

印花布匹疵点分析

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Project Description

印花布匹表面缺陷的识别有助于分析产生原因，数据集里印花布疵点瑕疵被划分为15类，瑕疵以成对图片（正确的图样以及问题图样）给出，并附上瑕疵的参数位置及类别，上述瑕疵图、瑕疵图及瑕疵参数位置均可作为已知信息用于瑕疵类型的判别。数据中划分的类别如下：0: 未知, 1: 连花, 2: 参花, 3: 破洞, 4: 缝头, 5: 水渍, 6: 脏污, 7: 白条, 8: 花棚, 9: 疵斑, 10: 纱眼, 11: 色花, 12: 网印, 13: 无疵点, 14: 未对齐

Task Description

取1、2、5及13共四类数据，按4类作分类

Data Processing

```
In [1]: import json
import glob, os
from matplotlib import image
import numpy as np

def load_fabric_data(path):
    Loads data from fabric_data folder.
    Returns:
        (list, list)
        A list of id in the file name
        A list of dictionary file containing data from json (f1aw type, bbox)
    Sample usage: fids, fdata = load_fabric_data('fabric_data/label_json/**/*.json')
    """
    fids = []
    fdata = []

    for filename in glob.iglob(path, recursive=True):
        # print(filename)
        filename = filename.replace('\\', '/')
        fids.append(filename.split('/')[-1].split('.')[0])
        with open(filename) as f:
            fdata.append(json.load(f))
    return fids, fdata

def extract_label_grouping(fdata):
    """
    Generates lists of labels according to different groupings.
    Type 1 grouping: original
    Type 2 grouping: 6-12 as group 6, 13 as group 7, 14 as group 8
    Type 3 grouping: only take 1,2,5 and 13
    """
    ftype1 = [] #original
    ftype2 = [] #6-12 as group 6, 13 as group 7, 14 as group 8
    ftype2_dict = {num:6 for num in range(6, 13)}
    ftype2_dict.update({num:7 for num in range(6)})
    ftype2_dict[13] = 7
    ftype2_dict[14] = 8
    for i in fdata:
        ftype1.append(i['f1aw_type'])
        ftype2.append(ftype2_dict[i['f1aw_type']])
    return ftype1, ftype2

def load_fabric_images(path, fids, fdata, ftype):
    labels = []
    imgs = []

    print(path)
    #random.sample(list(glob.iglob(path, recursive=True)), 50)
    for filename in glob.iglob(path, recursive=True):
        #find info about the image
        filename = filename.replace('\\', '/')

        fids = filename.split('/')[-1].split('.')[0]
        info = fdata[fids.index(fids)]

        filename_trgt = filename.replace("temp", "trgt")
        filename_trgt = r"C:\Users\Administrator\Desktop\FMML\Project\fabric_data\trgt" + "/" + fids + ".jpg"

        #get image
        size1 = os.stat(filename).st_size
        size2 = os.stat(filename_trgt).st_size
        if (size1 != 0) and (size2 != 0):
            #load image
            img_data_temp = image.imread(filename)
            img_data_trgt = image.imread(info['bbox']['x0':'x1'], info['bbox']['y0':'y1'], info['bbox']['x0':'x1'], info['bbox']['y0':'y1'])
            img_data_trgt = image.imread(filename_trgt)
            #append image
            if img_data_temp.shape == img_data_trgt.shape:
                imgs.append(np.concatenate([img_data_temp, img_data_trgt], axis = 2))
            labels.append(ftype(fdata[fids.index(fids)]))
    return (labels, imgs)

In [2]: path = r"C:\Users\Administrator\Desktop\FMML\Project\fabric_data\label_json/**/*.json"

fids, fdata = load_fabric_data(path)
ftype1, ftype2 = extract_label_grouping(fdata)

In [4]: path = r"C:\Users\Administrator\Desktop\FMML\Project\fabric_data/temp/"
labels, imgs = load_fabric_images(path, fids, fdata, ftype1)

C:\Users\Administrator\Desktop\FMML\Project\fabric_data/temp/**/*.jpg

In [5]: print(len(labels))
print(len(imgs))

3371
[[[130 130 128 155 147 171]
 [139 137 138 151 150 168]
 [147 145 148 146 154 167]
 ...
 [ 57 46 24 92 87 29]
 [ 73 51 28 83 64 34]
 [124 89 69 76 47 51]]

[[139 141 140 162 153 174]
 [143 144 146 157 155 168]
 [148 148 150 151 155 166]
 ...
 [ 69 61 38 121 124 69]
 [ 58 41 15 113 100 56]
 [ 69 39 15 88 63 33]]

[[143 147 150 160 149 166]
 [145 149 152 156 153 162]
 [150 151 156 153 156 161]
 ...
 [102 100 75 153 160 116]
 [ 90 79 49 140 133 79]
 [ 75 55 22 126 106 47]]

...

[[ 56 19 13 76 21 31]
 [ 55 16 11 77 28 31]
 [ 57 18 13 70 31 32]
 ...
 [208 213 219 210 213 206]
 [208 218 220 222 223 228]
 [200 210 211 216 213 234]]

...

[[ 74 55 28 103 31 34]
 [ 69 30 23 103 37 39]
 [ 72 31 25 95 39 40]
 ...
 [ 200 209 219 212 212]
 [220 231 237 209 209 221]
 [196 210 213 213 210 237]]

...

[[ 87 49 40 122 36 37]
 [ 82 42 34 123 41 43]
 [ 85 45 37 115 43 46]
 ...
 [185 193 204 214 212 223]
 [195 208 216 215 212 233]
 [193 208 215 217 216 248]]

In [6]: n_samples = len(labels)
print("Number of samples:", n_samples)

Number of samples: 3371

In [7]: print(imgs[1230].shape)

(400, 400, 6)

