https://www.pyimagesearch.com/2019/03/11/liveness-detection-with-opencv/

Liveness Detection with OpenCV

by Adrian Rosebrock on March 11, 2019 in Deep Learning, Faces, Tutorials

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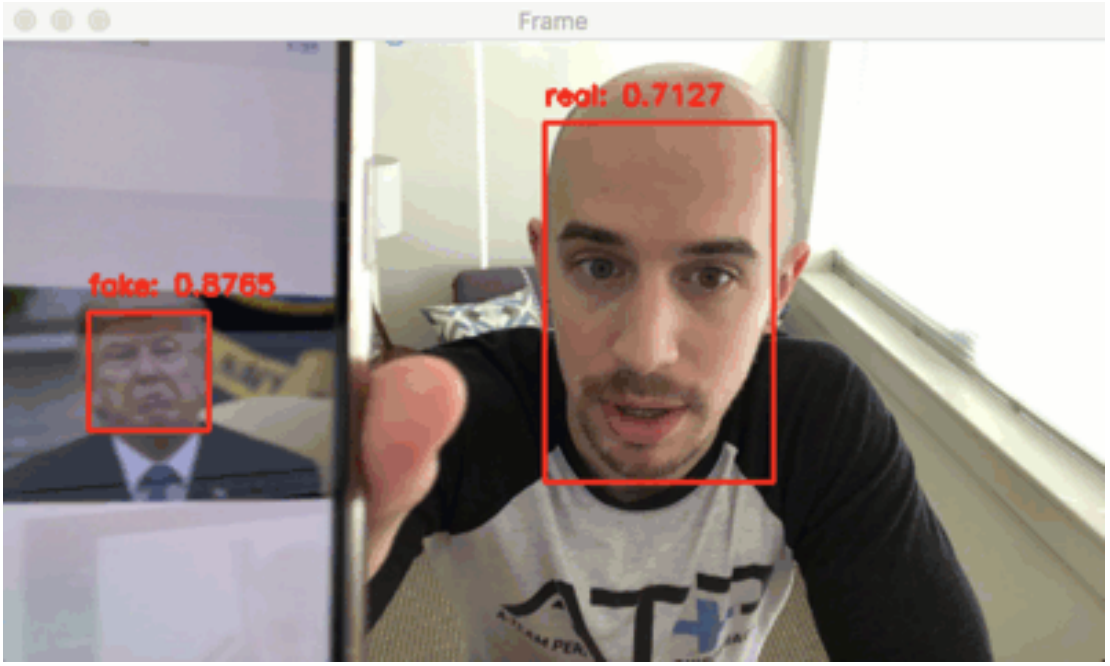


In this tutorial, you will learn how to perform liveness detection with OpenCV. You will create a liveness detector capable of spotting fake faces and performing anti-face spoofing in face recognition systems.

Over the past year, I have authored a number of face recognition tutorials, including:

- *OpenCV Face Recognition*
- *Face recognition with dlib, Python, and deep learning*
- *Raspberry Pi Face Recognition*

However, a common question I get asked over email and in the comments sections of the face recognition posts is:

How do I spot real versus fake faces?

Consider what would happen if a nefarious user tried to *purposely circumvent your face recognition system*.

Such a user could try to **hold up a photo of another person.** Maybe they even **have a photo or video on their smartphone that they could hold up to the camera** responsible for performing face recognition (such as in the image at the top of this post).

In those situations it's entirely possible for the face held up to the camera to be correctly recognized…but ultimately leading to an unauthorized user bypassing your face recognition system!

How would you go about spotting these "fake" versus "real/legitimate" faces? How could you apply anti-face spoofing algorithms into your facial recognition applications?

The answer is to apply ***liveness detection*** with OpenCV which is exactly what I'll be covering today.

To learn how to incorporate liveness detection with OpenCV into your own face recognition systems, *just keep reading!*

Looking for the source code to this post?

Jump right to the downloads section.

Liveness Detection with OpenCV

In the first part of this tutorial, we'll discuss liveness detection, including what it is and why we need it to improve our face recognition systems.

From there we'll review the dataset we'll be using to perform liveness detection, including:

- How to build to a dataset for liveness detection
- Our example real versus fake face images

We'll also review our project structure for the liveness detector project as well.

In order to create the liveness detector, we'll be training a deep neural network capable of distinguishing between real versus fake faces.

We'll, therefore, need to:

1. Build the image dataset itself.

2. Implement a CNN capable of performing liveness detector (we'll call this network *"LivenessNet"*).
3. Train the liveness detector network.
4. Create a Python + OpenCV script capable of taking our trained liveness detector model and apply it to real-time video.

Let's go ahead and get started!

What is liveness detection and why do we need it?

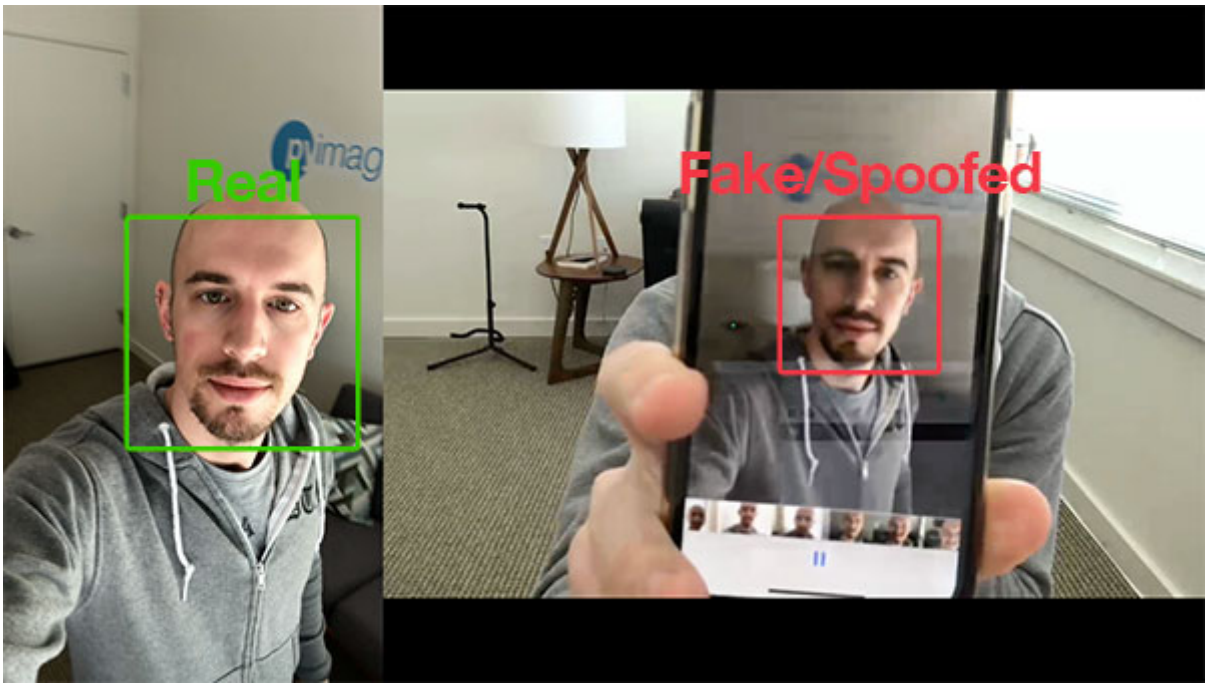


Figure 1: Liveness detection with OpenCV. On the *left* is a live (real) video of me and on the *right* you can see I am holding my iPhone (fake/spoofed).

