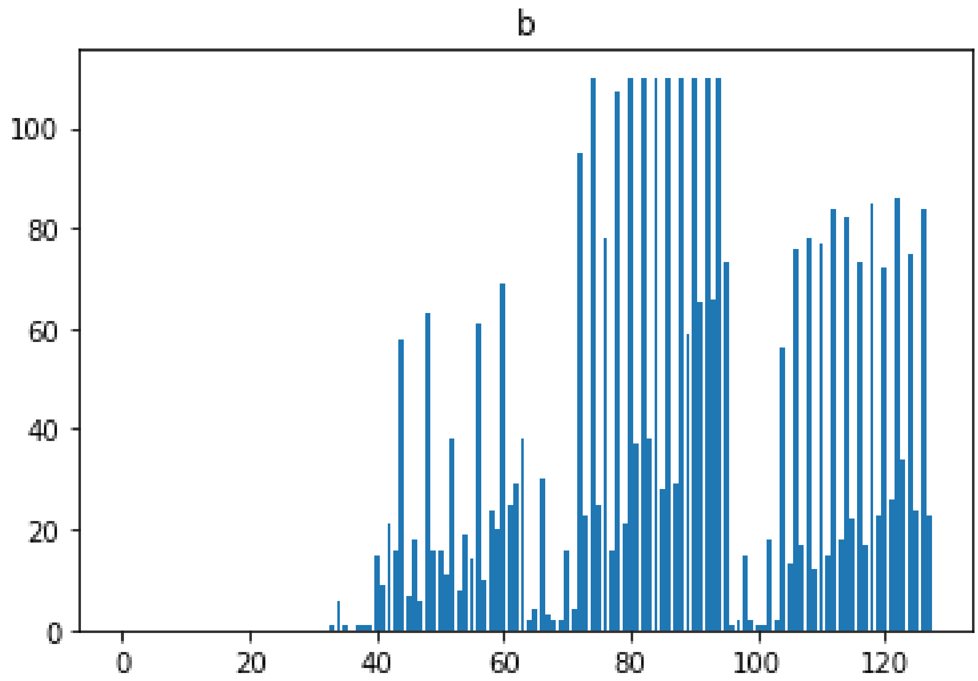
[16]:
```
# Processing image with sift
import cv2

def ExtractSIFTForGrid(board_image, row, col, center_x = 25, center_y = 25,␣
↪radius = 45):
    kps = [cv2.KeyPoint(x = center_x + 50 * col, y = center_y + 50 * row, _size␣
↪= 45)]

    # USE THE CORRECT VERSION OF CV2
    if cv2.__version__ == "4.4.0":
        keypoints, descriptors = cv2.SIFT_create(edgeThreshold = 0).
↪compute(image = board_image, keypoints = kps)
    else:
        keypoints, descriptors = cv2.xfeatures2d.SIFT_create(edgeThreshold = 0).
↪compute(image = board_image, keypoints = kps)

    return keypoints[0], descriptors[0, :]



def PreprocessImage_sift(image):
    # 1st and 2nd dim is 8
    desc=[]
```

```python
    for i in range(8):
        for j in range(8):
            kp, d= ExtractSIFTForGrid(image,i,j)
            desc.append(np.array(d))
    return desc

# atomic func:
def func_sift(file_name):
    img = ReadImage(file_name)
    x = PreprocessImage_sift(img)
    y = np.array(FENtoL(GetCleanNameByPath(file_name)))
    return x, y


# split into 64 small square from 1  - output of x: number of image x64 x128 ,␣
↪y:number of image x 64
def func_generator_sift(image_file_names):
    xs = []
    ys = []
    for image_file_name in image_file_names:
        x, y = func_sift(image_file_name)
        xs.append(np.array(x))
        ys.append(np.array(y))

    return xs, ys
```

[17]:
```python
# Example output for a file - SIFT

num_train = 1
train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg",num_return␣
↪= num_train)

x, y = func_generator_sift(train_file_names)

print("x type    :", type(x))
print("x[0] type :", type(x[0]))
print("x[0] shape:", x[0].shape)
print("y type    :", type(y))
print("y[0] type :", type(y[0]))
print("y[0] shape:", y[0].shape)

plt.bar(x = range(128), height = x[0][1])
plt.title(y[0][1])
plt.xticks(x = range(128))
plt.show()
```

```
x type    : <class 'list'>
```

```
x[0] type : <class 'numpy.ndarray'>
x[0] shape: (64, 128)
y type    : <class 'list'>
y[0] type : <class 'numpy.ndarray'>
y[0] shape: (64,)
```



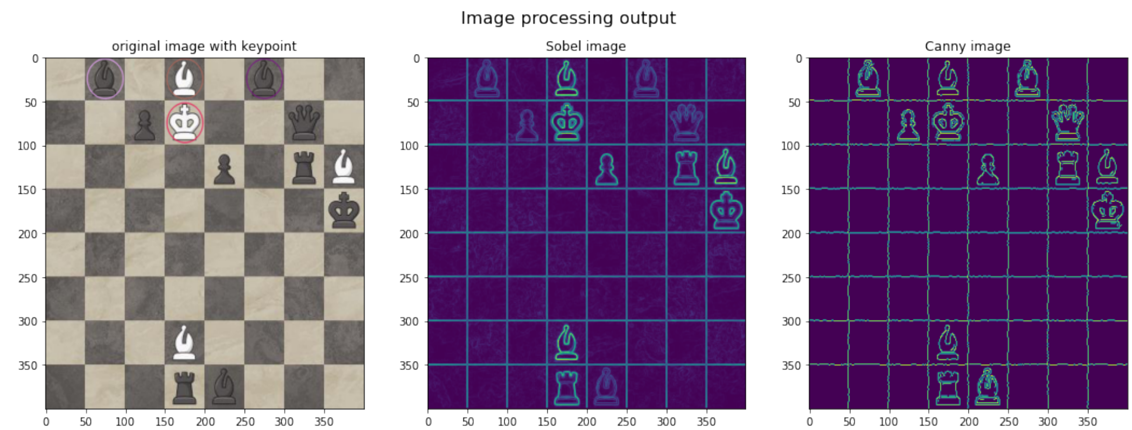
1.5.4 Example of image input, canny, SIFT

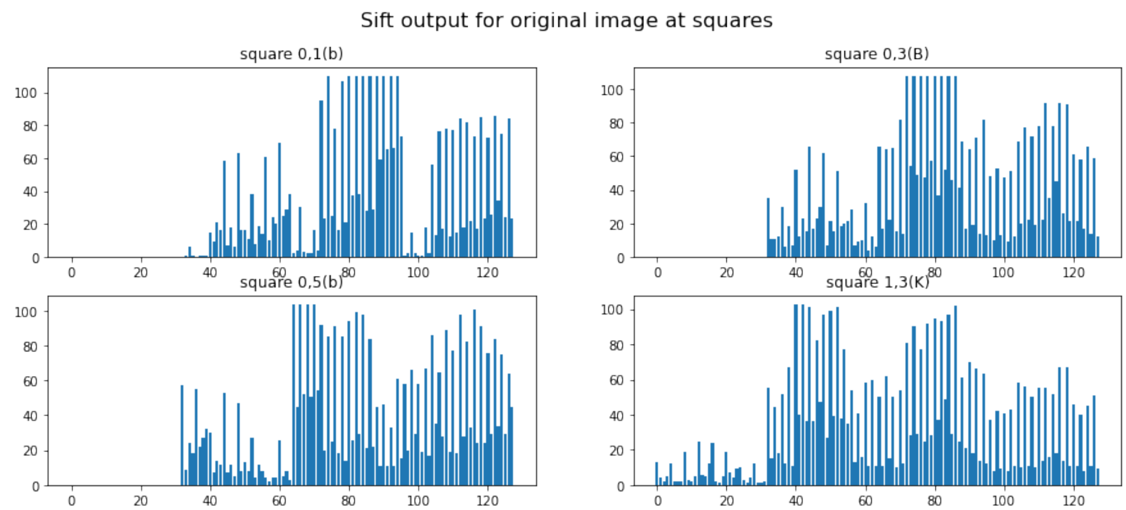
[18]:
```python
import cv2
from skimage.filters import sobel

#print("Sift: decriptor size:", cv2.SIFT_create().descriptorSize())
img = ReadImage(a_random_file)
img1 = cv2.Canny(img,100,200)
img2= sobel(img[:,:,0])
print(img.shape)
print(img1.shape)
print(img2.shape)

kp, desc = ExtractSIFTForGrid(img, 0, 1)
kp2, desc2 = ExtractSIFTForGrid(img, 0, 3)
kp3, desc3 = ExtractSIFTForGrid(img, 0, 5)
kp4, desc4 = ExtractSIFTForGrid(img, 1, 3)
```

```
img_kp = cv2.drawKeypoints(img, [kp, kp2,kp3,kp4], img, flags=cv2.
 ↪DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
img_kp1 = cv2.drawKeypoints(img1, [kp, kp2,kp3,kp4], img1, flags=cv2.
 ↪DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)


print('file name:',a_random_file)


plt.figure(figsize=(18,6))
plt.suptitle('Image processing output', fontsize=16)
plt.subplot(1, 3, 1)
plt.imshow(img_kp, aspect='auto')
plt.title('original image with keypoint')

plt.subplot(1, 3, 2)
plt.imshow(img2, aspect='auto')
plt.title('Sobel image')

plt.subplot(1, 3, 3)
plt.imshow(img1, aspect='auto')
plt.title('Canny image')
plt.show()

plt.figure(figsize=(15,6))
plt.suptitle('Sift output for original image at squares', fontsize=16)
#plt.tight_layout()
plt.subplot(2, 2, 1)
plt.title('square 0,1(b)')
plt.bar(x = range(128), height = desc)
plt.xticks(x = range(128))

plt.subplot(2,2, 2)
plt.title('square 0,3(B)')
plt.bar(x = range(128), height = desc2)
plt.xticks(x = range(128))

plt.subplot(2,2,3)
plt.title('square 0,5(b)')
plt.bar(x = range(128), height = desc3)
plt.xticks(x = range(128))


plt.subplot(2,2,4)
plt.title('square 1,3(K)')
plt.bar(x = range(128), height = desc4)
plt.xticks(x = range(128))
```

```
plt.show()
```

```
(400, 400, 3)
(400, 400)
(400, 400)
file name: ./dataset/train/1b1B1b2-2pK2q1-4p1rB-7k-8-8-3B4-3rb3.jpeg
```