In [8]: # another way of selecting categories
from numpy import array

myIndices = []
def find_indices_four_cat(listOfLabels):
    i = 0
    for i in range(0, len(listOfLabels)):
        if (listOfLabels[i] == 1) or (listOfLabels[i] == 2) or (listOfLabels[i] == 5) or (listOfLabels[i] == 13):
            res.append(i)
    return res

label_four_cat_indices = find_indices_four_cat(labels)

# select the four categories out of the sample
labels_four_cat = array(labels)[label_four_cat_indices]
samples_four_cat = array(imgs)[label_four_cat_indices]

In [9]: labels = labels_four_cat
imgs = samples_four_cat

print(len(imgs))

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Padding
• https://blog.csdn.net/wuzhouchen/article/details/74785643
• https://stackoverflow.com/questions/47077523/normalize-resizing-keeping-aspect-ratio-or-not/49882056#49882056
• https://stackoverflow.com/questions/43301205/gd-sd-padding-to-images-to-get-them-into-the-same-shape

In [10]: import cv2

In [11]: imgs = [cv2.resize(img, (200, 200)) for img in imgs]

Split data

In [12]: from sklearn.model_selection import train_test_split

train_images, test_images, train_labels, test_labels = train_test_split(imgs, labels, test_size=0.2, random_state=1)

Normalize data

In [14]: #first split, split to the training and testing (we will further split training later because we need va
train_images, test_images, train_labels, test_labels = np.array(train_images), np.array(test_images), n
p.array(train_labels), np.array(test_labels)
train_images, test_images = train_images / 255.0, test_images / 255.0

In [15]: train_images.shape
print(len(test_labels))
# note all the test labels are real images at this point. We are only going to generate fake data for t
he training set

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In [16]: # subset all the 5s
def find_indices_5(listOfLabels):
    i = 0
    for i in range(0, len(listOfLabels)):
        if (listOfLabels[i] == 5):
            res.append(i)
    return res

label_five = find_indices_5(train_labels)
print(len(label_five))

train_is_five = array(train_images)[label_five]

# the 1s is the training data that has labeled as "5"
print(train_is_five)

13
[[[0.14117647, 0.13333333, 0.13333333, 0.23529412, 0.18431373, 0.15666275]
 [0.21960784, 0.23529412, 0.13607843, 0.27843137, 0.37647059, 0.21372549]
 [0.41568627, 0.45409196, 0.38039216, 0.62862745, 0.18039216, 0.47058824]
 ...
 [0.5372549, 0.52156863, 0.38039216, 0.60392157, 0.58039216, 0.47058824]
 [0.56470588, 0.5372549, 0.38823529, 0.60392157, 0.58039216, 0.43173255]
 [0.58431373, 0.54901961, 0.39607843, 0.61960784, 0.58823529, 0.42745098]]

[[0.14117647, 0.1372549, 0.14901961, 0.18823529, 0.56078431, 0.16862745]
 [0.3254902, 0.33333333, 0.30588235, 0.42352941, 0.49803922, 0.45908039]
 [0.48235294, 0.49019608, 0.41960784, 0.60784314, 0.64313725, 0.5254902]
 ...
 [0.53333333, 0.51372549, 0.39215686, 0.58823529, 0.56078431, 0.43321569]
 [0.56470588, 0.53333333, 0.40784314, 0.6176471, 0.58039216, 0.44313725]
 [0.56862745, 0.5254902, 0.4, 0.63254912, 0.59607843, 0.45490196]]

[[0.12941176, 0.12594118, 0.13333333, 0.21960784, 0.24313725, 0.19607843]
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 [0.52941176, 0.50980392, 0.40784314, 0.62831569, 0.44313725, 0.5254902]
 ...
 [0.54901961, 0.53333333, 0.4, 0.59607843, 0.57254902, 0.44705882]
 [0.57254902, 0.54509804, 0.40784314, 0.6176471, 0.58039216, 0.45908039]
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...

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 ...
 [0.07843137, 0.07843137, 0.07843137, 0.11254902, 0.11764706, 0.11764706]
 [0.08627451, 0.08627451, 0.07843137, 0.11254902, 0.10980392, 0.10588235]
 [0.10196078, 0.10196078, 0.09411765, 0.1254902, 0.10980392, 0.10980392]

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 [0.08627451, 0.08235294, 0.0745098, 0.12156863, 0.11764706, 0.11372549]
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[[[0.08627451, 0.05490196, 0.10196078, 0.09019608, 0.09019608, 0.11764706]
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 ...
 [0.07058824, 0.08627451, 0.0745098, 0.11764706, 0.10980392, 0.10980392]
 [0.08235294, 0.05490196, 0.07843137, 0.13333333, 0.10980392, 0.10980392]
 [0.09411765, 0.09411765, 0.07843137, 0.1254902, 0.12156863, 0.13333333]

[[0.07843137, 0.07843137, 0.07843137, 0.11254902, 0.11764706, 0.11764706]
 [0.08627451, 0.08627451, 0.07843137, 0.11254902, 0.10980392, 0.10588235]
 [0.10196078, 0.10196078, 0.09411765, 0.1254902, 0.10980392, 0.10980392]

[[0.07
```


