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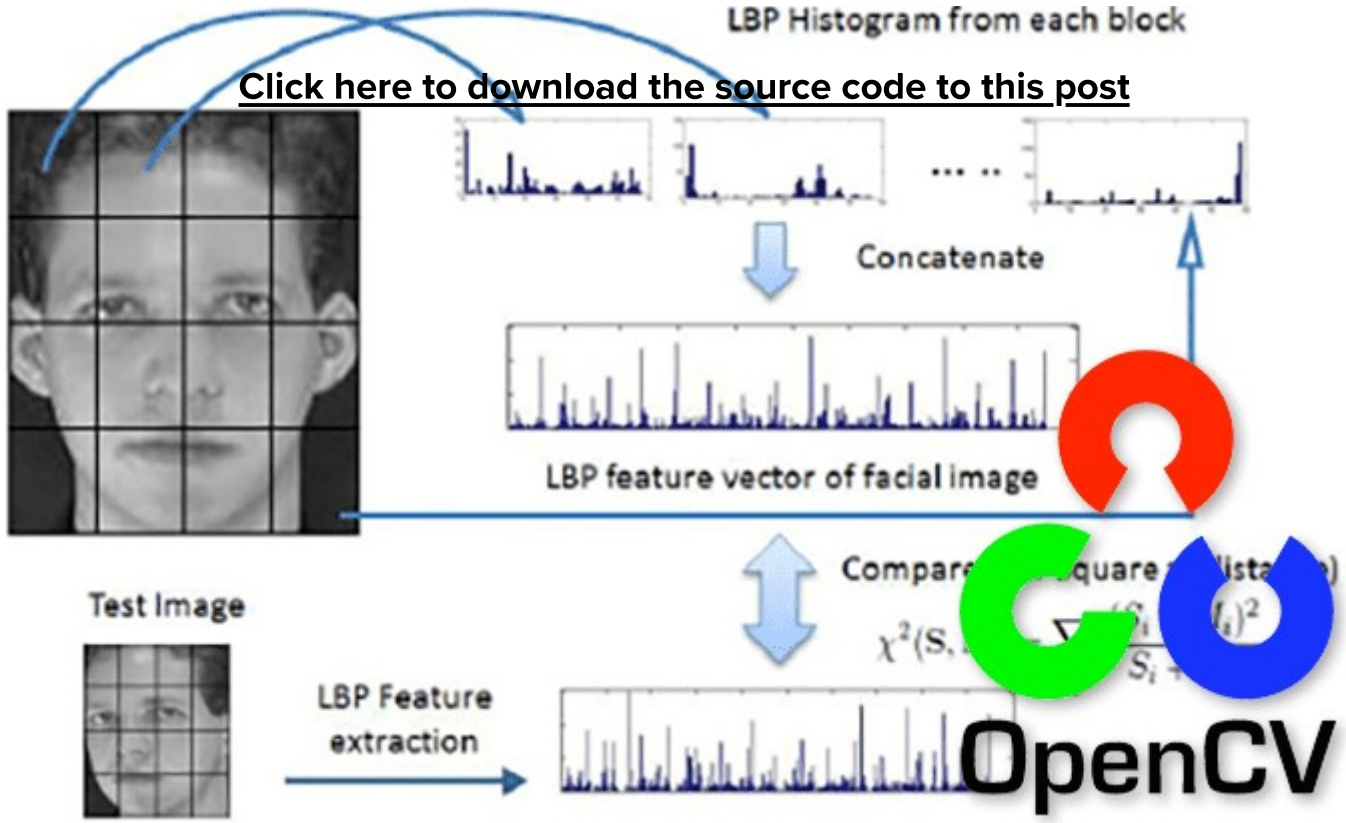
Face Recognition with Local Binary Patterns (LBPs) and OpenCV

by **Adrian Rosebrock (https://pyimagesearch.com/author/adrian/)** *on* **May 3, 2021**

6:31



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In our previous tutorial, we discussed the **fundamentals of face recognition (https://pyimagesearch.com/2021/05/01/what-is-face-recognition/)**, including:

- The difference between face detection and face recognition
- How face recognition algorithm works
- The difference between classical face recognition methods and deep learning-based face recognizers

Today we're going to get our first taste of implementing face recognition through the Local Binary Patterns algorithm. By the end of this tutorial you'll be able to implement your first face recognition system.

To learn how to perform face recognition with LBPs and OpenCV, *just keep reading*.

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Face Recognition with Local Binary Patterns (LBPs) and OpenCV

In the first part of this tutorial, we'll discuss the LBPs for face recognition algorithm, including how it works.

We'll then configure our development environment and review our project directory structure.