1.5.5 Read image - generic, canny, sift - run time

[19]:
```
if run_preprocessing_benchmark:
    start_time = time.time()
    num_train = 100
    train_file_names = GetFileNamesInDir(g_train_dir, extension =␣
 ↪"jpeg",num_return = num_train)
```

```
    X_org,Y_org = func_generator(train_file_names)
    print('runnning time for generic 100 images')
    print('--- {} seconds ---'.format(time.time() - start_time))

    X_sift,Y_sift = func_generator_sift(train_file_names)
    print('runnning time for sift 100 images')
    print('--- {} seconds ---'.format(time.time() - start_time))

    start_time = time.time()
    X_canny,Y_canny = func_generator_canny(train_file_names)
    print('runnning time for canny 100 images')
    print('--- {} seconds ---'.format(time.time() - start_time))
```

```
runnning time for generic 100 images
--- 1.9594979286193848 seconds ---
runnning time for sift 100 images
--- 28.49899911880493 seconds ---
runnning time for canny 100 images
--- 0.7249987125396729 seconds ---
```

1.5.6 Subset train data - high quality (image level)

[20]:
```
#https://www.researchgate.net/post/
↪How_to_use_clustering_to_reduce_data_set_samples

#subset data of high quality image (at image level)

#Output is
def file_names_highquality(image_file_names, min_piece =15):
    names = np.array(image_file_names)
    idx_sub = []
    for idx in range(len(image_file_names)):
        y = FENtoL(GetCleanNameByPath(image_file_names[idx]))
        piece_count = 64 - y.count('0')
        if piece_count >= min_piece:
            idx_sub.append(idx)

    return np.array(image_file_names)[idx_sub]
```

[21]:
```
# test
if run_preprocessing_benchmark:
    file_name_reduced = file_names_highquality(train_file_names, min_piece =15)
    print('reduced file number␣
↪from',len(train_file_names),'to',len(file_name_reduced))
```

```
reduced file number from 100 to 21
```

1.5.7 Undersempling -square (grid level)

[22]:
```
# install the package if needed.
if run_preprocessing_benchmark:
    !pip install imblearn
```

```
Looking in indexes: https://pypi.douban.com/simple
Requirement already satisfied: imblearn in g:\anaconda3\lib\site-packages (0.0)
Requirement already satisfied: imbalanced-learn in g:\anaconda3\lib\site-
packages (from imblearn) (0.7.0)
Requirement already satisfied: scikit-learn>=0.23 in g:\anaconda3\lib\site-
packages (from imbalanced-learn->imblearn) (0.23.2)
Requirement already satisfied: scipy>=0.19.1 in g:\anaconda3\lib\site-packages
(from imbalanced-learn->imblearn) (1.5.0)
Requirement already satisfied: joblib>=0.11 in g:\anaconda3\lib\site-packages
(from imbalanced-learn->imblearn) (0.16.0)
Requirement already satisfied: numpy>=1.13.3 in g:\anaconda3\lib\site-packages
(from imbalanced-learn->imblearn) (1.18.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in g:\anaconda3\lib\site-
packages (from scikit-learn>=0.23->imbalanced-learn->imblearn) (2.1.0)
```

[23]:
```
#subset data (in square level)
#ref: #https://www.researchgate.net/post/
↪How_to_use_clustering_to_reduce_data_set_samples
# implement using https://imbalanced-learn.readthedocs.io/en/stable/generated/
↪imblearn.under_sampling.ClusterCentroids.html

if run_preprocessing_benchmark:
    from imblearn.under_sampling import ClusterCentroids

    # output x: number of grid x 125, y: number of grid
    def undersampling_ClusterCentroids_canny(X,Y):
        trans = ClusterCentroids(random_state=0)
        length=len(np.array(Y))
        X= np.array(X).reshape(length*64,25*25)
        Y = np.array(Y).reshape(length*64)
        X_resampled, y_resampled = trans.fit_sample(X, Y)

        return X_resampled, y_resampled

    # output x: number of grid x 128, y: number of grid
    def undersampling_ClusterCentroids_sift(X,Y):
        trans = ClusterCentroids(random_state=0)
        length=len(np.array(Y))
        X= np.array(X).reshape(length*64,128)
        Y = np.array(Y).reshape(length*64)
        X_resampled, y_resampled = trans.fit_sample(X, Y)
```

```
        return X_resampled, y_resampled
```

[24]:
```
if run_preprocessing_benchmark:
    # test canny -resampled

    start_time = time.time()
    X_resampled_canny, Y_resampled_canny =␣
 ↪undersampling_ClusterCentroids_canny(X_canny,Y_canny)
    print('--- {} seconds ---'.format(time.time() - start_time))
    print('reduce grid number from',len(np.array(Y_canny))*64,'to',len(np.
 ↪array(Y_resampled_canny)))

    # test sift -resampled

    start_time = time.time()
    X_resampled_sift, Y_resampled_sift =␣
 ↪undersampling_ClusterCentroids_sift(X_sift,Y_sift)
    print('--- {} seconds ---'.format(time.time() - start_time))
    print('reduce grid number from',len(np.array(Y_sift))*64,'to',len(np.
 ↪array(Y_resampled_sift)))
```

```
--- 5.019449710845947 seconds ---
reduce grid number from 6400 to 455
--- 4.656001806259155 seconds ---
reduce grid number from 6400 to 455
```

1.5.8 Read Image - parallel version

[25]:
```
from joblib import Parallel, delayed

# note: functions are first-class objects in Python. we pass it directly as␣
 ↪parameter.
def Preprocess_parallel(func, file_names, job_count = 6):
    result = Parallel(n_jobs=job_count)(delayed(func)(file_name) for file_name␣
 ↪in file_names)
    return zip(*result)
```

[26]:
```
if run_preprocessing_benchmark:
    start_time = time.time()
    num_train = 100
    train_file_names = GetFileNamesInDir(g_train_dir, extension =␣
 ↪"jpeg",num_return = num_train)

    xs, ys = Preprocess_parallel(func_canny, train_file_names)
    print('--- {} seconds ---'.format(time.time() - start_time))
```

```
--- 1.9814999103546143 seconds ---
```

1.5.9 Read file names

[27]:
```
if do_hyper_parameter_tuning:
    # Using FEN to identify grid with chess

    num_train = 500 # small bath train
    num_test= 500   # small bath train

    # Reading lables
    train_file_names = GetFileNamesInDir(g_train_dir, extension =␣
↪"jpeg",num_return = num_train)
    test_file_names = GetFileNamesInDir(g_test_dir, extension =␣
↪"jpeg",num_return = num_test)
```

1.6 Section 3. Implement algorithms

1.6.1 Section 3.0 AdaBoostClassifier (ABC) Prototype

Import data - SIFT output (n x 128)

[28]:
```
if do_hyper_parameter_tuning:
    # import data - train

    start_time = time.time()
    #xs_train, ys_train = Preprocess_parallel(train_file_names)
    xs_train_sift, ys_train_sift = Preprocess_parallel(func_sift,␣
↪train_file_names)  #[JL - I broke Preprocess_parallel. use this instead ]
    print('xs_train_sift, ys_train_sift generated:',len(xs_train_sift))
    print(np.array(xs_train_sift).shape, np.array(ys_train_sift).shape)
    print('--- {} seconds ---'.format(time.time() - start_time))

    # import data - test

    start_time = time.time()
    #xs_train, ys_train = Preprocess_parallel(train_file_names)
    xs_test_sift, ys_test_sift = Preprocess_parallel(func_sift,␣
↪test_file_names)  #[JL - I broke Preprocess_parallel. use this instead ]
    print('xs_test_sift, ys_test_sift generated:',len(xs_test_sift))
    print(np.array(xs_test_sift).shape, np.array(ys_test_sift).shape)
    print('--- {} seconds ---'.format(time.time() - start_time))
```

intital prediction accuracy in sift data

[29]:
```
if do_hyper_parameter_tuning:
    xs_train_sift2= np.array(xs_train_sift).reshape(500*64,128)
    ys_train_sift2 = np.array(ys_train_sift).reshape(500*64)
    print('shape of train data:',np.array(xs_train_sift2).shape, np.
↪array(ys_train_sift2).shape)
```

```
    # ABC classifier

    from sklearn.ensemble import AdaBoostClassifier
    from sklearn.metrics import accuracy_score
    from sklearn.metrics import classification_report
    start_time = time.time()

    ada = AdaBoostClassifier(n_estimators=50, learning_rate=0.5,␣
↪random_state=42)
    ada.fit(xs_train_sift2,ys_train_sift2)
    y_pred= ada.predict(xs_train_sift2)

    #Evaluate its performance on the training and test set
    print("AdaBoost- accuracy on validation set:",␣
↪accuracy_score(ys_train_sift2 ,y_pred))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

Import data - canny output (n x 25 x 25)

[30]:
```
if do_hyper_parameter_tuning:
    # import data - train 500

    start_time = time.time()
    #xs_train, ys_train = Preprocess_parallel(train_file_names)
    xs_train_canny, ys_train_canny = func_generator_canny(train_file_names) ␣
↪#[JL - I broke Preprocess_parallel. use this instead ]
    print('xs_train_canny, ys_train_canny generated:',len(xs_train_canny))
    print(np.array(xs_train_canny).shape, np.array(ys_train_canny).shape)
    print('--- {} seconds ---'.format(time.time() - start_time))

    # import data - test 500

    start_time = time.time()
    #xs_train, ys_train = Preprocess_parallel(train_file_names)
    xs_test_canny, ys_test_canny = func_generator_canny(test_file_names)  #[JL␣
↪- I broke Preprocess_parallel. use this instead ]
    print('xs_test_canny, ys_test_canny generated:',len(xs_test_canny))
    print(np.array(xs_test_canny).shape, np.array(ys_test_canny).shape)
    print('--- {} seconds ---'.format(time.time() - start_time))
```

intital prediction accuracy in canny data

[31]:
```
if do_hyper_parameter_tuning:
    xs_train_canny2= np.array(xs_train_canny).reshape(500*64,25*25)
    ys_train_canny2 = np.array(ys_train_canny).reshape(500*64)
    print('shape of train data:',np.array(xs_train_canny2).shape, np.
↪array(ys_train_canny2).shape)
```

```
    # ABC classifier

    from sklearn.ensemble import AdaBoostClassifier
    from sklearn.metrics import accuracy_score
    from sklearn.metrics import classification_report
    start_time = time.time()

    ada = AdaBoostClassifier(n_estimators=50, learning_rate=0.5,␣
↪random_state=42)
    ada.fit(xs_train_canny2,ys_train_canny2)
    y_pred= ada.predict(xs_train_canny2)

    #Evaluate its performance on the training and test set
    print("AdaBoost- accuracy on validation set:",␣
↪accuracy_score(ys_train_canny2 ,y_pred))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

1.6.2 Proceed with canny data

Split train to train and validation

[32]:
```
if do_hyper_parameter_tuning:
    #split 500 training data
    start_time = time.time()

    test_size=0.33

    from sklearn.model_selection import train_test_split
    X_train, X_val, Y_train, Y_val = train_test_split(
        xs_train_canny,ys_train_canny, test_size=0.33, random_state=0)
    print(np.array(X_train).shape, np.array(X_val).shape, np.array(Y_train).
↪shape, np.array(Y_val).shape)
    print('--- {} seconds ---'.format(time.time() - start_time))
```