Face recognition systems are becoming more prevalent than ever. From face recognition on your iPhone/smartphone, to face recognition for mass surveillance in China, face recognition systems are being utilized everywhere.

However, face recognition systems are easily fooled by "spoofing" and "non-real" faces.

Face recognition systems can be circumvented simply by holding up a photo of a person (whether printed, on a smartphone, etc.) to the face recognition camera.

In order to make face recognition systems more secure, we need to be able to detect such fake/non-real faces — ***liveness detection*** **is the term used to refer to such algorithms.**

There are a number of approaches to liveness detection, including:

- **Texture analysis,** including computing Local Binary Patterns (LBPs) over face regions and using an SVM to classify the faces as real or spoofed.
- **Frequency analysis,** such as examining the Fourier domain of the face.
- **Variable focusing analysis,** such as examining the variation of pixel values between two consecutive frames.
- **Heuristic-based algorithms,** including **eye movement, lip movement,** and **blink detection.** These set of algorithms attempt to track eye movement and blinks to ensure the user is not holding up a photo of another person (since a photo will not blink or move its lips).
- **Optical Flow algorithms,** namely examining the differences and properties of optical flow generated from 3D objects and 2D planes.
- **3D face shape,** similar to what is used on Apple's iPhone face recognition system, enabling the face recognition system to distinguish between real faces and printouts/photos/images of another person.
- **Combinations of the above,** enabling a face recognition system engineer to pick and choose the liveness detections models appropriate for their particular application.

A full review of liveness detection algorithms can be found in Chakraborty and Das' 2014 paper, *An Overview of Face liveness Detection*.

For the purposes of today's tutorial, we'll be **treating liveness detection as a *binary classification* problem**.

Given an input image, we'll train a Convolutional Neural Network capable of distinguishing *real faces* from *fake/spoofed faces*.

But before we get to training our liveness detection model, let's first examine our dataset.

Our liveness detection videos

Figure 2: An example of gathering real versus fake/spoofed faces. The video on the *left* is a legitimate recording of my face. The video on the *right* is that same video played back while my laptop records it.

To keep our example straightforward, the liveness detector we are building in this blog post will focus on distinguishing ***real faces*** versus ***spoofed faces on a screen.***

This algorithm *can easily be extended to other types of spoofed faces*, including print outs, high-resolution prints, etc.

In order to build the liveness detection dataset, I:

1. Took my iPhone and put it in **portrait/selfie mode.**
2. **Recorded a ~25-second video of myself** walking around my office.
3. **Replayed the same 25-second video, this time facing my iPhone towards my desktop** where I recorded the video replaying.
4. This resulted in **two example videos**, one for "real" faces and another for "fake/spoofed" faces.
5. Finally, I applied **face detection** to both sets of videos to extract individual face ROIs for both classes.

I have provided you with both my real and fake video files in the ***"Downloads"*** section of the post.

You can use these videos as a starting point for your dataset but **I would recommend *gathering more data* to help make your liveness detector more robust and accurate.**

With testing, I determined that the model is slightly biased towards my own face which makes sense because that is all the model was trained on. And furthermore, since I am white/caucasian I wouldn't expect this same dataset to work as well with other skin tones.

Ideally, you would train a model with **faces of *multiple* people** and **include faces of *multiple ethnicities.*** Be sure to refer to the *"Limitations and further work"* section below for additional suggestions on improving your liveness detection models.

In the rest of the tutorial, you will learn how to take the dataset I recorded it and turn it into an actual liveness detector with OpenCV and deep learning.

Project structure

Go ahead and grab the code, dataset, and liveness model using the ***"Downloads"*** section of this post and then unzip the archive.

Once you navigate into the project directory, you'll notice the following structure:

```
liveness Detection with OpenCV
Python
$ tree --dirsfirst --filelimit 10
.
├── dataset
│   ├── fake [150 entries]
│   └── real [161 entries]
├── face_detector
│   ├── deploy.prototxt
│   └── res10_300x300_ssd_iter_140000.caffemodel
├── pyimagesearch
│   ├── __init__.py
│   └── livenessnet.py
├── videos
│   ├── fake.mp4
│   └── real.mov
├── gather_examples.py
├── train_liveness.py
├── liveness_demo.py
├── le.pickle
├── liveness.model
└── plot.png

6 directories, 12 files
```

There are four main directories inside our project:

- `dataset/` : Our dataset directory consists of two classes of images:
    - Fake images of me from a camera aimed at my screen while playing a video of my face.

    - Real images of me captured from a selfie video with my phone.
- `face_detector/` : Consists of our pretrained Caffe face *detector* to locate face ROIs.
- `pyimagesearch/` : This module contains our LivenessNet class.
- `videos/` : I've provided two input videos for training our LivenessNet classifier.

Today we'll be reviewing three Python scripts in detail. By the end of the post you'll be able to run them on your own data and input video feeds as well. In order of appearance in this tutorial, the three scripts are:

1. `gather_examples.py` : This script grabs face ROIs from input video files and helps us to create a deep learning face liveness dataset.
2. `train_liveness.py` : As the filename indicates, this script will train our LivenessNet classifier. We'll use Keras and TensorFlow to train the model. The training process results in a few files:
    - `le.pickle` : Our class label encoder.
    - `liveness.model` : Our serialized Keras model which detects face liveness.
    - `plot.png` : The training history plot shows accuracy and loss curves so we can assess our model (i.e. over/underfitting).
3. `liveness_demo.py` : Our demonstration script will fire up your webcam to grab frames to conduct face liveness detection in real-time.

Detecting and extracting face ROIs from our training (video) dataset

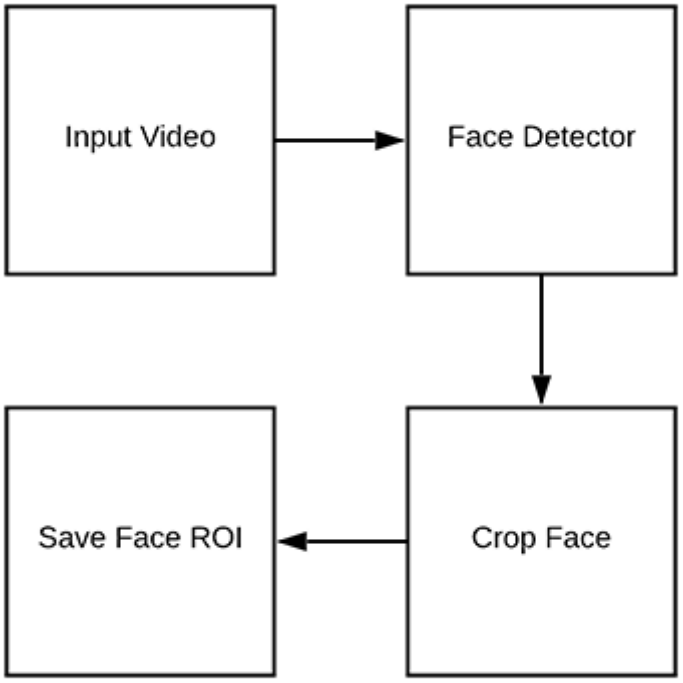


Figure 3: Detecting face ROIs in video for the purposes of building a liveness detection dataset.

Now that we've had a chance to review both our initial dataset and project structure, let's see how we can extract both real and fake face images from our input videos.