I'll then show you how to implement LBPs for face recognition using OpenCV.

The Local Binary Patterns (LBPs) for face recognition algorithm

The face recognition algorithm we're covering here today was first presented by Ahonen et al. on their 2004 publication, ***Face Recognition with Local Binary Patterns*** **(https://link.springer.com/chapter/10.1007/978-3-540-24670-1_36)**.

In this section, we'll present an overview of the algorithm. As you'll see, it's actually quite simple.

Given a face in a dataset, the first step of the algorithm is to divide the face into *7×7* equally sized cells:

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Figure 1: Once a face has been detected in an image, the first step is to divide the face ROI into *7×7* equally sized cells.

Then, for each of these cells, we compute a **Local Binary Pattern (https://pyimagesearch.com/2015/12/07/local-binary-patterns-with-python-opencv/)** histogram.

By definition, a histogram throws away all spatial information regarding how the patterns are oriented next to each other. **However, by computing a histogram for each of the cells, we actually are able to encode a level of spatial information such as the eyes, nose, mouth, etc., that we would otherwise not have.**

This spatial encoding also allows us to weigh the resulting histograms from each of the cells *differently*, giving more discriminative power to more distinguishing features of the face:

Figure 2: The original face image *(left)* followed by the weighting scheme for the *7×7* cells *(right)*.

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Here, we can see the original face image divided into *7×7* cells (*left*). Then, on the *right*, we can see the weighting scheme for each of the cells:

- LBP histograms for the white cells (such as the eyes) are weighed 4x more than the other cells**.** This simply means that we take the LBP histograms from the white cell regions and multiply them by 4 (taking into account any scaling/normalization of the histograms).
- Light gray cells (mouth and ears) contribute 2x more.
- Dark gray cells (inner cheek and forehead) only contribute 1x.
- Finally, the black cells, such as the nose and outer cheek, are totally disregarded and weighed 0x.

These weighting values were experimentally found by Ahonen et al. by running hyperparameter tuning algorithms on top of their training, validation, and testing data splits.

Finally, the weighted *7×7* LBP histograms are concatenated together to form the final feature vector.

Performing face recognition is done using the χ^2 distance and a nearest neighbor classifier:

- k-NN (with *k=1*) is performed with the χ^2 distance to find the closest face in the training data.
- The name of the person associated with the face with the smallest χ^2 distance is chosen as the final classification

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As you can see, the LBPs for face recognition algorithm is quite simple! Extracting Local Binary Patterns isn't a challenging task — and extending the extraction method to compute histograms for *7×7 = 49* cells is straightforward enough.

Before we close this section, it's important to note that the LBPs for face recognition algorithm has the added benefit of being updatable as new faces are introduced to the dataset.

Other popular algorithms, such as Eigenfaces, require that all faces to be identified be present at training time. This implies that if a new face is added to the dataset the entire Eigenfaces classifier has to be re-trained which can be quite computationally intensive.

Instead, the LBPs for face recognition algorithm can simply insert new face samples without having to be re-trained at all — an obvious benefit when working with face datasets where people are being added or removed from the dataset with routine frequency.

Configuring your development environment

To learn how to perform use Local Binary Patterns for face recognition, you need to have OpenCV installed on your machine:

Luckily, OpenCV is pip-installable:

```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
$ pip install opencv-contrib-python
$ pip install --upgrade imutils
```

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If you need help configuring your development environment for OpenCV, I *highly recommend* that you read my *pip install OpenCV* guide (https://pyimagesearch.com/2018/09/19/pip-install-opencv/) — it will have you up and running in a matter of minutes.

Having problems configuring your development environment?