[illegible]

```

9389 - val_accuracy: 0.6825
Epoch 8/10
27/27 [=====] - 75s 3s/step - loss: 0.5751 - accuracy: 0.7841 - val_loss: 0.
8716 - val_accuracy: 0.7251
Epoch 9/10
27/27 [=====] - 70s 3s/step - loss: 0.4186 - accuracy: 0.8529 - val_loss: 0.
6999 - val_accuracy: 0.7962
Epoch 10/10
27/27 [=====] - 73s 3s/step - loss: 0.3258 - accuracy: 0.8802 - val_loss: 1.
0708 - val_accuracy: 0.7935

In [31]: # make prediction
         predicted_label = model.predict_classes(test_images)

WARNING:tensorflow:From <python-input-31-0b36f4d8f883>:2: Sequential.predict_classes (from tensorflow.python.keras.engine.sequential) is deprecated and will be removed after 2021-01-01.
Instructions for updating:
Please use instead: "np.argmax(model.predict(x), axis=-1)", if your model does multi-class classification (e.g. if it uses a 'softmax' last-layer activation)." (model.predict(x) > 0.5).astype("int32")", if your model does binary classification (e.g. if it uses a 'sigmoid' last-layer activation).

In [32]: print(predicted_label)

[[0 3 3 3 3 3 0 1 3 0 3 0 2 0 3 1 3 0 0 3 2 0 1 0 1 2 3 0 1 0 3 3 0 0 3 2
  0 0 3 3 0 1 3 0 0 0 3 1 3 0 0 0 3 1 3 0 3 3 0 3 0 0 3 0 3 1 3 0 3 1 3
  0 0 0 1 3 3 3 3 3 1 1 1 3 3 0 3 0 3 0 1 1 0 3 3 1 0 0 0 0 3 1 3 2 0 3 3 1 0 2 3
  0 0 2 3 3 3 3 3 1 3 3 3 3 1 0 0 0 3 3 1 0 0 0 3 0 1 3 0 0 0 0 1 1 0 1 0 1 0 3 1
  3 3 3 0 0 1 0 0 0 1 3 0 2 3 3 0 1 3 3 0 3 0 2 0 1 3 3 1 1 3 0 0 3 0 0 3 0 0
  0 3 0 1 3 0 0 1 3 3 0 2 0 1 3 3 3 1 3 3 3 0 3 0 3 0 0 3 0 0 1 1 1 0 1 0 3 2 0
  1 0 0]]

In [33]: from sklearn.metrics import classification_report, confusion_matrix

         print(confusion_matrix(test_labels, predicted_label))
         print(classification_report(test_labels, predicted_label))

[[64  3  0  7]
 [13 40  1 10]
 [ 0  6  2]
 [ 4  0  4 71]]

         precision    recall  f1-score   support

0               0.00      0.79      0.86      0.83       74
1               1.00      0.93      0.62      0.75       64
2               2.00      0.55      0.75      0.63       8
3               3.00      0.79      0.90      0.84       79

 accuracy          0.80      225
 macro avg         0.76      0.78      0.76      225
weighted avg         0.82      0.80      0.80      225

Reason why accuracy does not further increase
1. imbalance of training set
2. learning rate too large

In [34]: plt.plot(history.history['accuracy'], label='accuracy')
         plt.plot(history.history['val_accuracy'], label='val_accuracy')
         plt.xlabel('Epoch')
         plt.ylabel('Accuracy')
         plt.ylim(0.5, 1)
         plt.legend(loc='lower right')

         test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)

         8/8 - 4s - loss: 0.6599 - accuracy: 0.8044



```

3. Google Net: failed (<40%)
4. VGG: failed (<40%)

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For complete work on this project, go to <https://github.com/503800265/PRML>.