The end goal if this script will be to populate two directories:

1. `dataset/fake/`: Contains face ROIs from the `fake.mp4` file
2. `dataset/real/`: Holds face ROIs from the `real.mov` file.

Given these frames, we'll later train a deep learning-based liveness detector on the images.

Open up the `gather_examples.py` file and insert the following code:

```
liveness Detection with OpenCV
Python
```

```python
# import the necessary packages
import numpy as np
import argparse
import cv2
import os

# construct the argument parse and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-i", "--input", type=str, required=True,
        help="path to input video")
ap.add_argument("-o", "--output", type=str, required=True,
        help="path to output directory of cropped faces")
ap.add_argument("-d", "--detector", type=str, required=True,
        help="path to OpenCV's deep learning face detector")
ap.add_argument("-c", "--confidence", type=float, default=0.5,
        help="minimum probability to filter weak detections")
```

```
ap.add_argument("-s", "--skip", type=int, default=16,
        help="# of frames to skip before applying face detection")
args = vars(ap.parse_args())
```

Lines 2-5 import our required packages. This script only requires OpenCV and NumPy in addition to built-in Python modules.

From there **Lines 8-19** parse our command line arguments:

- `--input` : The path to our input video file.
- `--output` : The path to the output directory where each of the cropped faces will be stored.
- `--detector` : The path to the face detector. We'll be using OpenCV's deep learning face detector. This Caffe model is included with today's ***"Downloads"*** for your convenience.
- `--confidence` : The minimum probability to filter weak face detections. By default, this value is 50%.
- `--skip` : We don't need to detect and store every image because adjacent frames will be similar. Instead, we'll skip *N* frames between detections. You can alter the default of 16 using this argument.

Let's go ahead and load the face detector and initialize our video stream:

liveness Detection with OpenCV

Python

```
# load our serialized face detector from disk
print("[INFO] loading face detector...")
protoPath = os.path.sep.join([args["detector"], "deploy.prototxt"])
modelPath = os.path.sep.join([args["detector"],
        "res10_300x300_ssd_iter_140000.caffemodel"])
net = cv2.dnn.readNetFromCaffe(protoPath, modelPath)

# open a pointer to the video file stream and initialize the total
# number of frames read and saved thus far
vs = cv2.VideoCapture(args["input"])
read = 0
saved = 0
```

Lines 23-26 load OpenCV's deep learning face detector.

From there we open our video stream on **Line 30**.

We also initialize two variables for the number of frames read as well as the number of frames saved while our loop executes (**Lines 31 and 32**).

Let's go ahead create a loop to process the frames:

liveness Detection with OpenCV

Python

```
# loop over frames from the video file stream
while True:
```

```
36          # grab the frame from the file
37          (grabbed, frame) = vs.read()
38
39          # if the frame was not grabbed, then we have reached the end
40          # of the stream
41          if not grabbed:
42                  break
43
44          # increment the total number of frames read thus far
45          read += 1
46
47          # check to see if we should process this frame
48          if read % args["skip"] != 0:
49                  continue
```

Our `while` loop begins on **Lines 35**.

From there we grab and verify a `frame` (**Lines 37-42**).

At this point, since we've read a `frame`, we'll increment our `read` counter (**Line 48**). If we are skipping this particular frame, we'll continue without further processing (**Lines 48 and 49**).

Let's go ahead and detect faces:

liveness Detection with OpenCV

Python

```
51          # grab the frame dimensions and construct a blob from the frame
52          (h, w) = frame.shape[:2]
53          blob = cv2.dnn.blobFromImage(cv2.resize(frame, (300, 300)), 1.0,
54                  (300, 300), (104.0, 177.0, 123.0))
55
56          # pass the blob through the network and obtain the detections and
57          # predictions
58          net.setInput(blob)
59          detections = net.forward()
60
61          # ensure at least one face was found
62          if len(detections) > 0:
63                  # we're making the assumption that each image has only ONE
64                  # face, so find the bounding box with the largest probability
65                  i = np.argmax(detections[0, 0, :, 2])
66                  confidence = detections[0, 0, i, 2]
```

In order to perform face detection, we need to [create a blob from the image](#) (**Lines 53 and 54**). This `blob` has a *300×300* width and height to accommodate our Caffe face detector. Scaling the bounding boxes will be necessary later, so **Line 52**, grabs the frame dimensions.

Lines 58 and 59 perform a `forward` pass of the `blob` through the deep learning face detector.

Our script *makes the assumption that there is only one face in each frame* of the video (**Lines 62-65**). This helps prevent false positives. If you're working

with a video containing more than one face, I recommend that you adjust the logic accordingly.

Thus, **Line 65** grabs the highest probability face detection index. **Line 66** extracts the confidence of the detection using the index.

Let's filter weak detections and write the face ROI to disk:

liveness Detection with OpenCV

Python

```
68                  # ensure that the detection with the largest probability also
69                  # means our minimum probability test (thus helping filter out
70                  # weak detections)
71                  if confidence > args["confidence"]:
72                          # compute the (x, y)-coordinates of the bounding box for
73                          # the face and extract the face ROI
74                          box = detections[0, 0, i, 3:7] * np.array([w, h, w, h])
75                          (startX, startY, endX, endY) = box.astype("int")
76                          face = frame[startY:endY, startX:endX]
77
78                          # write the frame to disk
79                          p = os.path.sep.join([args["output"],
80                                  "{}.png".format(saved)])
81                          cv2.imwrite(p, face)
82                          saved += 1
83                          print("[INFO] saved {} to disk".format(p))
84
85  # do a bit of cleanup
86  vs.release()
87  cv2.destroyAllWindows()
```

Line 71 ensures that our face detection ROI meets the minimum threshold to reduce false positives.

From there we extract the face ROI bounding `box` coordinates and face ROI itself (**Lines 74-76**).

We generate a path + filename for the face ROI and write it to disk on **Lines 79-81**. At this point, we can increment the number of `saved` faces.

Once processing is complete, we'll perform cleanup on **Lines 86 and 87**.

Building our liveness detection image dataset

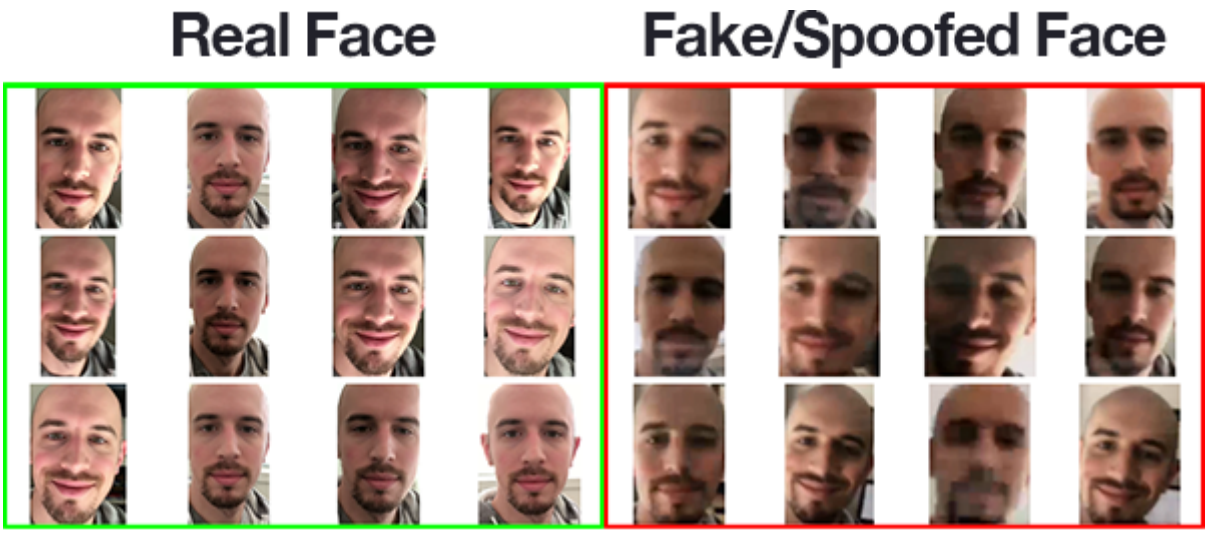


Figure 4: Our OpenCV face liveness detection dataset. We'll use Keras and OpenCV to train and demo a liveness model.