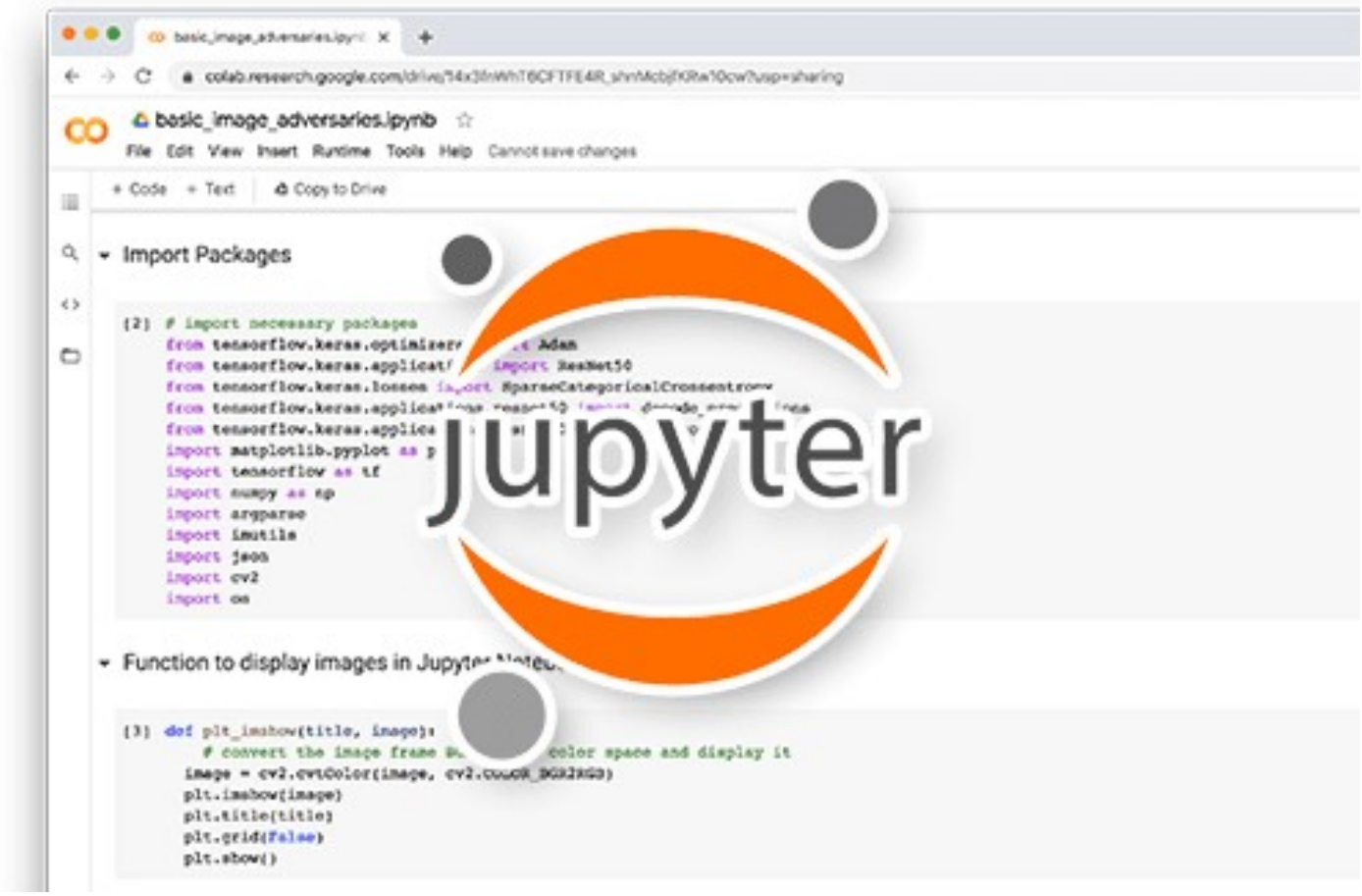

Figure 3: Having trouble configuring your dev environment? Want access to pre-configured Jupyter Notebooks running on Google Colab? Be sure to join **PyImageSearch University (https://pyimagesearch.com/pyimagesearch-university/)** — you'll be up and running with this tutorial in a matter of minutes.

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The CALTECH Faces dataset

Figure 4: A sample of the CALTECH Faces dataset.

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The CALTECH Faces challenge is a benchmark dataset for face recognition algorithms. Overall, the dataset consists of 450 images of approximately 27 unique people. Each subject was captured under various lighting conditions, background scenes, and facial expressions, as seen in **Figure 4**.

The overall goal of this tutorial is to apply the Eigenfaces face recognition algorithm to *identify each of the subjects* in the CALTECH Faces dataset.

Note: I've included a slightly modified version of the CALTECH Faces dataset in the "Downloads" associated with this tutorial. *The slightly modified version includes an easier to parse directory structure with faux names assigned to each of the subjects, making it easier to evaluate the accuracy of our face recognition system. Again, you* ***do not*** *need to download the CALTECH Faces dataset from CALTECH's servers — just use the "Downloads" associated with this guide*

Project structure

Before we can implement face recognition with Local Binary Patterns, let's first review our project directory structure.