Undersampling traing set

[33]:
```
if do_hyper_parameter_tuning:
    # test sift -resampled

    start_time = time.time()

    X_resampled, Y_resampled =␣
↪undersampling_ClusterCentroids_canny(X_train,Y_train)
    print('--- {} seconds ---'.format(time.time() - start_time))
    print('reduce grid number from',len(np.array(Y_train))*64,'to',len(np.
↪array(Y_resampled)))
```

```
    print('shape of resampled data:',np.array(X_resampled).shape, np.
↪array(Y_resampled).shape)
```

[34]:
```
if do_hyper_parameter_tuning:
    # reshpe train daa, validation data, and testing data as resampled

    X_train= np.array(X_train).reshape(335*64,25*25)
    Y_train = np.array(Y_train).reshape(335*64)
    print('shape of train data:',np.array(X_train).shape, np.array(Y_train).
↪shape)

    X_val= np.array(X_val).reshape(165*64,25*25)
    Y_val = np.array(Y_val).reshape(165*64)
    print('shape of validation data:',np.array(X_val).shape, np.array(Y_val).
↪shape)

    xs_test_canny= np.array(xs_test_canny).reshape(num_test*64,25*25)
    ys_test_canny = np.array(ys_test_canny).reshape(num_test*64)
    print('shape of test data:',np.array(xs_test_canny).shape, np.
↪array(ys_test_canny).shape)
```

Base classifier- Tree (with canny & canny resampling)

[35]:
```
if do_hyper_parameter_tuning:
    # Tree classifier - Canny data
    from sklearn.tree import DecisionTreeClassifier

    start_time = time.time()
    #Apply pre-pruning by limiting the depth of the tree - max_depth=2
    tree = DecisionTreeClassifier(criterion='gini', max_depth=5)
    tree.fit(X_train, Y_train)
    #Evaluate its performance on the training and test set
    print("Accuracy on training set: {:.3f}".format(tree.score(X_train,␣
↪Y_train)))
    print("Accuracy on validation set: {:.3f}".format(tree.score(X_val, Y_val)))
    print("Accuracy on testing set: {:.3f}".format(tree.score(xs_test_canny,␣
↪ys_test_canny)))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

[36]:
```
if do_hyper_parameter_tuning:
    # Tree classifier - Canny & resampling data
    from sklearn.tree import DecisionTreeClassifier

    start_time = time.time()
    #Apply pre-pruning by limiting the depth of the tree
    tree = DecisionTreeClassifier(criterion='gini', max_depth=5)
    tree.fit(X_resampled, Y_resampled)
```

```
    #Evaluate its performance on the training and test set
    print("Accuracy on training set: {:.3f}".format(tree.score(X_train,␣
↪Y_train)))
    print("Accuracy on validation set: {:.3f}".format(tree.score(X_val, Y_val)))
    print("Accuracy on testing set: {:.3f}".format(tree.score(xs_test_canny,␣
↪ys_test_canny)))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

AdaBoostClassifier- Tree (with canny & canny resampling)

[37]:
```
if do_hyper_parameter_tuning:
    # ABC classifier- Canny data

    from sklearn.ensemble import AdaBoostClassifier
    from sklearn.metrics import accuracy_score
    from sklearn.metrics import classification_report
    start_time = time.time()

    ada = AdaBoostClassifier(n_estimators=50,
                             base_estimator =␣
↪DecisionTreeClassifier(criterion='gini', max_depth=5),
                             learning_rate=0.5,
                             random_state=42)
    ada.fit(X_train, Y_train)
    y_pred_val = ada.predict(X_val)
    y_pred_test = ada.predict(xs_test_canny)

    #Evaluate its performance on the training and test set
    print("AdaBoost- accuracy on validation set:", accuracy_score(Y_val,␣
↪y_pred_val))
    print("AdaBoost- accuracy on testing set:", accuracy_score(ys_test_canny,␣
↪y_pred_test))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

[38]:
```
if do_hyper_parameter_tuning:
    # ABC classifier- Canny & resampling  data

    start_time = time.time()

    ada = AdaBoostClassifier(n_estimators=50,
                             base_estimator =␣
↪DecisionTreeClassifier(criterion='gini', max_depth=5),
                             learning_rate=0.5,
                             random_state=42)
    ada.fit(X_resampled, Y_resampled)
    y_pred_val = ada.predict(X_val)
    y_pred_test = ada.predict(xs_test_canny)
```

```
    #Evaluate its performance on the training and test set
    print("AdaBoost- accuracy on validation set:", accuracy_score(Y_val,␣
↪y_pred_val))
    print("AdaBoost- accuracy on testing set:", accuracy_score(ys_test_canny,␣
↪y_pred_test))
    print('--- {} seconds ---'.format(time.time() - start_time))
```

Hyper parameter tunning

[39]:
```
###https://machinelearningmastery.com/adaboost-ensemble-in-python/

if do_hyper_parameter_tuning:

    from sklearn.ensemble import AdaBoostClassifier
    from sklearn.model_selection import GridSearchCV

    # AdaBoost
    param_grid = [{'n_estimators': np.arange(10,50,5),
                  'learning_rate': [0.01, 0.05, 0.1, 1,5,10]
                 }]

    start_time = time.time()
    abc = GridSearchCV(AdaBoostClassifier(random_state=42), param_grid)
    abc.fit(X_resampled, Y_resampled)

    print('--- {} seconds ---'.format(time.time() - start_time))

    # SVC
    param_grid = [{'n_estimators': np.arange(10,50,5),
                  'learning_rate': [0.01, 0.05, 0.1, 1,5,10],
                   "kernel" : ["linear", "poly", "rbf", "sigmoid"],
                   "C" : [0.01, 1, 10, 100]
                 }]

    start_time = time.time()
    svc = GridSearchCV(svm.SVC(random_state=42), param_grid)
    abc.fit(X_resampled, Y_resampled)

    print('--- {} seconds ---'.format(time.time() - start_time))



else:
    print("Hyper parameter tuning skipped.")
```

```
Hyper parameter tuning skipped.
```

GridSearchCV Result

[40]:
```
if do_hyper_parameter_tuning:

    # Print grid search results
    from sklearn.metrics import classification_report

    means = abc.cv_results_['mean_test_score']
    stds = abc.cv_results_['std_test_score']
    params = abc.cv_results_['params']

    print('Grid search mean and stdev:\n')

    for mean, std, p in zip(means, stds, params):
        print("%0.3f (+/-%0.03f) for %r"% (mean, std * 2, p))

    # Print best params
    print('\nBest parameters:', abc.best_params_)
    print("Detailed classification report:")
    print()
    print(classification_report(Y_val, abc.predict(X_val)))
    print()
else:
    print("Adaboost: Hyper parameter report skipped.")
```

```
Adaboost: Hyper parameter report skipped.
```

1.7 Section 3.1 SVM Classifier (SVC)

Base class for all classifiers

[41]:
```
import abc

# interface of the classifiers
class IClassifier:

    # this method should accept a list of file names of the training data
    @abc.abstractmethod
    def Train(self, train_file_names):
        raise NotImplementedError()

    # this should accept a 400 * 400 * 3 numpy array as query data, and returns␣
↪the fen notation of the board.
    @abc.abstractmethod
    def Predict(self, query_data):
        raise NotImplementedError()

    # this should accept a list of file names, and returns the predicted labels␣
↪as 1d numpy array.
```

```
    @abc.abstractmethod
    def Predict(self, query_data):
        raise NotImplementedError()
```

Class definition for SVC

[42]:
```
from sklearn import svm
import numpy as np

# image io and plotting
from skimage import io, transform
import skimage.util
from skimage.util.shape import view_as_blocks
from matplotlib import pyplot as plt

# parallel processing
from joblib import Parallel, delayed
# model save and load
import pickle
import os
# profiling
import time

# joblib needs the kernel to be a top-level function, so we defined it here.
def PreprocessKernel(name):
    img = ReadImage(name, gray = True)
    grids = SVCClassifier.SVCPreprocess(img)
    labels = np.array(FENtoOneHot(GetCleanNameByPath(name))).argmax(axis=1)
    return grids, labels

# SVM Classifier
class SVCClassifier(IClassifier):

    def __init__(self):
        self.__svc__ = svm.SVC(C=1.0, cache_size=200, class_weight=None,␣
↪coef0=0.0,
                          decision_function_shape='ovr', degree=3, gamma=0.001,␣
↪kernel='rbf',
                          max_iter=-1, probability=False, random_state=None,␣
↪shrinking=True,
                          tol=0.001, verbose=False)

    # this method should accept a list of file names of the training data
    def Train(self, train_file_names):
        print("svc: reading image.")
        start_time = time.time()
        xs, ys = SVCClassifier.PreprocessParallelWrapperFunc(train_file_names)
```

```
        print("svc: finished reading image, {} sec.".format(time.time() -␣
↪start_time))
        # train
        print("svc: start training.")
        start_time = time.time()
        self.__svc__.fit(xs, ys)
        print("svc: finished. {} sec.".format(time.time() - start_time))

    # this should accept a 400 * 400 * 3 numpy array as query data, and returns␣
↪the fen notation of the board.
    def Predict(self, query_data):
        grids = SVCClassifier.SVCPreprocess(query_data)
        y_pred = self.__svc__.predict(grids)

        return LabelArrayToL(y_pred)

    # predict by file name:
    def PredictMultiple(self, file_names):
        preds = []
        truth = []
        for f in file_names:
            img = ReadImage(f, gray = True)
            y_pred = self.Predict(img)
            y_true = FENtoL(GetCleanNameByPath(f))
            preds.append(y_pred)
            truth.append(y_true)

        all_pred = np.vstack(preds)
        all_truth = np.vstack(truth)
        return all_pred, all_truth

    # parallel pre-process wrapper:
    @staticmethod
    def PreprocessParallelWrapperFunc(file_names, num_thread = g_thread_num):
        result = Parallel(n_jobs =␣
↪num_thread)(delayed(PreprocessKernel)(file_name) for file_name in file_names)
        xs, ys = zip(*result)
        xs = np.concatenate(xs, axis=0)
        ys = np.concatenate(ys)
        return xs, ys

    @staticmethod
    def SVCPreprocess(img):
        img = transform.resize(img, (g_down_sampled_size, g_down_sampled_size),␣
↪mode='constant')
        grids = skimage.util.shape.view_as_blocks(img, block_shape =␣
↪(g_down_sampled_grid_size, g_down_sampled_grid_size))
```