Now that we've implemented the `gather_examples.py` script, let's put it to work.

Make sure you use the ***"Downloads"*** section of this tutorial to grab the source code and example input videos.

From there, open up a terminal and execute the following command to extract faces for our **"fake/spoofed"** class:

```
liveness Detection with OpenCV
Shell
```

```
$ python gather_examples.py --input videos/fake.mp4 --output dataset/fake \
        --detector face_detector --skip 1
[INFO] loading face detector...
[INFO] saved datasets/fake/0.png to disk
[INFO] saved datasets/fake/1.png to disk
[INFO] saved datasets/fake/2.png to disk
[INFO] saved datasets/fake/3.png to disk
[INFO] saved datasets/fake/4.png to disk
[INFO] saved datasets/fake/5.png to disk
...
[INFO] saved datasets/fake/145.png to disk
[INFO] saved datasets/fake/146.png to disk
[INFO] saved datasets/fake/147.png to disk
[INFO] saved datasets/fake/148.png to disk
[INFO] saved datasets/fake/149.png to disk
```

Similarly, we can do the same for the **"real"** class as well:

```
liveness Detection with OpenCV
Shell
```

```
$ python gather_examples.py --input videos/real.mov --output dataset/real \
        --detector face_detector --skip 4
[INFO] loading face detector...
[INFO] saved datasets/real/0.png to disk
[INFO] saved datasets/real/1.png to disk
[INFO] saved datasets/real/2.png to disk
[INFO] saved datasets/real/3.png to disk
[INFO] saved datasets/real/4.png to disk
```

```
...
[INFO] saved datasets/real/156.png to disk
[INFO] saved datasets/real/157.png to disk
[INFO] saved datasets/real/158.png to disk
[INFO] saved datasets/real/159.png to disk
[INFO] saved datasets/real/160.png to disk
```

Since the "real" video file is longer than the "fake" video file, we'll use a longer skip frames value to help balance the number of output face ROIs for each class.

After executing the scripts you should have the following image counts:

- **Fake:** 150 images
- **Real:** 161 images
- ***Total:*** 311 images

Implementing "LivenessNet", our deep learning liveness detector

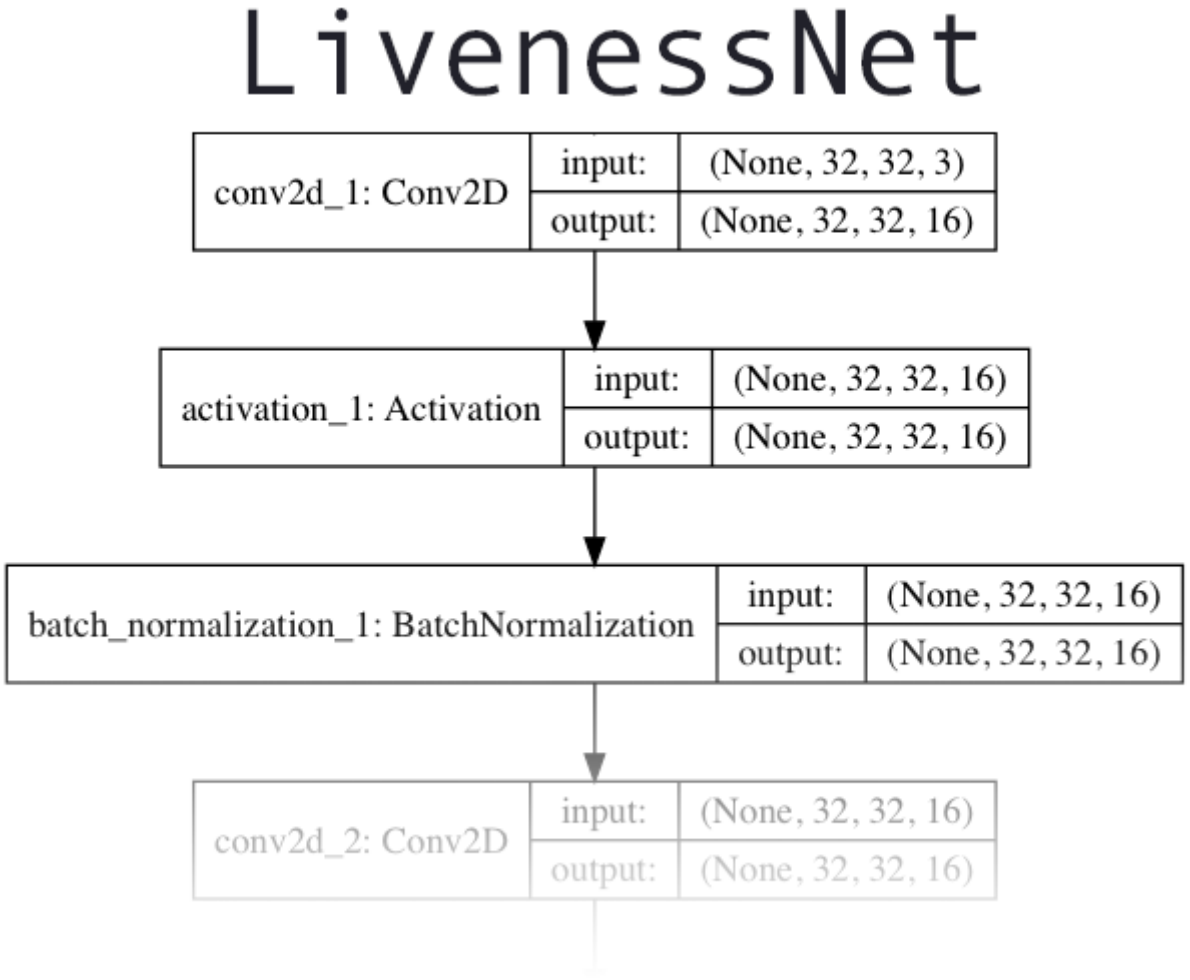


Figure 5: Deep learning architecture for LivenessNet, a CNN designed to detect face liveness in images and videos.

The next step is to implement "LivenessNet", our deep learning-based liveness detector.

At the core, `LivenessNet` is actually just a simple Convolutional Neural Network.

We'll be *purposely* keeping this network as *shallow* and *with as few parameters as possible* for two reasons:

1. To reduce the chances of overfitting on our small dataset.
2. To ensure our liveness detector is fast, capable of running in real-time (even on resource-constrained devices, such as the Raspberry Pi).