Start by accessing the ***"Downloads"*** section of this tutorial to retrieve the source code, pre-trained face detector, and example CALTECH Faces dataset:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
$ tree --dirsfirst --filelimit 20
.
├── caltech_faces [26 entries exceeds filelimit, not opening dir]
├── face_detector
```

```
11. |
12. |  4 directories, 7 files
```

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The `face_detector` directory contains our **OpenCV deep learning-based face detector (https://pyimagesearch.com/2018/02/26/face-detection-with-opencv-and-deep-learning/)**. This detector is both fast and accurate, capable of running in real-time without a GPU.

We'll be applying the face detector model to each image in the `caltech_faces` dataset. Inside this directory is a subdirectory containing images for each of the people we want to recognize:

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```
1.  $ ls -l caltech_faces/
2.  abraham
3.  alberta
4.  allen
5.  carmen
6.  conrad
7.  cynthia
8.  darrell
9.  flyod
10. frank
11. glen
12. gloria
13. jacques
14. judy
15. julie
16. kathleen
17. kenneth
18. lewis
19. mae
20. phil
21. raymond
22. rick
23. ronald
24. sherry
25. tiffany
26. willie
27. winston
28.
29. $ ls -l caltech_faces/abraham/*.jpg
```

As you can see, we have multiple images for each person we want to recognize. These images will serve as our training data so that our LBP face recognizer can learn what each individual looks like.

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From there, we have two Python scripts to review today.

The first, `faces.py`, lives in the `pyimagesearch` module. This file contains two functions:

1. `detect_faces`: Applies our face detector to a given image, returning the bounding box coordinates of the face(s)
2. `load_face_dataset`: Loops over all images in `caltech_faces` and applies the `detect_faces` function to each

Finally, `lbp_face_reco.py` glues all the pieces together and forms our final Local Binary Patterns face recognition implementation.

Creating our face detector

As we learned in our **introduction to face recognition guide (https://pyimagesearch.com/2021/05/01/what-is-face-recognition/)**, prior to performing face recognition we need to:

1. Detect the presence of a face in an image/video stream
2. Extract the region of interest (ROI), which is the face itself

Once we have the face ROI we can apply our face recognition algorithms to learn discerning patterns from the face of the individual. Once training is complete we can actually *recognize* people in images and video.

Let's learn how to apply our OpenCV face detector to detect faces in images. Open

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
# import the necessary packages
from imutils import paths
import numpy as np
import cv2
import os
```

We start on **Lines 2-5** with our required Python packages. We'll need the `paths` submodule of `imutils` to grab the paths to all CALTECH Faces images residing on disk. The `cv2` import provides our OpenCV bindings.

Let's now define the `detect_faces` function:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
def detect_faces(net, image, minConfidence=0.5):
    # grab the dimensions of the image and then construct a blob
    # from it
    (h, w) = image.shape[:2]
    blob = cv2.dnn.blobFromImage(image, 1.0, (300, 300),
        (104.0, 177.0, 123.0))
```

This method accepts three parameters:

1. `net` : Our deep neural network used for face detection
2. `image` : The image we are going to apply face detection to
3. `minConfidence` : The minimum confidence for a positive face detection — detections with a probability less than this value will be discarded as a false-positive result

From there, we grab the spatial dimensions of the input `image` and construct a `blob` such that it can be passed through our deep neural network.

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
    # pass the blob through the network to obtain the face detections,
    # then initialize a list to store the predicted bounding boxes
    net.setInput(blob)
    detections = net.forward()
    boxes = []
```

We also initialize a list of `boxes` to store our bounding box coordinates after applying face detection.

Speaking of which, let's loop over our `detections` and populate the `boxes` list now:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
    # loop over the detections
    for i in range(0, detections.shape[2]):
        # extract the confidence (i.e., probability) associated with
        # the detection
        confidence = detections[0, 0, i, 2]

        # filter out weak detections by ensuring the confidence is
        # greater than the minimum confidence
        if confidence > minConfidence:
            # compute the (x, y)-coordinates of the bounding box for
            # the object
            box = detections[0, 0, i, 3:7] * np.array([w, h, w, h])
            (startX, startY, endX, endY) = box.astype("int")

            # update our bounding box results list
            boxes.append((startX, startY, endX, endY))

    # return the face detection bounding boxes
    return boxes
```

Line 21 loops over all `detections`, while **Line 24** extracts the `confidence` of the current detection.

Line 28 filters out weak/false-positive detections by throwing out any face detections

The final bounding boxes are returned to the calling function on **Line 38**.

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Note: *If you need a more detailed review of OpenCV's deep learning face detector, be sure to refer to my guide on* ***Face detection with OpenCV and deep learning (https://pyimagesearch.com/2018/02/26/face-detection-with-opencv-and-deep-learning/)****. That article goes into far greater detail and will give you a deeper understanding of how the face detector works.*

Loading the CALTECH Faces dataset

With our face detection helper function implemented, we can move to implementing a second helper utility, `load_face_dataset`.