```
        grids = grids.reshape((-1, grids.shape[3], grids.shape[3]))
        grids = grids.reshape((grids.shape[0], grids.shape[1] * grids.shape[1]))
        return grids

    def SaveModel(self, save_file_name):
        os.makedirs(os.path.dirname(save_file_name), exist_ok = True)
        with open(save_file_name, 'wb') as file:
            pickle.dump(self.__svc__, file)

    def LoadModel(self, load_file_name):
        with open(load_file_name, 'rb') as file:
            self.__svc__ = pickle.load(file)
```

Test code for SVC

[43]:
```
if run_test_code_for_classifiers:
    svc = SVCClassifier()
    train_names = GetFileNamesInDir(g_train_dir)

    if load_saved_model:
        print("svc: loading model from " + svc_model_file)
        svc.LoadModel(svc_model_file)
    else:
        svc.Train(train_names[:500])

    y_truth = FENtoL(GetCleanNameByPath(a_random_file))
    img = ReadImage(a_random_file, gray = True)
    pred = svc.Predict(img)
    print("truth:  ", ''.join(y_truth))
    print("pred :  ", ''.join(pred))

    # save model
    if not load_saved_model:
        print("svc: saving model to " + svc_model_file)
        svc.SaveModel(svc_model_file)
```

```
svc: loading model from ./saved_model/svc_dump.pkl
truth:   0b0B0b0000pK00q00000p0rB0000000k0000000000000000000B0000000rb000
pred :   000B0000000K00000000p0rB0000000k0000000000000000000B0000000r0000
```

1.7.1 Section 3.2 Convolutional Neural Network Classifier (CNN)

Class definition for CNN

[44]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

import cv2
```

```python
from skimage import io, transform
import numpy as np
import os

#import tensorflow as tf
#from tensorflow import keras
#from tf.keras.models import Sequential
#from tf.keras.layers.core import Flatten, Dense, Dropout, Activation
#from tf.keras.layers.convolutional import Convolution2D

class CNNClassifier(IClassifier):

    # the file name format does not accept batch as parameter. link:
    # https://github.com/tensorflow/tensorflow/issues/38668
    s_check_point_file_name = "./CNN_training_checkpoint/cp_{epoch:
↪02d}-{accuracy:.2f}.ckpt"
    s_check_point_path = os.path.dirname(s_check_point_file_name)
    s_save_frequence = 10000 # save a checkpoint every s_save_frequence batches

    def __init__(self):

        #tf.config.threading.set_inter_op_parallelism_threads(3)
        #tf.config.threading.set_intra_op_parallelism_threads(3)

        # define our model
        self.__model__ = keras.Sequential(
            [
                layers.Convolution2D(32, (3, 3), input_shape =␣
↪(g_down_sampled_grid_size, g_down_sampled_grid_size, 3)),
                layers.Activation('relu'),
                layers.Dropout(0.1),
                layers.Convolution2D(32, (3, 3)),
                layers.Activation('relu'),

                layers.Convolution2D(32, (3, 3)),
                layers.Activation('relu'),

                layers.Flatten(),

                layers.Dense(128),
                layers.Activation('relu'),
                layers.Dropout(0.3),

                layers.Dense(13),
                layers.Activation("softmax")
            ]
        )
```

```python
        self.__model__.compile(loss = "categorical_crossentropy", optimizer =␣
↪'adam', metrics = ["accuracy"])

        self.__save_check_point_callback__ = tf.keras.callbacks.ModelCheckpoint(
            filepath = CNNClassifier.s_check_point_file_name,
            monitor='val_accuracy',
            save_weights_only = True,
            save_freq = CNNClassifier.s_save_frequence,
            verbose = 1
            )


     # generator
    @staticmethod
    def func_generator(train_file_names):
        for image_file_name in train_file_names:
            img = ReadImage(image_file_name)
            x = CNNClassifier.PreprocessImage(img)
            y = np.array(FENtoOneHot(GetCleanNameByPath(image_file_name)))
            yield x, y

    # this method should accept N * 64 * m * n numpy array as train data, and N␣
↪lists of 64 chars as label.
    def Train(self, train_data_names):
        train_size = len(train_data_names)

        ## try load last checkpoint
        #if not self.LoadMostRecentModel():
        #    os.makedirs(CNNClassifier.s_check_point_path, exist_ok = True)

        # train
        self.__model__.fit(CNNClassifier.func_generator(train_data_names),
                           use_multiprocessing = False,
                           #batch_size = 1000,
                           steps_per_epoch = train_size / 20,
                           epochs = 2,
                           #callbacks = [self.__save_check_point_callback__],
                           verbose = 1)


    # this should accept a 64 * m * n numpy array as query data, and returns␣
↪the fen notation of the board.
    def Predict(self, query_data):
        grids = CNNClassifier.PreprocessImage(query_data)
        y_pred = self.__model__.predict(grids).argmax(axis=1)
```

```python
        return y_pred


    # predict by file name:
    def PredictMultiple(self, file_names):
        preds = []
        truth = []
        for f in file_names:
            img = ReadImage(f, gray = False)
            y_pred = LabelArrayToL(self.Predict(img))
            y_true = FENtoL(GetCleanNameByPath(f))
            preds.append(y_pred)
            truth.append(y_true)

        all_pred = np.vstack(preds)
        all_truth = np.vstack(truth)
        return all_pred, all_truth


    def LoadModel(self, name):
        self.__model__.load_weights(name)

    def SaveModel(self, name):
        os.makedirs(os.path.dirname(name), exist_ok = True)
        self.__model__.save_weights(name)

    def PrintModel(self):
        self.__model__.summary()

    def LoadMostRecentModel(self):
        return self.LoadMostRecentModelFromDirectory(CNNClassifier.
↪s_check_point_path)

    def LoadMostRecentModelFromDirectory(self, path):
        try:
            last_cp = tf.train.latest_checkpoint(path)
            self.__model__.load_weights(last_cp)
            print("Loaded checkpoint from " + last_cp)
            return True
        except:
            print("No checkpoint is loaded.")
            return False

    def TestAccuracy(self, test_file_names):
        num_files = len(test_file_names)
```

```
        predict_result = self.__model__.predict(CNNClassifier.
↪func_generator(test_file_names)).argmax(axis=1)
        predict_result = predict_result.reshape(num_files, -1)
        predicted_fen_arr = np.array([LtoFEN(LabelArrayToL(labels)) for labels␣
↪in predict_result])
        test_fens = np.array([GetCleanNameByPath(file_name) for file_name in␣
↪test_file_names])

        final_accuracy = (predicted_fen_arr == test_fens).astype(np.float).
↪mean()
        return final_accuracy

    @staticmethod
    def PreprocessImage(image):
        image = transform.resize(image, (g_down_sampled_size,␣
↪g_down_sampled_size), mode='constant')

        # 1st and 2nd dim is 8
        grids = ImageToGrids(image, g_down_sampled_grid_size,␣
↪g_down_sampled_grid_size)

        # debug
        #plt.imshow(grids[0][3])
        #plt.show()

        return grids.reshape(g_grid_row * g_grid_col, g_down_sampled_grid_size,␣
↪g_down_sampled_grid_size, 3)
```

test code for CNN

[45]:
```
if run_test_code_for_classifiers:
    if not load_saved_model:
        cnn = CNNClassifier()
        train_names = GetFileNamesInDir(g_train_dir)
        cnn.Train(train_names)
        cnn.SaveModel(cnn_model_file)
    else:
        cnn = CNNClassifier()
        cnn.PrintModel()
        print("cnn: loading model from " + cnn_model_file)
        cnn.LoadModel(cnn_model_file)
        predicted_label = cnn.Predict(ReadImage(a_random_file))
        L = predicted_label
        FEN = LtoFEN(LabelArrayToL(L))
        print("predicted: " + FEN)
        print("Original:  " + GetCleanNameByPath(a_random_file))
```

```
        #test_file_names = GetFileNamesInDir(g_test_dir)[:1000]
        #print("CNN: Testing accuracy for {} board images".
↪format(len(test_file_names)))
        #accuracy = cnn.TestAccuracy(test_file_names)
        #print("CNN: Final accuracy: {}".format(accuracy))

        labels = cnn.PredictMultiple(GetFileNamesInDir(g_test_dir)[:100])
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 23, 23, 32)        896
_________________________________________________________________
activation (Activation)      (None, 23, 23, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 23, 23, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 21, 21, 32)        9248
_________________________________________________________________
activation_1 (Activation)    (None, 21, 21, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 19, 19, 32)        9248
_________________________________________________________________
activation_2 (Activation)    (None, 19, 19, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 11552)             0
_________________________________________________________________
dense (Dense)                (None, 128)               1478784
_________________________________________________________________
activation_3 (Activation)    (None, 128)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 13)                1677
_________________________________________________________________
activation_4 (Activation)    (None, 13)                0
=================================================================
Total params: 1,499,853
Trainable params: 1,499,853
Non-trainable params: 0

_________________________________________________________________
cnn: loading model from ./saved_model/cnn_weights
predicted: 1b1B1b2-2pK2q1-4p1rB-7k-8-8-3B4-3rb3
Original:  1b1B1b2-2pK2q1-4p1rB-7k-8-8-3B4-3rb3
```

1.7.2 Section 3.3 AdaBoost Classifier

class definition

```
[46]: from sklearn.ensemble import AdaBoostClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import numpy as np

# image io and plotting
from skimage import io, transform
import skimage.util
from skimage.util.shape import view_as_blocks
from matplotlib import pyplot as plt
# parallel processing
from joblib import Parallel, delayed
# model save and load
import pickle
import os
# profiling
import time

# joblib needs the kernel to be a top-level function, so we defined it here.
def PreprocessKernel(name):
    img = ReadImage(name, gray = True)
    grids = ABClassifier.ABCPreprocess(img)
    labels = np.array(FENtoOneHot(GetCleanNameByPath(name))).argmax(axis=1)
    return grids, labels

# Adaboost Classifier
class ABClassifier(IClassifier):

    def __init__(self):
        self.__abc__ = AdaBoostClassifier(n_estimators=30,
                                          base_estimator =␣
↪DecisionTreeClassifier(criterion='gini', max_depth=5),
                                          learning_rate=0.5)

    # this method should accept a list of file names of the training data
    def Train(self, train_file_names):
        print("abc: reading image.")
        start_time = time.time()
        xs, ys = ABClassifier.PreprocessParallelWrapperFunc(train_file_names)
        print("abc: finished reading image, {} sec.".format(time.time() -␣
↪start_time))
        # train
        print("abc: start training.")
        start_time = time.time()
        self.__abc__.fit(xs, ys)
```

```
        print("abc: finished. {} sec.".format(time.time() - start_time))


    # this should accept a 400 * 400 * 3 numpy array as query data, and returns␣
↪the fen notation of the board.
    def Predict(self, query_data):
        grids = ABClassifier.ABCPreprocess(query_data)
        y_pred = self.__abc__.predict(grids)

        return LabelArrayToL(y_pred)


    # parallel pre-process wrapper:
    @staticmethod
    def PreprocessParallelWrapperFunc(file_names, num_thread = g_thread_num):
        result = Parallel(n_jobs =␣
↪num_thread)(delayed(PreprocessKernel)(file_name) for file_name in file_names)
        xs, ys = zip(*result)
        xs = np.concatenate(xs, axis=0)
        ys = np.concatenate(ys)
        return xs, ys


    @staticmethod
    def ABCPreprocess(img):
        img = transform.resize(img, (g_down_sampled_size, g_down_sampled_size),␣
↪mode='constant')
        grids = skimage.util.shape.view_as_blocks(img, block_shape =␣
↪(g_down_sampled_grid_size, g_down_sampled_grid_size))
        grids = grids.reshape((-1, grids.shape[3], grids.shape[3]))
        grids = grids.reshape((grids.shape[0], grids.shape[1] * grids.shape[1]))
        return grids

    def SaveModel(self, save_file_name):
        os.makedirs(os.path.dirname(save_file_name), exist_ok = True)
        with open(save_file_name, 'wb') as file:
            pickle.dump(self.__abc__, file)

    def LoadModel(self, load_file_name):
        with open(load_file_name, 'rb') as file:
            self.__abc__ = pickle.load(file)

    # predict by file name:
    def PredictMultiple(self, file_names):
        preds = []
        truth = []
        for f in file_names:
```

```
            img = ReadImage(f, gray = True)
            y_pred = self.Predict(img)
            y_true = FENtoL(GetCleanNameByPath(f))
            preds.append(y_pred)
            truth.append(y_true)

        all_pred = np.vstack(preds)
        all_truth = np.vstack(truth)
        return all_pred, all_truth
```