Let's implement LivenessNet now — open up `livenessnet.py` and insert the following code:

```
liveness Detection with OpenCV
Python
```

```python
# import the necessary packages
from keras.models import Sequential
from keras.layers.normalization import BatchNormalization
from keras.layers.convolutional import Conv2D
from keras.layers.convolutional import MaxPooling2D
from keras.layers.core import Activation
from keras.layers.core import Flatten
from keras.layers.core import Dropout
from keras.layers.core import Dense
from keras import backend as K

class LivenessNet:
	@staticmethod
	def build(width, height, depth, classes):
		# initialize the model along with the input shape to be
		# "channels last" and the channels dimension itself
		model = Sequential()
		inputShape = (height, width, depth)
		chanDim = -1

		# if we are using "channels first", update the input shape
		# and channels dimension
		if K.image_data_format() == "channels_first":
			inputShape = (depth, height, width)
			chanDim = 1
```

All of our imports are from Keras (**Lines 2-10**). For an in-depth review of each of these layers and functions, be sure to refer to *Deep Learning for Computer Vision with Python*.

Our `LivenessNet` class is defined on **Line 12**. It consists of one static method, `build` (**Line 14**). The `build` method accepts four parameters:

- `width`: How wide the image/volume is.
- `height`: How tall the image is.

- `depth` : The number of channels for the image (in this case 3 since we' ll be working with RGB images).
- `classes` : The number of classes. We have two total classes: "real" and "fake" .

Our `model` is initialized on **Line 17**.

The `inputShape` to our model is defined on **Line 18** while channel ordering is determined on **Lines 23-25.**

Let' s begin adding layers to our CNN:

liveness Detection with OpenCV

Python

```
27                  # first CONV => RELU => CONV => RELU => POOL layer set
28                  model.add(Conv2D(16, (3, 3), padding="same",
29                          input_shape=inputShape))
30                  model.add(Activation("relu"))
31                  model.add(BatchNormalization(axis=chanDim))
32                  model.add(Conv2D(16, (3, 3), padding="same"))
33                  model.add(Activation("relu"))
34                  model.add(BatchNormalization(axis=chanDim))
35                  model.add(MaxPooling2D(pool_size=(2, 2)))
36                  model.add(Dropout(0.25))
37
38                  # second CONV => RELU => CONV => RELU => POOL layer set
39                  model.add(Conv2D(32, (3, 3), padding="same"))
40                  model.add(Activation("relu"))
41                  model.add(BatchNormalization(axis=chanDim))
42                  model.add(Conv2D(32, (3, 3), padding="same"))
43                  model.add(Activation("relu"))
44                  model.add(BatchNormalization(axis=chanDim))
45                  model.add(MaxPooling2D(pool_size=(2, 2)))
46                  model.add(Dropout(0.25))
```

Our CNN exhibits VGGNet-esque qualities. It is very shallow with only a few learned filters. Ideally, we won' t need a deep network to distinguish between real and spoofed faces.

The first `CONV => RELU => CONV => RELU => POOL` layer set is specified on **Lines 28-36** where batch normalization and dropout are also added.

Another `CONV => RELU => CONV => RELU => POOL` layer set is appended on **Lines 39-46**.

Finally, we' ll add our `FC => RELU` layers:

liveness Detection with OpenCV

Python

```
48                  # first (and only) set of FC => RELU layers
49                  model.add(Flatten())
50                  model.add(Dense(64))
51                  model.add(Activation("relu"))
52                  model.add(BatchNormalization())
53                  model.add(Dropout(0.5))
```

```
54
55                  # softmax classifier
56                  model.add(Dense(classes))
57                  model.add(Activation("softmax"))
58
59                  # return the constructed network architecture
60                  return model
```

Lines 49-57 consist of fully connected and ReLU activated layers with a softmax classifier head.

The model is returned to the training script on **Line 60**.,

Creating the liveness detector training script

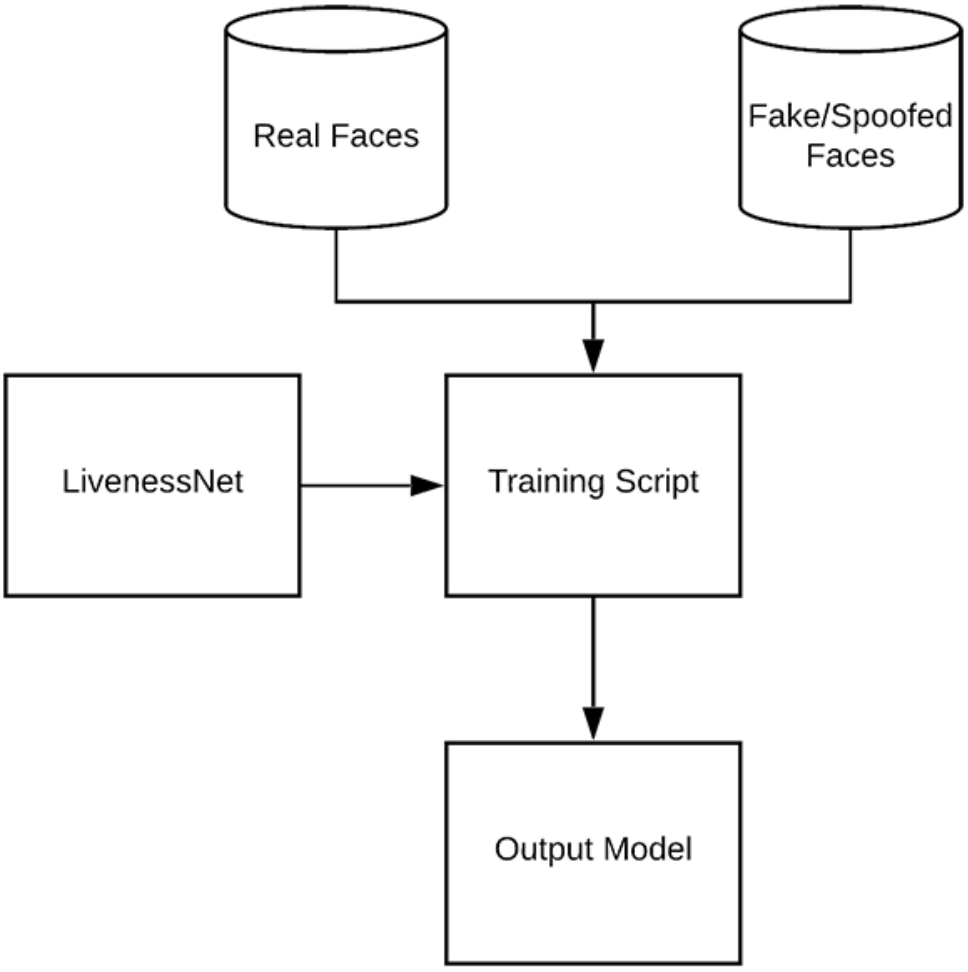


Figure 6: The process of training LivenessNet. Using both "real" and "spoofed/fake" images as our dataset, we can train a liveness detection model with OpenCV, Keras, and deep learning.

Given our dataset of real/spoofed images as well as our implementation of LivenessNet, we are now ready to train the network.