This function is responsible for:

1. Looping over all images in the CALTECH Faces dataset
2. Counting the number of example images we have for each individual
3. Throwing out any individuals who have less than *N* faces for training data (otherwise we would run into a class imbalance problem)
4. Applying our `detect_faces` function
5. Extracting each individual face ROI
6. Returning the face ROIs and class labels (i.e., names of the people) to the calling function

Let's get started implementing `load_face_dataset` now. Again, open the `faces.py` file inside the `pyimagesearch` module and append the following code at the bottom of the file:

```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
def load_face_dataset(inputPath, net, minConfidence=0.5,
    minSamples=20):
    # grab the paths to all images in our input directory, extract
    # the name of the person (i.e., class label) from the directory
    # structure, and count the number of example images we have per
    # face
    imagePaths = list(paths.list_images(inputPath))
    names = [p.split(os.path.sep)[-2] for p in imagePaths]
    (names, counts) = np.unique(names, return_counts=True)
    names = names.tolist()
```


Our `load_face_dataset` function accepts four arguments:

1. `inputPath` : The face to the input dataset we want to train our LBP face recognizer on (in this case, the `caltech_faces` directory)
2. `net` : Our OpenCV deep learning face detector network
3. `minConfidence` : Minimum probability/confidence of a face detection used to filter out weak/false-positive detections
4. `minSamples` : Minimum number of images required per individual

Line 46 grabs the paths to all images in our `inputPath` . We then extract the names from these `imagePaths` on **Line 47**.

Line 48 performs two operations:

1. First, it determines the set of *unique* class labels from the `names` (i.e., the names of the people we want to recognize)
2. Secondly, it *counts* the number of times each individual's name appears

We perform this counting operation because we want to discard any individuals who have less than `minSamples` . If we tried to train our LBP face recognizer on individuals with a low number of training examples we would run into a class

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Face Recognition with Local Binary Patterns (LBPs) and OpenCV

```
51.     # initialize lists to store our extracted faces and associated
52.     # labels
53.     faces = []
54.     labels = []
55.
56.     # loop over the image paths
57.     for imagePath in imagePaths:
58.         # load the image from disk and extract the name of the person
59.         # from the subdirectory structure
60.         image = cv2.imread(imagePath)
61.         name = imagePath.split(os.path.sep)[-2]
62.
63.         # only process images that have a sufficient number of
64.         # examples belonging to the class
65.         if counts[names.index(name)] < minSamples:
66.             continue
```

Lines 53 and 54 initialize two lists — one to store the extracted face ROIs and the other to store the names of the individual each face ROI contains.

We then loop over all `imagePaths` on **Line 57**. For each face, we:

1. Load it from disk
2. Extract the name of the individual from the subdirectory structure
3. Check to see if the `name` has less than `minSamples` associated with it

If the minimum test fails (**Lines 65 and 66**), meaning there are not sufficient training images for this individual, we throw out the image and do not consider it for training.

Otherwise, we assume the minimum test passed and then proceed to process the image:

```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
        # perform face detection
        boxes = detect_faces(image, net, minConfidence)

        # loop over the bounding boxes
        for (startX, startY, endX, endY) in boxes:
            # extract the face ROI, resize it, and convert it to
            # grayscale
            faceROI = image[startY:endY, startX:endX]
            faceROI = cv2.resize(faceROI, (47, 62))
            faceROI = cv2.cvtColor(faceROI, cv2.COLOR_BGR2GRAY)

            # update our faces and labels lists
            faces.append(faceROI)
            labels.append(name)

    # convert our faces and labels lists to NumPy arrays
    faces = np.array(faces)
    labels = np.array(labels)

    # return a 2-tuple of the faces and labels
    return (faces, labels)
```

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A call to `detect_faces` on **Line 69** performs face detection, resulting in a set of bounding boxes which we loop over on **Line 72.**

For each bounding box, we:

1. Use NumPy array slicing to extract the face ROI
2. Resize the face ROI to a fixed size
3. Convert the face ROI to grayscale
4. Update our `faces` and `labels` lists

The resulting `faces` and `labels` are then returned to the calling function.

Implementing Local Binary Patterns for face recognition

With our helper utilities implemented, we can move on to creating the driver script responsible for extracting LBPs from the face ROIs, training the model, and then

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Face Recognition with Local Binary Patterns (LBPs) and OpenCV

```
1.  # import the necessary packages
2.  from sklearn.preprocessing import LabelEncoder
3.  from sklearn.model_selection import train_test_split
4.  from sklearn.metrics import classification_report
5.  from pyimagesearch.faces import load_face_dataset
6.  import numpy as np
7.  import argparse
8.  import imutils
9.  import time
10. import cv2
11. import os
```

Lines 2-11 import our required Python packages. Notable imports include:

- `LabelEncoder` : Used to encode the class labels (i.e., names of the individuals) as *integers* rather than *strings* (this is a *requirement* to utilize OpenCV's LBP face recognizer)
- `train_test_split` : Constructs a training and testing split from our CALTECH Faces dataset
- `load_face_dataset` : Loads our CALTECH Faces dataset from disk