Test code for ABC

[47]:
```
if run_test_code_for_classifiers:
    abc = ABClassifier()
    train_names = GetFileNamesInDir(g_train_dir)

    if load_saved_model:
        print("abc: loading model from " + abc_model_file)
        abc.LoadModel(abc_model_file)
    else:
        abc.Train(train_names)

    y_truth = FENtoL(GetCleanNameByPath(a_random_file))
    img = ReadImage(a_random_file, gray = True)
    pred = abc.Predict(img)
    print("truth:  ", ''.join(y_truth))
    print("pred :  ", ''.join(pred))

    # save model
    if not load_saved_model:
        print("abc: saving model to " + abc_model_file)
        abc.SaveModel(abc_model_file)
```

```
abc: loading model from ./saved_model/abc_dump.pkl
truth:   0b0B0b0000pK00q00000p0rB0000000k0000000000000000000B0000000rb000
pred :   0k0B0k0000pP00q00000p0rB0000000k0000000000000000000B0000000rb000
```

1.8 10-fold cross validation for 3 classifiers

Cv reference https://scikit-learn.org/stable/modules/cross_validation.html

options for 10 fold 1. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.ShuffleSplit.html 2. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedKFold.html (Preferred) " StratifiedKFold is a variation of k-fold which returns stratified folds: each set contains approximately the same percentage of samples of each target class as the complete set."

1.8.1 helper functions

[48]:
```python
# filters accepts a list of file names, and return the data matrix and labels
import random
from sklearn.metrics import confusion_matrix

# get balanced accuracy from confusion matrix
def BalancedAccuracyFromConfusionMatrix(cm):
    ret = np.empty((cm.shape[0]))

    for idx, row in enumerate(cm):
        ret[idx] = row[idx] / row.sum()

    return ret.mean()

# dummy filter to return all files
def DefaultFilter(file_names, rate = 1):
    return file_names

# filter using random_sampling:
def RandomFilter(file_names, rate = 1):
    # we fix the random part to assure the results are consistent
    random_seed = 4242
    random.seed(random_seed)
    return random.sample(file_names, k = int(len(file_names) * rate))

def ConfusionMatrix(classifier, test_file_names, filter = RandomFilter, sampling_rate = 0.001):

    confusion_matrices = []
    accuracies = []
    accuracies_balanced = []
    train_time_cost = []
    validation_time_cost = []

    # split name list into 10 equal parts
    division = len(test_file_names) / float(10)
    complete_name_folds = [ test_file_names[int(round(division * i)):int(round(division * (i + 1)))] for i in range(10) ]
    filtered_name_folds = complete_name_folds.copy()
    for i in range(10):
        filtered_name_folds[i] = filter(complete_name_folds[i], rate = sampling_rate)

    # we use filtered name folds to train, and validation.
    for iv in range(10):
```

```
        # merge the 9 folds:
        train_names = []
        validation_names = []
        for i in range(10):
            if i != iv:
                train_names.extend(filtered_name_folds[i])
            else:
                # validation_names = complete_name_folds[i].copy()
                validation_names = filtered_name_folds[i].copy()


        # train the classifier:
        print("training started:    ", type(classifier).__name__, "for fold #",␣
↪iv, "# train files:", len(train_names))
        t = time.time()
        classifier.Train(train_names)
        train_time_cost.append(time.time() - t)
        print("training finished:   ", type(classifier).__name__, "for fold #",␣
↪iv,
              "time: {}s".format(time.time() - t))

        print("predicting started:  ", type(classifier).__name__, "for fold #",␣
↪iv)
        t = time.time()
        ypreds, y_true = classifier.PredictMultiple(validation_names)
        validation_time_cost.append(time.time() - t)

        ypreds = ypreds.reshape((-1, 1))
        y_true = y_true.reshape((-1, 1))

        conf_mat = confusion_matrix(y_true, ypreds, labels = g_labels)
        confusion_matrices.append(conf_mat)
        accuracy = np.trace(conf_mat) / float(np.sum(conf_mat))
        accuracies.append(accuracy)
        accuracy_balanced = BalancedAccuracyFromConfusionMatrix(conf_mat)
        accuracies_balanced.append(accuracy_balanced)



        print("predicting finished: ", type(classifier).__name__, "for fold #",␣
↪iv,
              "time: {}s".format(time.time() - t), " accuracy: ", accuracy, "␣
↪balanced_accuracy:", accuracy_balanced)

    return confusion_matrices, accuracies, accuracies_balanced,␣
↪train_time_cost, validation_time_cost
```

1.8.2 10-fold routine

[49]:
```
if run_ten_fold:
    # 10-fold for ABC
    train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg")
    # random sampling rate of the each fold in 10-fold
    abc_random_sampling_rate = 0.005

    abc_tf = ABClassifier()

    confusion_matrices_abc, accuracies_abc, accuracies_balanced_abc,␣
↪train_time_cost_abc, validation_time_cost_abc = \
    ConfusionMatrix(abc_tf, train_file_names, RandomFilter, sampling_rate =␣
↪abc_random_sampling_rate)
```

```
training started:     ABClassifier for fold # 0 # train files: 360
abc: reading image.
abc: finished reading image, 5.398272275924683 sec.
abc: start training.
abc: finished. 105.41199851036072 sec.
training finished:    ABClassifier for fold # 0 time: 110.818776845932s
predicting started:   ABClassifier for fold # 0
predicting finished:  ABClassifier for fold # 0 time: 1.8081109523773193s
accuracy:  0.915234375  balanced_accuracy: 0.9887159507361434
training started:     ABClassifier for fold # 1 # train files: 360
abc: reading image.
abc: finished reading image, 1.353529453277588 sec.
abc: start training.
abc: finished. 106.2824718952179 sec.
training finished:    ABClassifier for fold # 1 time: 107.64400005340576s
predicting started:   ABClassifier for fold # 1
predicting finished:  ABClassifier for fold # 1 time: 0.588024377822876s
accuracy:  0.9953125  balanced_accuracy: 0.9773043222050123
training started:     ABClassifier for fold # 2 # train files: 360
abc: reading image.
abc: finished reading image, 1.4164981842041016 sec.
abc: start training.
abc: finished. 108.95200252532959 sec.
training finished:    ABClassifier for fold # 2 time: 110.37699913978577s
predicting started:   ABClassifier for fold # 2
predicting finished:  ABClassifier for fold # 2 time: 0.5855247974395752s
accuracy:  0.994921875  balanced_accuracy: 0.9726729328379256
training started:     ABClassifier for fold # 3 # train files: 360
abc: reading image.
abc: finished reading image, 1.3769776821136475 sec.
abc: start training.
abc: finished. 105.25149726867676 sec.
training finished:    ABClassifier for fold # 3 time: 106.63697409629822s
```

```
predicting started:   ABClassifier for fold # 3
predicting finished:  ABClassifier for fold # 3 time: 0.5955328941345215s
accuracy:  0.997265625  balanced_accuracy: 0.9829801695186311
training started:     ABClassifier for fold # 4 # train files: 360
abc: reading image.
abc: finished reading image, 1.3645029067993164 sec.
abc: start training.
abc: finished. 105.66096711158752 sec.
training finished:    ABClassifier for fold # 4 time: 107.03396940231323s
predicting started:   ABClassifier for fold # 4
predicting finished:  ABClassifier for fold # 4 time: 0.6035027503967285s
accuracy:  0.9984375  balanced_accuracy: 0.9871866850188351
training started:     ABClassifier for fold # 5 # train files: 360
abc: reading image.
abc: finished reading image, 1.3729960918426514 sec.
abc: start training.
abc: finished. 106.87903761863708 sec.
training finished:    ABClassifier for fold # 5 time: 108.26099824905396s
predicting started:   ABClassifier for fold # 5
predicting finished:  ABClassifier for fold # 5 time: 0.5815010070800781s
accuracy:  0.996484375  balanced_accuracy: 0.9763087452358707
training started:     ABClassifier for fold # 6 # train files: 360
abc: reading image.
abc: finished reading image, 1.3584940433502197 sec.
abc: start training.
abc: finished. 104.68600416183472 sec.
training finished:    ABClassifier for fold # 6 time: 106.0530149936676s
predicting started:   ABClassifier for fold # 6
predicting finished:  ABClassifier for fold # 6 time: 0.6030011177062988s
accuracy:  0.9984375  balanced_accuracy: 0.9848901098901099
training started:     ABClassifier for fold # 7 # train files: 360
abc: reading image.
abc: finished reading image, 1.4029998779296875 sec.
abc: start training.
abc: finished. 106.33550238609314 sec.
training finished:    ABClassifier for fold # 7 time: 107.74799847602844s
predicting started:   ABClassifier for fold # 7
predicting finished:  ABClassifier for fold # 7 time: 0.5720021724700928s
accuracy:  0.994140625  balanced_accuracy: 0.9539770270297656
training started:     ABClassifier for fold # 8 # train files: 360
abc: reading image.
abc: finished reading image, 1.4405317306518555 sec.
abc: start training.
abc: finished. 103.98052430152893 sec.
training finished:    ABClassifier for fold # 8 time: 105.43050003051758s
predicting started:   ABClassifier for fold # 8
predicting finished:  ABClassifier for fold # 8 time: 0.6030175685882568s
accuracy:  0.989453125  balanced_accuracy: 0.9828409905842151
```

```
training started:     ABClassifier for fold # 9 # train files: 360
abc: reading image.
abc: finished reading image, 1.3639986515045166 sec.
abc: start training.
abc: finished. 104.17997884750366 sec.
training finished:    ABClassifier for fold # 9 time: 105.55300045013428s
predicting started:   ABClassifier for fold # 9
predicting finished:  ABClassifier for fold # 9 time: 0.5954928398132324s
accuracy:  0.97421875  balanced_accuracy: 0.9726182149323749
```