Open up the `train_liveness.py` file and insert the following code:

liveness Detection with OpenCV

Python

```
1  # set the matplotlib backend so figures can be saved in the background
2  import matplotlib
3  matplotlib.use("Agg")
```

```
4
5   # import the necessary packages
6   from pyimagesearch.livenessnet import LivenessNet
7   from sklearn.preprocessing import LabelEncoder
8   from sklearn.model_selection import train_test_split
9   from sklearn.metrics import classification_report
10  from keras.preprocessing.image import ImageDataGenerator
11  from keras.optimizers import Adam
12  from keras.utils import np_utils
13  from imutils import paths
14  import matplotlib.pyplot as plt
15  import numpy as np
16  import argparse
17  import pickle
18  import cv2
19  import os
20
21  # construct the argument parser and parse the arguments
22  ap = argparse.ArgumentParser()
23  ap.add_argument("-d", "--dataset", required=True,
24          help="path to input dataset")
25  ap.add_argument("-m", "--model", type=str, required=True,
26          help="path to trained model")
27  ap.add_argument("-l", "--le", type=str, required=True,
28          help="path to label encoder")
29  ap.add_argument("-p", "--plot", type=str, default="plot.png",
30          help="path to output loss/accuracy plot")
31  args = vars(ap.parse_args())
```

Our face liveness training script consists of a number of imports (**Lines 2-19**). Let's review them now:

- `matplotlib` : Used to generate a training plot. We specify the `"Agg"` backend so we can easily save our plot to disk on **Line 3**.
- `LivenessNet` : The liveness CNN that we defined in the previous section.
- `train_test_split` : A function from scikit-learn which constructs splits of our data for training and testing.
- `classification_report` : Also from scikit-learn, this tool will generate a brief statistical report on our model's performance.
- `ImageDataGenerator` : Used for performing data augmentation, providing us with batches of randomly mutated images.
- `Adam` : An optimizer that worked well for this model. (alternatives include SGD, RMSprop, etc.).
- `paths` : From my imutils package, this module will help us to gather the paths to all of our image files on disk.
- `pyplot` : Used to generate a nice training plot.

- `numpy` : A numerical processing library for Python. It is an OpenCV requirement as well.
- `argparse` : For processing command line arguments.
- `pickle` : Used to serialize our label encoder to disk.
- `cv2` : Our OpenCV bindings.
- `os` : This module can do quite a lot, but we' ll just be using it for it' s operating system path separator.

That was a mouthful, but now that you know what the imports are for, reviewing the rest of the script should be more straightforward.

This script accepts four command line arguments:

- `--dataset` : The path to the input dataset. Earlier in the post we created the dataset with the `gather_examples.py` script.
- `--model` : Our script will generate an output model file — here you supply the path to it.
- `--le` : The path to our output serialized label encoder file also needs to be supplied.
- `--plot` : The training script will generate a plot. If you wish to override the default value of `"plot.png"` , you should specify this value on the command line.

This next code block will perform a number of initializations and build our data:

liveness Detection with OpenCV

Python

```
# initialize the initial learning rate, batch size, and number of
# epochs to train for
INIT_LR = 1e-4
BS = 8
EPOCHS = 50

# grab the list of images in our dataset directory, then initialize
# the list of data (i.e., images) and class images
print("[INFO] loading images...")
imagePaths = list(paths.list_images(args["dataset"]))
data = []
labels = []

for imagePath in imagePaths:
	# extract the class label from the filename, load the image and
	# resize it to be a fixed 32x32 pixels, ignoring aspect ratio
	label = imagePath.split(os.path.sep)[-2]
	image = cv2.imread(imagePath)
	image = cv2.resize(image, (32, 32))

	# update the data and labels lists, respectively
```

```
54          data.append(image)
55          labels.append(label)
56
57  # convert the data into a NumPy array, then preprocess it by scaling
58  # all pixel intensities to the range [0, 1]
59  data = np.array(data, dtype="float") / 255.0
```

Training parameters including initial learning rate, batch size, and number of epochs are set on **Lines 35-37**.

From there, our `imagePaths` are grabbed. We also initialize two lists to hold our `data` and class `labels` (**Lines 42-44**).

The loop on **Lines 46-55** builds our `data` and `labels` lists. The `data` consists of our images which are loaded and resized to be *32×32* pixels. Each image has a corresponding label stored in the `labels` list.

All pixel intensities are scaled to the range *[0, 1]* while the list is made into a NumPy array via **Line 59**.

Now let's encode our labels and partition our data:

liveness Detection with OpenCV

Python

```
61  # encode the labels (which are currently strings) as integers and then
62  # one-hot encode them
63  le = LabelEncoder()
64  labels = le.fit_transform(labels)
65  labels = np_utils.to_categorical(labels, 2)
66
67  # partition the data into training and testing splits using 75% of
68  # the data for training and the remaining 25% for testing
69  (trainX, testX, trainY, testY) = train_test_split(data, labels,
70          test_size=0.25, random_state=42)
```

Lines 63-65 one-hot encode the labels.

We utilize scikit-learn to partition our data — 75% is used for training while 25% is reserved for testing (**Lines 69 and 70**).

Next, we'll initialize our data augmentation object and compile + train our face liveness model:

liveness Detection with OpenCV

Python

```
72  # construct the training image generator for data augmentation
73  aug = ImageDataGenerator(rotation_range=20, zoom_range=0.15,
74          width_shift_range=0.2, height_shift_range=0.2, shear_range=0.15,
75          horizontal_flip=True, fill_mode="nearest")
76
77  # initialize the optimizer and model
78  print("[INFO] compiling model...")
79  opt = Adam(lr=INIT_LR, decay=INIT_LR / EPOCHS)
80  model = LivenessNet.build(width=32, height=32, depth=3,
81          classes=len(le.classes_))
82  model.compile(loss="binary_crossentropy", optimizer=opt,
```

```
83          metrics=["accuracy"])
84
85  # train the network
86  print("[INFO] training network for {} epochs...".format(EPOCHS))
87  H = model.fit_generator(aug.flow(trainX, trainY, batch_size=BS),
88          validation_data=(testX, testY), steps_per_epoch=len(trainX) // BS,
89          epochs=EPOCHS)
```

Lines 73-75 construct a data augmentation object which will generate images with random rotations, zooms, shifts, shears, and flips. To read more about data augmentation, read my previous blog post.

Our `LivenessNet` model is built and compiled on **Lines 79-83**.

We then commence training on **Lines 87-89**. This process will be relatively quick considering our shallow network and small dataset.

Once the model is trained we can evaluate the results and generate a training plot:

`liveness Detection with OpenCV`

Python

```
91  # evaluate the network
92  print("[INFO] evaluating network...")
93  predictions = model.predict(testX, batch_size=BS)
94  print(classification_report(testY.argmax(axis=1),
95          predictions.argmax(axis=1), target_names=le.classes_))
96
97  # save the network to disk
98  print("[INFO] serializing network to '{}'...".format(args["model"]))
99  model.save(args["model"])
100
101 # save the label encoder to disk
102 f = open(args["le"], "wb")
103 f.write(pickle.dumps(le))
104 f.close()
105
106 # plot the training loss and accuracy
107 plt.style.use("ggplot")
108 plt.figure()
109 plt.plot(np.arange(0, EPOCHS), H.history["loss"], label="train_loss")
110 plt.plot(np.arange(0, EPOCHS), H.history["val_loss"], label="val_loss")
111 plt.plot(np.arange(0, EPOCHS), H.history["acc"], label="train_acc")
112 plt.plot(np.arange(0, EPOCHS), H.history["val_acc"], label="val_acc")
113 plt.title("Training Loss and Accuracy on Dataset")
114 plt.xlabel("Epoch #")
115 plt.ylabel("Loss/Accuracy")
116 plt.legend(loc="lower left")
117 plt.savefig(args["plot"])
```

Predictions are made on the testing set (**Line 93**). From there a `classification_report` is generated and printed to the terminal (**Lines 94 and 95**).

The `LivenessNet` model is serialized to disk along with the label encoder on **Lines 99-104**.