Let's now parse our command line arguments:

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Face Recognition with Local Binary Patterns (LBPs) and OpenCV

```
13. # construct the argument parser and parse the arguments
14. ap = argparse.ArgumentParser()
15. ap.add_argument("-i", "--input", type=str, required=True,
16.    help="path to input directory of images")
17. ap.add_argument("-f", "--face", type=str,
18.    default="face_detector",
```

We have one required and two optional command line arguments to parse:

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1. `--input` : The path to our input dataset containing images of the individuals we want to train our LBP face recognizer on
2. `--face` : Path to our OpenCV deep learning face detector
3. `--confidence` : Minimum probability used to filter out weak detections

With our command line arguments taken care of we can load the face detector from disk:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
# load our serialized face detector model from disk
print("[INFO] loading face detector model...")
prototxtPath = os.path.sep.join([args["face"], "deploy.prototxt"])
weightsPath = os.path.sep.join([args["face"],
   "res10_300x300_ssd_iter_140000.caffemodel"])
net = cv2.dnn.readNet(prototxtPath, weightsPath)
```

From there we apply the `load_face_dataset` function to load our face data:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
# load the CALTECH faces dataset
print("[INFO] loading dataset...")
(faces, labels) = load_face_dataset(args["input"], net,
   minConfidence=0.5, minSamples=20)
print("[INFO] {} images in dataset".format(len(faces)))

# encode the string labels as integers
le = LabelEncoder()
labels = le.fit_transform(labels)

# construct our training and testing split
```

and the minimum number of faces required for a person to be included in the training process (`20`).

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We then encode the `labels` using our `LabelEncoder` (**Lines 38 and 39**) followed by constructing our training and testing split, using 75% of the data for training and 25% for evaluation (**Lines 42 and 43**).

We are now ready to train our face recognizer using LBPs and OpenCV:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
45. | # train our LBP face recognizer
46. | print("[INFO] training face recognizer...")
47. | recognizer = cv2.face.LBPHFaceRecognizer_create(
48. |    radius=2, neighbors=16, grid_x=8, grid_y=8)
49. | start = time.time()
50. | recognizer.train(trainX, trainY)
51. | end = time.time()
52. | print("[INFO] training took {:.4f} seconds".format(end - start))
```

The `cv2.face.LBPHFaceRecognizer_create` function accepts a few (optional) arguments that I explicitly define to make this example clear.

The `radius=2` and `neighbors=16` parameters are part of the **Local Binary Patterns image descriptor (https://pyimagesearch.com/2015/12/07/local-binary-patterns-with-python-opencv/)**. These values control the number of pixels included in the computation of the histogram, along with the radius these pixels lie on. Please see the **Local Binary Patterns tutorial (https://pyimagesearch.com/2015/12/07/local-binary-patterns-with-python-opencv/)** if you need a refresher on these parameters.

The `grid_x` and `grid_y` controls the number of *MxN* cells in the face recognition algorithm.

While the original paper by Ahonen et al. suggested using a *7×7* grid, I prefer using

jumping from 49 to 64), and perhaps more importantly, (2) considerably more memory consumption to store the feature vectors.

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In practice, you should tune the `grid_x` and `grid_y` hyperparameters on your own dataset and see which values yield the highest accuracy.

To train our LBP face recognizer, we simply call the `train` method, passing in our CALTECH Faces training data along with the (integer) labels for each subject.

Let's now gather predictions using the LBP face recognizer:

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Face Recognition with Local Binary Patterns (LBPs) and OpenCV