[50]:
```
if run_ten_fold:
    # 10-fold for CNN
    # random sampling rate of the each fold in 10-fold
    cnn_random_sampling_rate = 0.5

    train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg")

    cnn_tf = CNNClassifier()

    confusion_matrices_cnn, accuracies_cnn, accuracies_balanced_cnn,␣
 ↪train_time_cost_cnn, validation_time_cost_cnn = \
    ConfusionMatrix(cnn_tf, train_file_names, RandomFilter, sampling_rate =␣
 ↪cnn_random_sampling_rate)
```

```
training started:     CNNClassifier for fold # 0 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 92s 51ms/step - loss: 0.0742 -
accuracy: 0.9811
Epoch 2/2
1800/1800 [==============================] - 92s 51ms/step - loss: 0.0129 -
accuracy: 0.9967
training finished:    CNNClassifier for fold # 0 time: 184.50335025787354s
predicting started:   CNNClassifier for fold # 0
predicting finished:  CNNClassifier for fold # 0 time: 255.72573709487915s
accuracy:  0.9953046875  balanced_accuracy: 0.972284597528154
training started:     CNNClassifier for fold # 1 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 88s 49ms/step - loss: 0.0044 -
accuracy: 0.9987
Epoch 2/2
1800/1800 [==============================] - 88s 49ms/step - loss: 0.0026 -
accuracy: 0.9992
training finished:    CNNClassifier for fold # 1 time: 176.32050108909607s
predicting started:   CNNClassifier for fold # 1
predicting finished:  CNNClassifier for fold # 1 time: 203.46679401397705s
accuracy:  0.99998828125  balanced_accuracy: 0.9999432022567637
training started:     CNNClassifier for fold # 2 # train files: 36000
Epoch 1/2
```

```
1800/1800 [==============================] - 86s 48ms/step - loss: 0.0042 -
accuracy: 0.9990
Epoch 2/2
1800/1800 [==============================] - 87s 49ms/step - loss: 0.0023 -
accuracy: 0.9994
training finished:    CNNClassifier for fold # 2 time: 173.61347317695618s
predicting started:   CNNClassifier for fold # 2
predicting finished:  CNNClassifier for fold # 2 time: 258.44522190093994s
accuracy:  0.999921875  balanced_accuracy: 0.9993312211503912
training started:     CNNClassifier for fold # 3 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 81s 45ms/step - loss: 0.0023 -
accuracy: 0.9994
Epoch 2/2
1800/1800 [==============================] - 83s 46ms/step - loss: 0.0053 -
accuracy: 0.9993
training finished:    CNNClassifier for fold # 3 time: 164.83446884155273s
predicting started:   CNNClassifier for fold # 3
predicting finished:  CNNClassifier for fold # 3 time: 253.1358721256256s
accuracy:  1.0  balanced_accuracy: 1.0
training started:     CNNClassifier for fold # 4 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 81s 45ms/step - loss: 0.0039 -
accuracy: 0.9993
Epoch 2/2
1800/1800 [==============================] - 86s 48ms/step - loss: 0.0014 -
accuracy: 0.9996
training finished:    CNNClassifier for fold # 4 time: 167.50047063827515s
predicting started:   CNNClassifier for fold # 4
predicting finished:  CNNClassifier for fold # 4 time: 257.837361574173s
accuracy:  1.0  balanced_accuracy: 1.0
training started:     CNNClassifier for fold # 5 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 89s 50ms/step - loss: 0.0028 -
accuracy: 0.9995
Epoch 2/2
1800/1800 [==============================] - 88s 49ms/step - loss: 0.0025 -
accuracy: 0.9995
training finished:    CNNClassifier for fold # 5 time: 176.9005012512207s
predicting started:   CNNClassifier for fold # 5
predicting finished:  CNNClassifier for fold # 5 time: 255.32304525375366s
accuracy:  1.0  balanced_accuracy: 1.0
training started:     CNNClassifier for fold # 6 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 87s 48ms/step - loss: 2.2082e-04 -
accuracy: 0.9999
Epoch 2/2
1800/1800 [==============================] - 87s 48ms/step - loss: 0.0058 -
```

```
accuracy: 0.9994
training finished:    CNNClassifier for fold # 6 time: 174.0054988861084s
predicting started:   CNNClassifier for fold # 6
predicting finished:  CNNClassifier for fold # 6 time: 254.33951449394226s
accuracy:  0.99997265625  balanced_accuracy: 0.9996995388807377
training started:     CNNClassifier for fold # 7 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 86s 48ms/step - loss: 6.0853e-04 -
accuracy: 0.9999
Epoch 2/2
1800/1800 [==============================] - 91s 51ms/step - loss: 0.0046 -
accuracy: 0.9994
training finished:    CNNClassifier for fold # 7 time: 177.45500087738037s
predicting started:   CNNClassifier for fold # 7
predicting finished:  CNNClassifier for fold # 7 time: 260.65016198158264s
accuracy:  1.0  balanced_accuracy: 1.0
training started:     CNNClassifier for fold # 8 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 87s 48ms/step - loss: 0.0012 -
accuracy: 0.9997
Epoch 2/2
1800/1800 [==============================] - 87s 48ms/step - loss: 0.0066 -
accuracy: 0.9993
training finished:    CNNClassifier for fold # 8 time: 173.66347432136536s
predicting started:   CNNClassifier for fold # 8
predicting finished:  CNNClassifier for fold # 8 time: 258.1064829826355s
accuracy:  0.999984375  balanced_accuracy: 0.9999181962289339
training started:     CNNClassifier for fold # 9 # train files: 36000
Epoch 1/2
1800/1800 [==============================] - 87s 48ms/step - loss: 0.0017 -
accuracy: 0.9997
Epoch 2/2
1800/1800 [==============================] - 91s 51ms/step - loss: 6.9238e-04 -
accuracy: 0.9999
training finished:    CNNClassifier for fold # 9 time: 178.00898122787476s
predicting started:   CNNClassifier for fold # 9
predicting finished:  CNNClassifier for fold # 9 time: 261.0290925502777s
accuracy:  1.0  balanced_accuracy: 1.0
```

[51]:
```python
if run_ten_fold:
    # 10-fold for SVM
    train_file_names = GetFileNamesInDir(g_train_dir, extension = "jpeg")
    # random sampling rate of the each fold in 10-fold
    svc_random_sampling_rate = 0.01

    svc_tf = SVCClassifier()
```

```
confusion_matrices_svc, accuracies_svc, accuracies_balanced_svc,␣
↪train_time_cost_svc, validation_time_cost_svc = \
   ConfusionMatrix(svc_tf, train_file_names, RandomFilter, sampling_rate =␣
↪svc_random_sampling_rate)
```

```
training started:     SVCClassifier for fold # 0 # train files: 720
svc: reading image.
svc: finished reading image, 4.1754982471466064 sec.
svc: start training.
svc: finished. 275.877498626709 sec.
training finished:    SVCClassifier for fold # 0 time: 280.06999683380127s
predicting started:   SVCClassifier for fold # 0
predicting finished:  SVCClassifier for fold # 0 time: 25.094476461410522s
accuracy:  0.9755859375  balanced_accuracy: 0.8390801614481257
training started:     SVCClassifier for fold # 1 # train files: 720
svc: reading image.
svc: finished reading image, 4.161530256271362 sec.
svc: start training.
svc: finished. 276.26797008514404 sec.
training finished:    SVCClassifier for fold # 1 time: 280.44550037384033s
predicting started:   SVCClassifier for fold # 1
predicting finished:  SVCClassifier for fold # 1 time: 25.063472747802734s
accuracy:  0.97578125  balanced_accuracy: 0.851003508486225
training started:     SVCClassifier for fold # 2 # train files: 720
svc: reading image.
svc: finished reading image, 4.096996545791626 sec.
svc: start training.
svc: finished. 273.4409935474396 sec.
training finished:    SVCClassifier for fold # 2 time: 277.56246972084045s
predicting started:   SVCClassifier for fold # 2
predicting finished:  SVCClassifier for fold # 2 time: 25.160999536514282s
accuracy:  0.9748046875  balanced_accuracy: 0.8442856239581942
training started:     SVCClassifier for fold # 3 # train files: 720
svc: reading image.
svc: finished reading image, 2.193498373031616 sec.
svc: start training.
svc: finished. 271.1005029678345 sec.
training finished:    SVCClassifier for fold # 3 time: 273.30952429771423s
predicting started:   SVCClassifier for fold # 3
predicting finished:  SVCClassifier for fold # 3 time: 24.9065043926239s
accuracy:  0.9771484375  balanced_accuracy: 0.8418881733972017
training started:     SVCClassifier for fold # 4 # train files: 720
svc: reading image.
svc: finished reading image, 2.113495111465454 sec.
svc: start training.
svc: finished. 271.2329773902893 sec.
training finished:    SVCClassifier for fold # 4 time: 273.3629765510559s
```

```
predicting started:   SVCClassifier for fold # 4
predicting finished:  SVCClassifier for fold # 4 time: 24.966519832611084s
accuracy:  0.9759765625  balanced_accuracy: 0.8401999249500759
training started:     SVCClassifier for fold # 5 # train files: 720
svc: reading image.
svc: finished reading image, 2.094999074935913 sec.
svc: start training.
svc: finished. 270.80147099494934 sec.
training finished:    SVCClassifier for fold # 5 time: 272.9129693508148s
predicting started:   SVCClassifier for fold # 5
predicting finished:  SVCClassifier for fold # 5 time: 24.80652356147766s
accuracy:  0.9701171875  balanced_accuracy: 0.8018837193943575
training started:     SVCClassifier for fold # 6 # train files: 720
svc: reading image.
svc: finished reading image, 2.1854727268218994 sec.
svc: start training.
svc: finished. 276.1960005760193 sec.
training finished:    SVCClassifier for fold # 6 time: 278.39747190475464s
predicting started:   SVCClassifier for fold # 6
predicting finished:  SVCClassifier for fold # 6 time: 25.331998825073242s
accuracy:  0.980078125  balanced_accuracy: 0.8347615121472585
training started:     SVCClassifier for fold # 7 # train files: 720
svc: reading image.
svc: finished reading image, 3.927501916885376 sec.
svc: start training.
svc: finished. 274.04150009155273 sec.
training finished:    SVCClassifier for fold # 7 time: 277.98550176620483s
predicting started:   SVCClassifier for fold # 7
predicting finished:  SVCClassifier for fold # 7 time: 25.360967874526978s
accuracy:  0.9787109375  balanced_accuracy: 0.8173997864853184
training started:     SVCClassifier for fold # 8 # train files: 720
svc: reading image.
svc: finished reading image, 2.1504993438720703 sec.
svc: start training.
svc: finished. 273.974002122879 sec.
training finished:    SVCClassifier for fold # 8 time: 276.14250111579895s
predicting started:   SVCClassifier for fold # 8
predicting finished:  SVCClassifier for fold # 8 time: 25.19000005722046s
accuracy:  0.97578125  balanced_accuracy: 0.8372536721897584
training started:     SVCClassifier for fold # 9 # train files: 720
svc: reading image.
svc: finished reading image, 2.29949951171875 sec.
svc: start training.
svc: finished. 273.2610285282135 sec.
training finished:    SVCClassifier for fold # 9 time: 275.57649850845337s
predicting started:   SVCClassifier for fold # 9
predicting finished:  SVCClassifier for fold # 9 time: 25.151024341583252s
accuracy:  0.9740234375  balanced_accuracy: 0.8392838619821293
```