The remaining **Lines 107-117** generate a training history plot for later inspection.

Training our liveness detector

We are now ready to train our liveness detector.

Make sure you've used the *"Downloads"* section of the tutorial to download the source code and dataset — from, there execute the following command:

liveness Detection with OpenCV

Shell

```
$ python train.py --dataset dataset --model liveness.model --le le.pickle
[INFO] loading images...
[INFO] compiling model...
[INFO] training network for 50 epochs...
Epoch 1/50
29/29 [==============================] - 2s 58ms/step - loss: 1.0113 - acc: 0.5862
val_acc: 0.7436
Epoch 2/50
29/29 [==============================] - 1s 21ms/step - loss: 0.9418 - acc: 0.6127
val_acc: 0.7949
Epoch 3/50
29/29 [==============================] - 1s 21ms/step - loss: 0.8926 - acc: 0.6472
val_acc: 0.8077
...
Epoch 48/50
29/29 [==============================] - 1s 21ms/step - loss: 0.2796 - acc: 0.9094
val_acc: 1.0000
Epoch 49/50
29/29 [==============================] - 1s 21ms/step - loss: 0.3733 - acc: 0.8792
val_acc: 0.9872
Epoch 50/50
29/29 [==============================] - 1s 21ms/step - loss: 0.2660 - acc: 0.9008
val_acc: 0.9872
[INFO] evaluating network...
              precision    recall  f1-score   support

        fake       0.97      1.00      0.99        35
        real       1.00      0.98      0.99        43

   micro avg       0.99      0.99      0.99        78
   macro avg       0.99      0.99      0.99        78
weighted avg       0.99      0.99      0.99        78

[INFO] serializing network to 'liveness.model'...
```

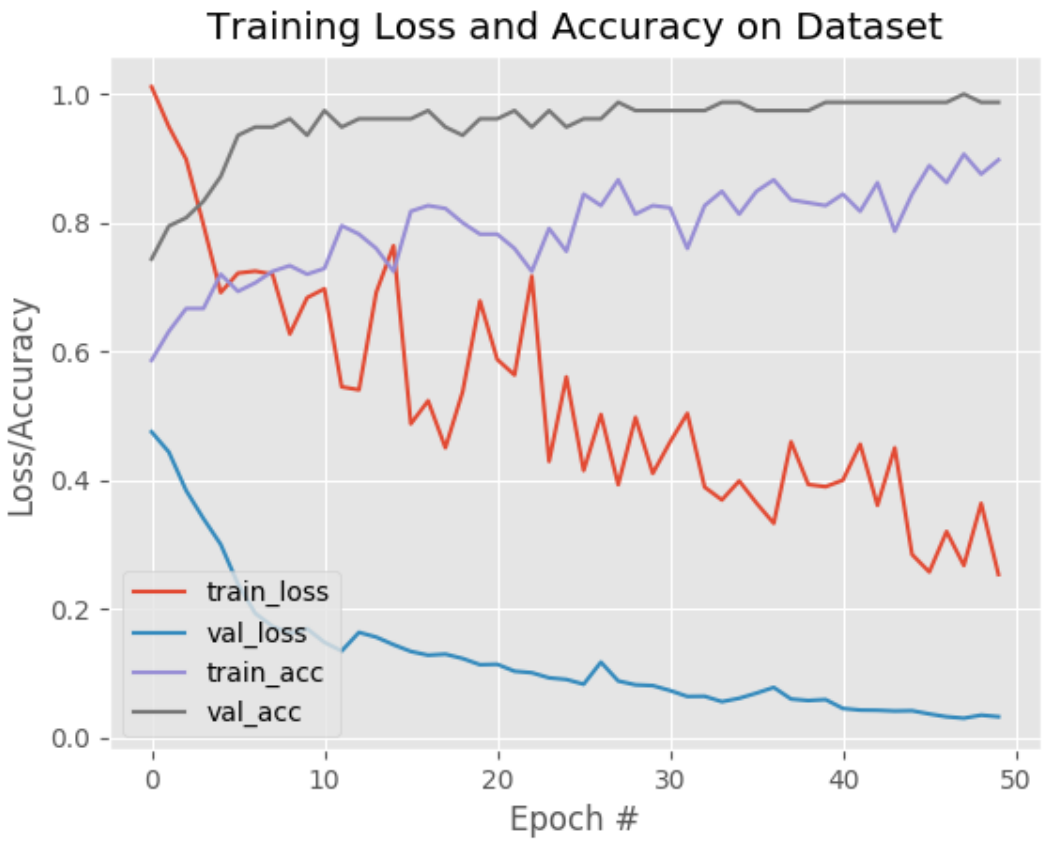


Figure 6: A plot of training a face liveness model using OpenCV, Keras, and deep learning.

As our results show, we are able to obtain 99% liveness detection accuracy on our validation set!

Putting the pieces together: Liveness detection with OpenCV

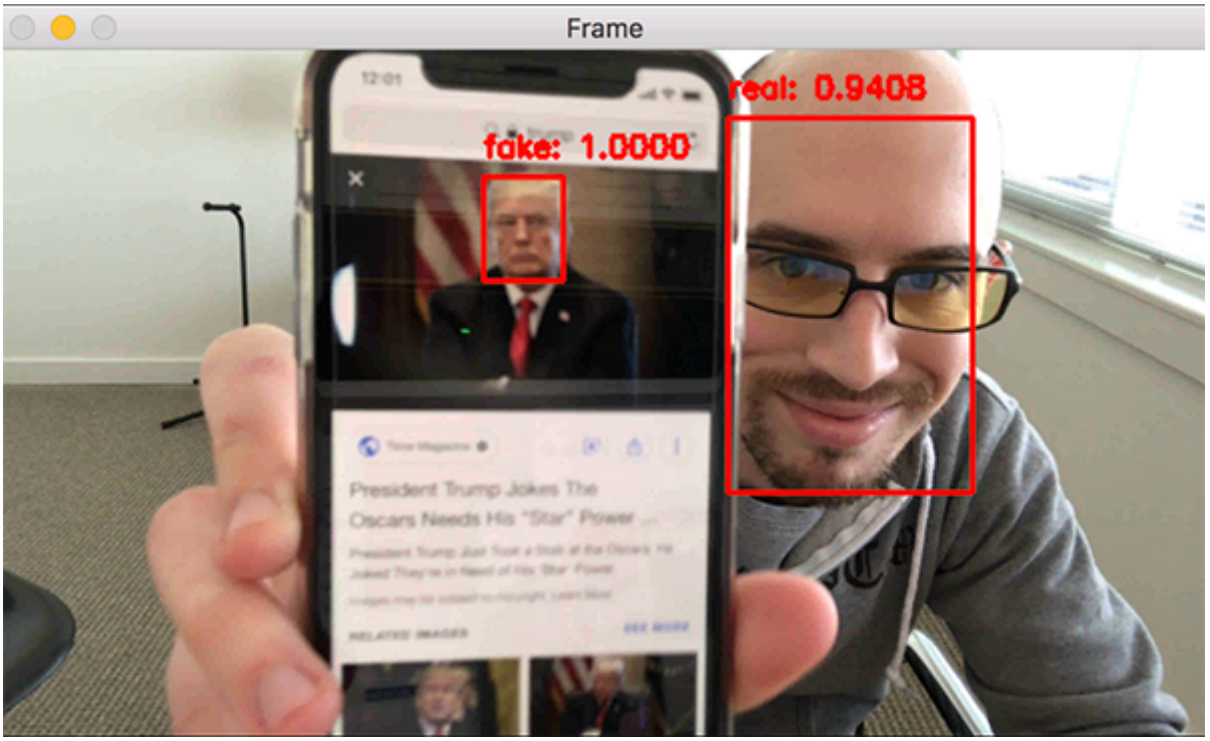


Figure 7: Face liveness detection with OpenCV and deep learning.