```
54. # initialize the list of predictions and confidence scores
55. print("[INFO] gathering predictions...")
56. predictions = []
57. confidence = []
58. start = time.time()
59.
60. # loop over the test data
61. for i in range(0, len(testX)):
62.     # classify the face and update the list of predictions and
63.     # confidence scores
64.     (prediction, conf) = recognizer.predict(testX[i])
65.     predictions.append(prediction)
66.     confidence.append(conf)
67.
68. # measure how long making predictions took
69. end = time.time()
70. print("[INFO] inference took {:.4f} seconds".format(end - start))
71.
72. # show the classification report
73. print(classification_report(testY, predictions,
74.     target_names=le.classes_))
```

We initialize two lists, `predictions` and `confidences`, to store the predicted class label and the confidence/probability of the prediction.

From there, we loop over all images in our testing set (**Line 61**).

testing vector and the closest data point in the training data. **The lower the distance, more likely the two faces are of the same subject.**

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Finally, a classification report is displayed on **Lines 73 and 74.**

Our final step is to visualize a subset of our face recognition results:

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```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
 76. | # generate a sample of testing data
 77. | idxs = np.random.choice(range(0, len(testY)), size=10, replace=False)
 78. |
 79. | # loop over a sample of the testing data
 80. | for i in idxs:
 81. |    # grab the predicted name and actual name
 82. |    predName = le.inverse_transform([predictions[i]])[0]
 83. |    actualName = le.classes_[testY[i]]
 84. |
 85. |    # grab the face image and resize it such that we can easily see
 86. |    # it on our screen
 87. |    face = np.dstack([testX[i]] * 3)
 88. |    face = imutils.resize(face, width=250)
 89. |
 90. |    # draw the predicted name and actual name on the image
 91. |    cv2.putText(face, "pred: {}".format(predName), (5, 25),
 92. |        cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 0), 2)
 93. |    cv2.putText(face, "actual: {}".format(actualName), (5, 60),
 94. |        cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 0, 255), 2)
 95. |
 96. |    # display the predicted name, actual name, and confidence of the
 97. |    # prediction (i.e., chi-squared distance; the *lower* the distance
 98. |    # is the *more confident* the prediction is)
 99. |    print("[INFO] prediction: {}, actual: {}, confidence: {:.2f}".format(
100. |        predName, actualName, confidence[i]))
101. |
102. |    # display the current face to our screen
103. |    cv2.imshow("Face", face)
104. |    cv2.waitKey(0)
```

Line 77 randomly samples all testing data indexes.

We then loop over each of these indexes on **Line 80**. For each index, we:

1. Extract the *predicted* name of the person from our label encoder (**Line 82**)

4. Draw the predicted name and actual name on the face (**Lines 91-94**)

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5. Display the final output to our screen (**Lines 99-104**)

And that's all there is to it! Congratulations on implementing face recognition with Local Binary Patterns and LBPs!

Local Binary Pattern face recognition results

We are now ready to perform face recognition with Local Binary Patterns and OpenCV!

Be sure to access the ***"Downloads"*** section of this tutorial to retrieve the source code and example CALTECH Faces dataset.

From there, open a terminal and execute the following command:

→ **Launch Jupyter Notebook on Google Colab**

```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
$ python lbp_face_reco.py --input caltech_faces
[INFO] loading face detector model...
[INFO] loading dataset...
[INFO] 397 images in dataset
[INFO] training face recognizer...
[INFO] training took 3.0534 seconds
[INFO] gathering predictions...
[INFO] inference took 127.8610 seconds
               precision    recall  f1-score   support

      abraham       1.00      1.00      1.00         5
        allen       1.00      1.00      1.00         8
       carmen       1.00      0.80      0.89         5
       conrad       0.86      1.00      0.92         6
      cynthia       1.00      1.00      1.00         5
      darrell       1.00      1.00      1.00         5
        frank       1.00      1.00      1.00         5
       gloria       1.00      1.00      1.00         5
```

```
25. |          rick       1.00      1.00      1.00         6
26. |        sherry       1.00      0.83      0.91         6
27. |       tiffany       0.83      1.00      0.91         5
28. |        willie       1.00      1.00      1.00         6
29. |
30. |      accuracy                           0.98       100
31. |     macro avg       0.98      0.98      0.98       100
32. |  weighted avg       0.98      0.98      0.98       100
```

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As our output shows, we first loop over all input images in our dataset, detect faces, and then extract LBPs using the face recognition algorithm. This process takes a bit of time due to LBPs needing to be computed for each cell.

From there we perform inference, obtaining **98% accuracy.**

The downside to this method is that it took just over 2 minutes to recognize all faces in our dataset. The reason inference is so slow is because we have to perform a nearest neighbor search across our entire training set.

To improve the speed of our algorithm we should consider using specialized approximate nearest neighbor algorithms which can *dramatically reduce* the amount of time it takes to perform a nearest neighbor search.

Now, let's apply our LBP face recognizer to individual images:

→ **Launch Jupyter Notebook on Google Colab**

```
Face Recognition with Local Binary Patterns (LBPs) and OpenCV
 1. | [INFO] prediction: jacques, actual: jacques, confidence: 163.11
 2. | [INFO] prediction: jacques, actual: jacques, confidence: 164.36
 3. | [INFO] prediction: allen, actual: allen, confidence: 192.58
 4. | [INFO] prediction: abraham, actual: abraham, confidence: 167.72
 5. | [INFO] prediction: mae, actual: mae, confidence: 154.34
 6. | [INFO] prediction: rick, actual: rick, confidence: 170.42
 7. | [INFO] prediction: rick, actual: rick, confidence: 171.12
 8. | [INFO] prediction: tiffany, actual: carmen, confidence: 204.12
 9. | [INFO] prediction: allen, actual: allen, confidence: 192.51
10. | [INFO] prediction: mae, actual: mae, confidence: 167.03
```