1.8.3 Serialize the results (export to hard drive)

[52]:
```
if run_ten_fold:
    # dump the matrices for report.
    os.makedirs(os.path.dirname(ten_fold_result_path), exist_ok = True)

    np.save(ten_fold_result_path + "confusion_matrices_abc.npy",␣
↪confusion_matrices_abc)
    np.save(ten_fold_result_path + "accuracies_abc.npy", accuracies_abc)
    np.save(ten_fold_result_path + "accuracies_balanced_abc.npy",␣
↪accuracies_balanced_abc)
    np.save(ten_fold_result_path + "train_time_cost_abc.npy",␣
↪train_time_cost_abc)
    np.save(ten_fold_result_path + "validation_time_cost_abc.npy",␣
↪validation_time_cost_abc)

    np.save(ten_fold_result_path + "confusion_matrices_cnn.npy",␣
↪confusion_matrices_cnn)
    np.save(ten_fold_result_path + "accuracies_cnn.npy", accuracies_cnn)
    np.save(ten_fold_result_path + "accuracies_balanced_cnn.npy",␣
↪accuracies_balanced_cnn)
    np.save(ten_fold_result_path + "train_time_cost_cnn.npy",␣
↪train_time_cost_cnn)
    np.save(ten_fold_result_path + "validation_time_cost_cnn.npy",␣
↪validation_time_cost_cnn)

    np.save(ten_fold_result_path + "confusion_matrices_svc.npy",␣
↪confusion_matrices_svc)
    np.save(ten_fold_result_path + "accuracies_svc.npy", accuracies_svc)
    np.save(ten_fold_result_path + "accuracies_balanced_svc.npy",␣
↪accuracies_balanced_svc)
    np.save(ten_fold_result_path + "train_time_cost_svc.npy",␣
↪train_time_cost_svc)
    np.save(ten_fold_result_path + "validation_time_cost_svc.npy",␣
↪validation_time_cost_svc)


    svc_tf.SaveModel(svc_model_file)
    abc_tf.SaveModel(abc_model_file)
    cnn_tf.SaveModel(cnn_model_file)
```

1.8.4 Read the results from hard drive

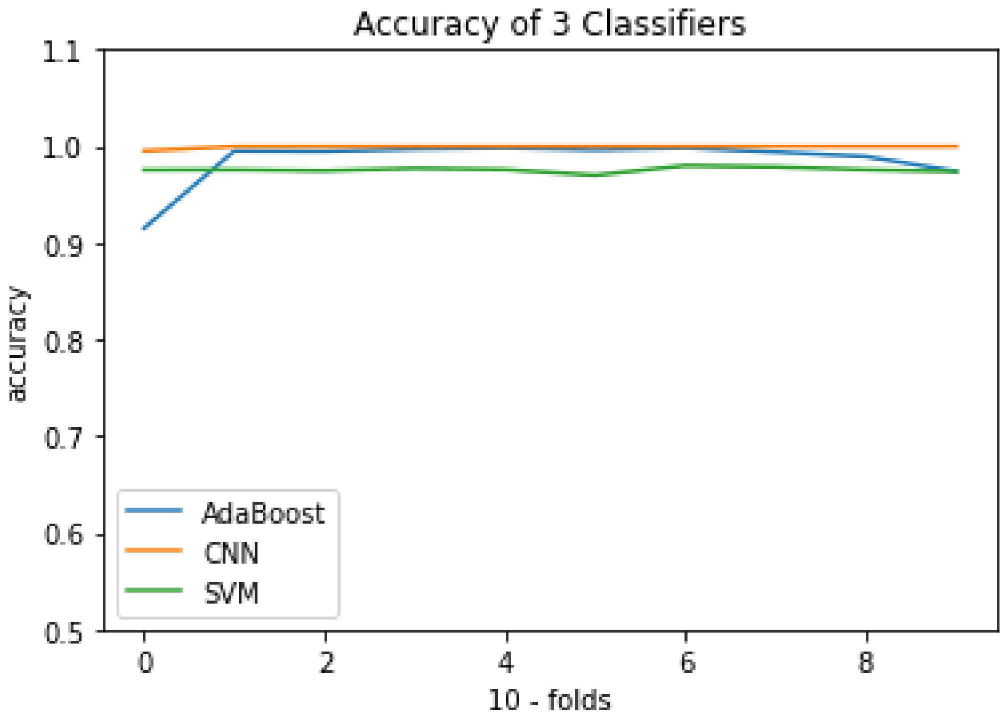
[54]:
```
if not run_ten_fold:

    import numpy as np
```

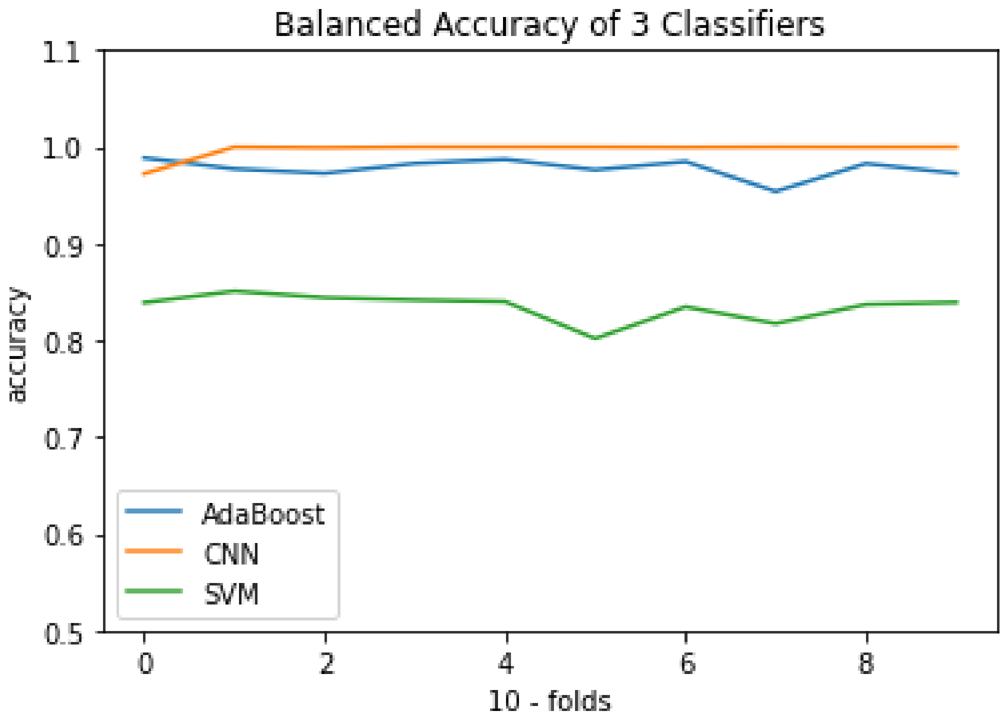
```
    confusion_matrices_abc = np.load(ten_fold_result_path +␣
↪"confusion_matrices_abc.npy")
    accuracies_abc = np.load(ten_fold_result_path + "accuracies_abc.npy")
    accuracies_balanced_abc = np.load(ten_fold_result_path +␣
↪"accuracies_balanced_abc.npy")
    train_time_cost_abc = np.load(ten_fold_result_path + "train_time_cost_abc.
↪npy")
    validation_time_cost_abc = np.load(ten_fold_result_path +␣
↪"validation_time_cost_abc.npy")

    confusion_matrices_cnn = np.load(ten_fold_result_path +␣
↪"confusion_matrices_cnn.npy")
    accuracies_cnn = np.load(ten_fold_result_path + "accuracies_cnn.npy")
    accuracies_balanced_cnn = np.load(ten_fold_result_path +␣
↪"accuracies_balanced_cnn.npy")
    train_time_cost_cnn = np.load(ten_fold_result_path + "train_time_cost_cnn.
↪npy")
    validation_time_cost_cnn = np.load(ten_fold_result_path +␣
↪"validation_time_cost_cnn.npy")

    confusion_matrices_svc = np.load(ten_fold_result_path +␣
↪"confusion_matrices_svc.npy")
    accuracies_svc = np.load(ten_fold_result_path + "accuracies_svc.npy")
    accuracies_balanced_svc = np.load(ten_fold_result_path +␣
↪"accuracies_balanced_svc.npy")
    train_time_cost_svc = np.load(ten_fold_result_path + "train_time_cost_svc.
↪npy")
    validation_time_cost_svc = np.load(ten_fold_result_path +␣
↪"validation_time_cost_svc.npy")
```

1.8.5 Plot the results

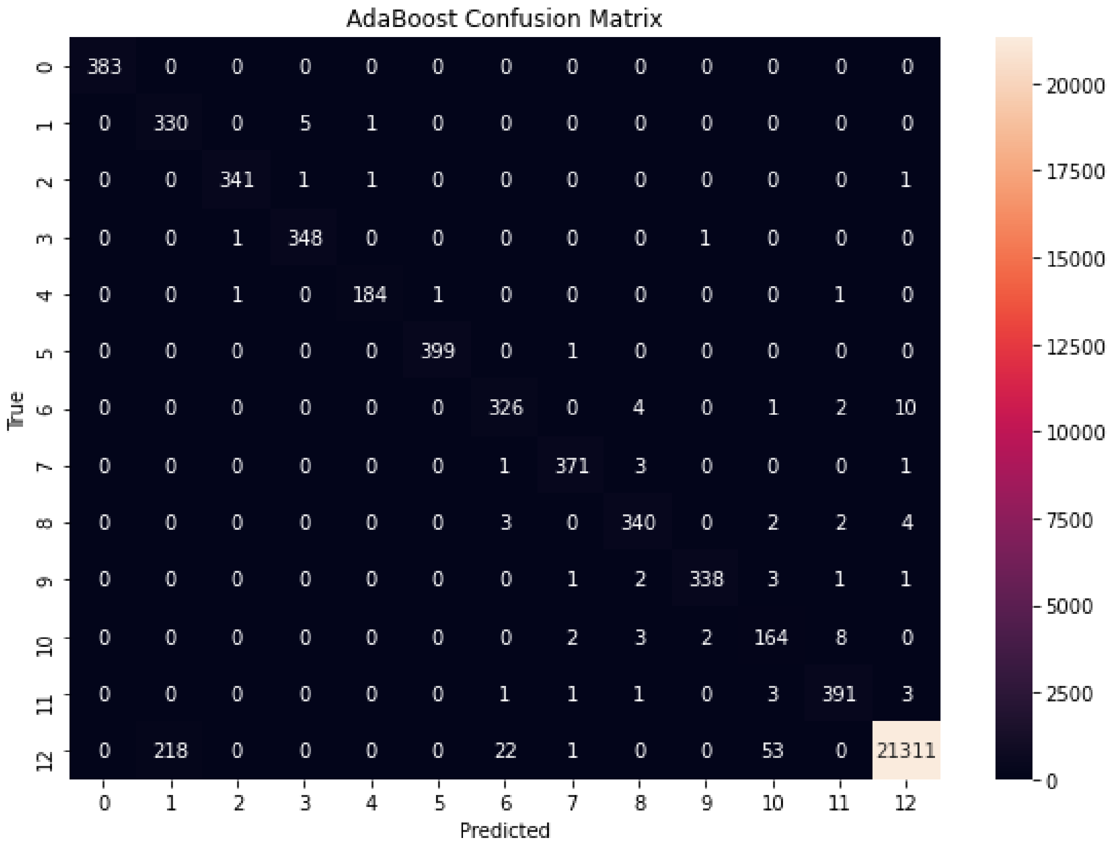
[55]:
```
import matplotlib.pyplot as plt
def plot_accuracy(mat_abc, mat_cnn, mat_svc, title):
    line, = plt.plot([i for i in range(len(mat_abc))],mat_abc)
    line.set_label('AdaBoost')
    line, = plt.plot([i for i in range(len(mat_cnn))],mat_cnn)
    line.set_label('CNN')
    line, = plt.plot([i for i in range(len(mat_svc))],mat_svc)
    line.set_label('SVM')
    plt.title(title)
    plt.xlabel('10 - folds')
    plt.ylabel('accuracy')
    plt.ylim(0.5, 1.1)
    plt.legend()
    plt.show()
```

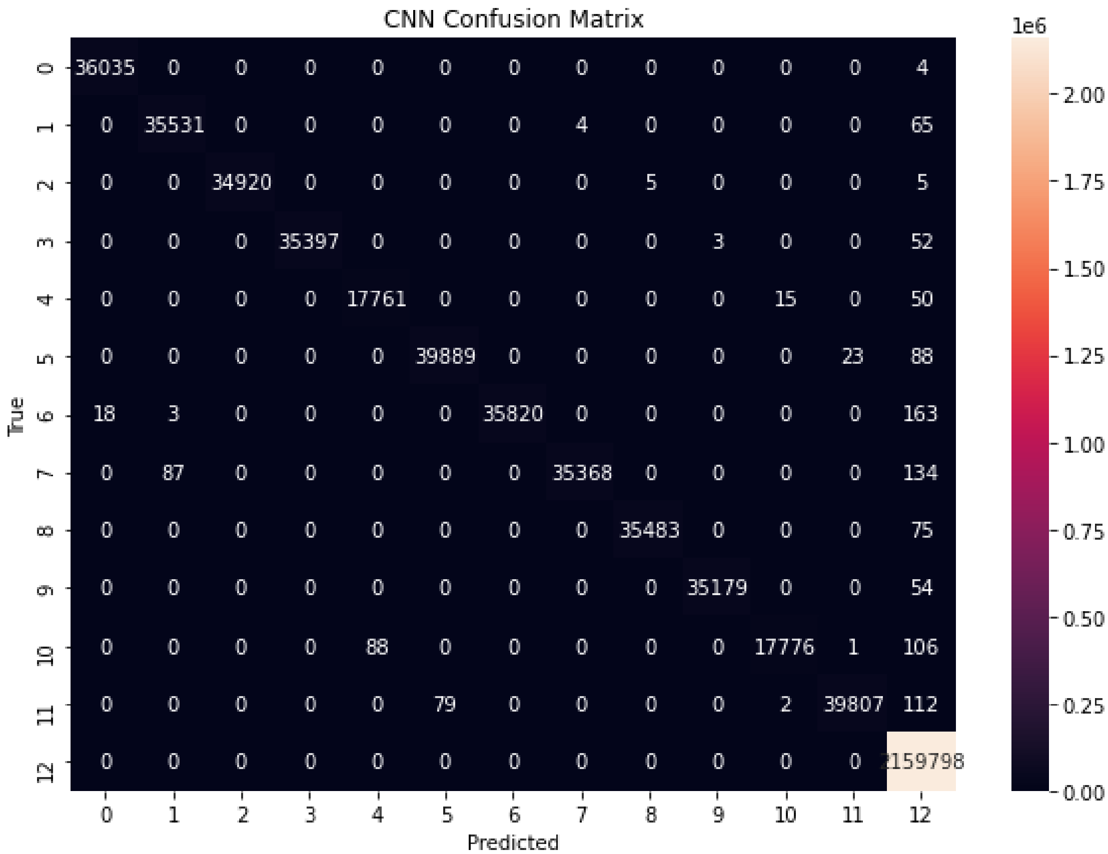
```python
plot_accuracy(accuracies_abc, accuracies_cnn, accuracies_svc, "Accuracy of 3␣
↪Classifiers")
plot_accuracy(accuracies_balanced_abc, accuracies_balanced_cnn,␣
↪accuracies_balanced_svc, "Balanced Accuracy of 3 Classifiers")
```

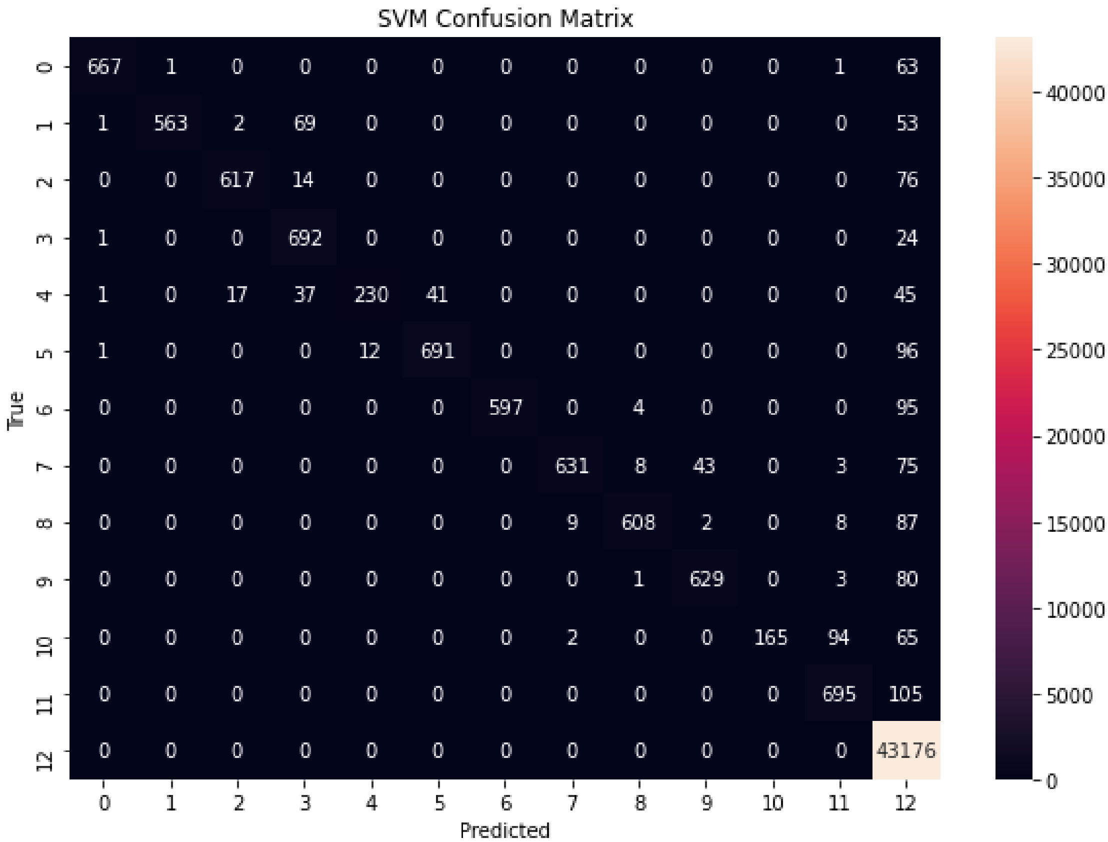




[56]:
```
import seaborn as sns
def plot_confusion_mat(conf_mat, title = ""):
    plt.figure(figsize=(10,7))
    ax = sns.heatmap(conf_mat, annot=True, fmt="d")
    plt.ylabel('True')
    plt.xlabel('Predicted')
    plt.title(title)
    plt.show()

plot_confusion_mat(sum(confusion_matrices_abc), title = "AdaBoost Confusion␣
↪Matrix" )
plot_confusion_mat(sum(confusion_matrices_cnn), title = "CNN Confusion Matrix" )
plot_confusion_mat(sum(confusion_matrices_svc), title = "SVM Confusion Matrix" )
```


AdaBoost Confusion Matrix
True
Predicted
20000
17500
15000
12500
10000
7500
5000
2500
0


CNN Confusion Matrix
True
Predicted
0 1 2 3 4 5 6 7 8 9 10 11 12
36035 0 0 0 0 0 0 0 0 0 0 0 4
0 35531 0 0 0 0 0 4 0 0 0 0 65
0 0 34920 0 0 0 0 0 5 0 0 0 5
0 0 0 35397 0 0 0 0 0 3 0 0 52
0 0 0 0 17761 0 0 0 0 0 15 0 50
0 0 0 0 0 39889 0 0 0 0 0 23 88
18 3 0 0 0 0 35820 0 0 0 0 0 163
0 87 0 0 0 0 0 35368 0 0 0 0 134
0 0 0 0 0 0 0 0 35483 0 0 0 75
0 0 0 0 0 0 0 0 0 35179 0 0 54
0 0 0 0 88 0 0 0 0 0 17776 1 106
0 0 0 0 0 79 0 0 0 0 2 39807 112
0 0 0 0 0 0 0 0 0 0 0 0 2159798
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00



1.8.6 Bonus: GUI: see GUI_with_Classifiers.ipynb