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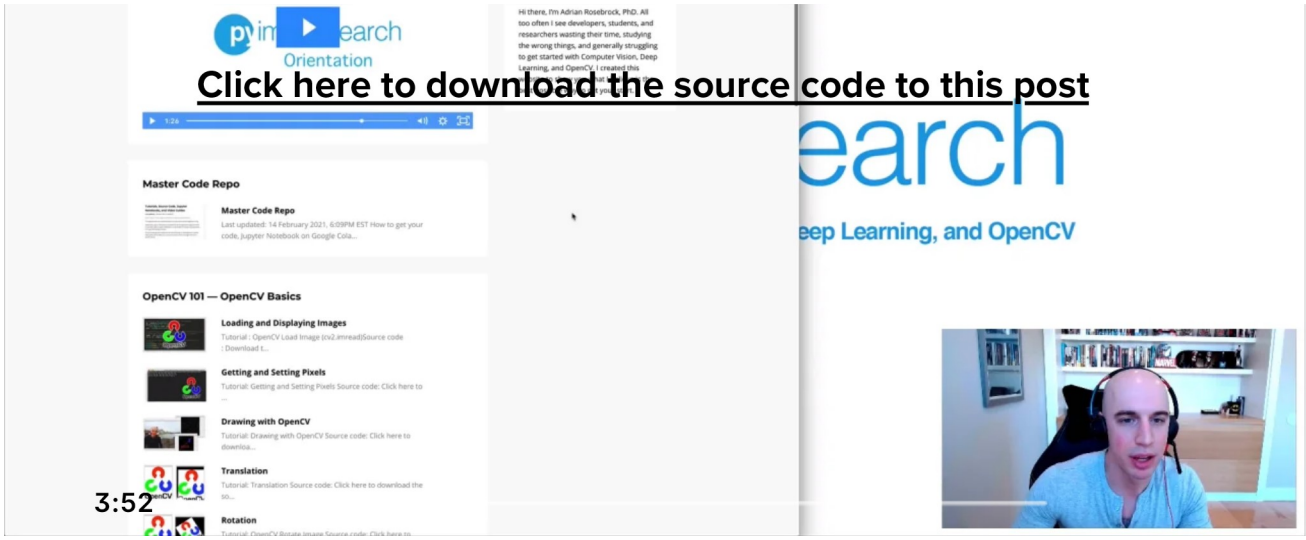
(https://pyimagesearch.com/wp-content/uploads/2021/04/face_reco_lbps_output.png)

Figure 5: A sample of our face recognition results using Local Binary Patterns and OpenCV.

Figure 5 displays a montage of results from our LBP face recognition algorithm. We're able to correctly identify each of the individuals using the LBP method.

What's next? We recommend PyImageSearch University (https://pyimagesearch.com/pyimagesearch-university/?utm_source=blogPost&utm_medium=bottomBanner&utm_campaign=What%27s%20next%3F%20I%20recommend).



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works. We started by reviewing the CALTECH Faces dataset, a popular benchmark for evaluating face recognition algorithms.

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From there, we reviewed the LBPs face recognition algorithm introduced by Ahonen et al. in their 2004 paper, *Face Recognition with Local Binary Patterns*. This method is quite simple, yet effective. The entire algorithm essentially consists of three steps:

1. Divide each input image into *7×7* equally sized cells
2. Extract Local Binary Patterns from each of the cells; weight them according to how discriminating each cell is for face recognition; and finally concatenate the *7×7 = 49* histograms to form the final feature vector
3. Perform face recognition by using a k-NN classifier with *k=1* and the χ^2 distance metric

While the algorithm itself is quite simple to implement, OpenCV comes pre-built with a class dedicated to performing face recognition using LBPs. We used the `cv2.face.LBPHFaceRecognizer_create` to train our face recognizer on the CALTECH Faces dataset and obtained 98% accuracy, a good start in our face recognition journey.

To download the source code to this post (and be notified when future tutorials are published here on PyImageSearch), *simply enter your email address in the form below!*

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Instead, my goal is to *do the most good* for the computer vision, deep learning, and OpenCV community at large by focusing my time on authoring high-quality blog posts, tutorials, and books/courses.

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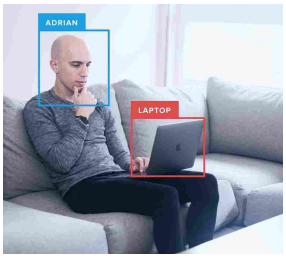

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