The final step is to combine all the pieces:

1. We'll access our webcam/video stream
2. Apply face detection to each frame
3. For each face detected, apply our liveness detector model

Open up the `liveness_demo.py` and insert the following code:

```
liveness Detection with OpenCV
Python
```

```python
# import the necessary packages
from imutils.video import VideoStream
from keras.preprocessing.image import img_to_array
from keras.models import load_model
import numpy as np
import argparse
import imutils
import pickle
import time
import cv2
import os

# construct the argument parse and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-m", "--model", type=str, required=True,
        help="path to trained model")
ap.add_argument("-l", "--le", type=str, required=True,
        help="path to label encoder")
ap.add_argument("-d", "--detector", type=str, required=True,
        help="path to OpenCV's deep learning face detector")
ap.add_argument("-c", "--confidence", type=float, default=0.5,
        help="minimum probability to filter weak detections")
args = vars(ap.parse_args())
```

Lines 2-11 import our required packages. Notably, we'll use

- `VideoStream` to access our camera feed.
- `img_to_array` so that our frame will be in a compatible array format.
- `load_model` to load our serialized Keras model.
- `imutils` for its convenience functions.
- `cv2` for our OpenCV bindings.

Let's parse our command line arguments via **Lines 14-23:**

- `--model` : The path to our pretrained Keras model for liveness detection.
- `--le` : Our path to the label encoder.
- `--detector` : The path to OpenCV's deep learning face detector, used to find the face ROIs.

- `--confidence` : The minimum probability threshold to filter out weak detections.

Now let's go ahead an initialize the face detector, LivenessNet model + label encoder, and our video stream:

liveness Detection with OpenCV

Python

```
25  # load our serialized face detector from disk
26  print("[INFO] loading face detector...")
27  protoPath = os.path.sep.join([args["detector"], "deploy.prototxt"])
28  modelPath = os.path.sep.join([args["detector"],
29          "res10_300x300_ssd_iter_140000.caffemodel"])
30  net = cv2.dnn.readNetFromCaffe(protoPath, modelPath)
31
32  # load the liveness detector model and label encoder from disk
33  print("[INFO] loading liveness detector...")
34  model = load_model(args["model"])
35  le = pickle.loads(open(args["le"], "rb").read())
36
37  # initialize the video stream and allow the camera sensor to warmup
38  print("[INFO] starting video stream...")
39  vs = VideoStream(src=0).start()
40  time.sleep(2.0)
```

The OpenCV face detector is loaded via **Lines 27-30**.

From there we load our serialized, pretrained model (`LivenessNet`) and the label encoder (**Lines 34 and 35**).

Our `VideoStream` object is instantiated and our camera is allowed two seconds to warm up (**Lines 39 and 40**).

At this point, it's time to start looping over frames to detect real versus fake/spoofed faces:

liveness Detection with OpenCV

Python

```
42  # loop over the frames from the video stream
43  while True:
44          # grab the frame from the threaded video stream and resize it
45          # to have a maximum width of 600 pixels
46          frame = vs.read()
47          frame = imutils.resize(frame, width=600)
48
49          # grab the frame dimensions and convert it to a blob
50          (h, w) = frame.shape[:2]
51          blob = cv2.dnn.blobFromImage(cv2.resize(frame, (300, 300)), 1.0,
52                  (300, 300), (104.0, 177.0, 123.0))
53
54          # pass the blob through the network and obtain the detections and
55          # predictions
56          net.setInput(blob)
57          detections = net.forward()
```

Line 43 opens an infinite `while` loop block where we begin by capturing + resizing individual frames (**Lines 46 and 47**).

After resizing, dimensions of the frame are grabbed so that we can later perform scaling (**Line 50**).

Using OpenCV's `blobFromImage` function we generate a `blob` (**Lines 51 and 52**) and then proceed to perform inference by passing it through the face detector network (**Lines 56 and 57**).

Now we're ready for the fun part — liveness detection with OpenCV and deep learning:

liveness Detection with OpenCV

Python

```
59          # loop over the detections
60          for i in range(0, detections.shape[2]):
61                  # extract the confidence (i.e., probability) associated with the
62                  # prediction
63                  confidence = detections[0, 0, i, 2]
64
65                  # filter out weak detections
66                  if confidence > args["confidence"]:
67                          # compute the (x, y)-coordinates of the bounding box for
68                          # the face and extract the face ROI
69                          box = detections[0, 0, i, 3:7] * np.array([w, h, w, h])
70                          (startX, startY, endX, endY) = box.astype("int")
71
72                          # ensure the detected bounding box does fall outside the
73                          # dimensions of the frame
74                          startX = max(0, startX)
75                          startY = max(0, startY)
76                          endX = min(w, endX)
77                          endY = min(h, endY)
78
79                          # extract the face ROI and then preproces it in the exact
80                          # same manner as our training data
81                          face = frame[startY:endY, startX:endX]
82                          face = cv2.resize(face, (32, 32))
83                          face = face.astype("float") / 255.0
84                          face = img_to_array(face)
85                          face = np.expand_dims(face, axis=0)
86
87                          # pass the face ROI through the trained liveness detector
88                          # model to determine if the face is "real" or "fake"
89                          preds = model.predict(face)[0]
90                          j = np.argmax(preds)
91                          label = le.classes_[j]
92
93                          # draw the label and bounding box on the frame
94                          label = "{}: {:.4f}".format(label, preds[j])
95                          cv2.putText(frame, label, (startX, startY - 10),
96                                  cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255), 2)
97                          cv2.rectangle(frame, (startX, startY), (endX, endY),
98                                  (0, 0, 255), 2)
```

On **Line 60**, we begin looping over face detections. Inside we:

- Filter out weak detections (**Lines 63-66**).
- Extract the face bounding `box` coordinates and ensure they do not fall outside the dimensions of the frame (**Lines 69-77**).
- Extract the face ROI and *preprocess* it in the same manner as our training data (**Lines 81-85**).
- Employ our **liveness detector model to determine if the face is *"real"* or *"fake/spoofed"*** (**Lines 89-91**).
- **Line 91 is where you would insert your own code to perform face recognition** but only on real images. The pseudo code would similar to `if label == "real": run_face_reconition()` *directly after* **Line 91**).
- Finally (for this demo), we draw the `label` text and a `rectangle` around the face (**Lines 94-98**).

Let's display our results and clean up:

liveness Detection with OpenCV

Python

```
100         # show the output frame and wait for a key press
101         cv2.imshow("Frame", frame)
102         key = cv2.waitKey(1) & 0xFF
103
104         # if the `q` key was pressed, break from the loop
105         if key == ord("q"):
106                 break
107
108 # do a bit of cleanup
109 cv2.destroyAllWindows()
110 vs.stop()
```

The ouput frame is displayed on each iteration of the loop while keypresses are captured (**Lines 101-102**). Whenever the user presses "q" ("quit") we'll break out of the loop and release pointers and close windows (**Lines 105-110**).

Deploying our liveness detector to real-time video

To follow along with our liveness detection demo make sure you have used the ***"Downloads"*** section of the blog post to download the source code and pre-trained liveness detection model.

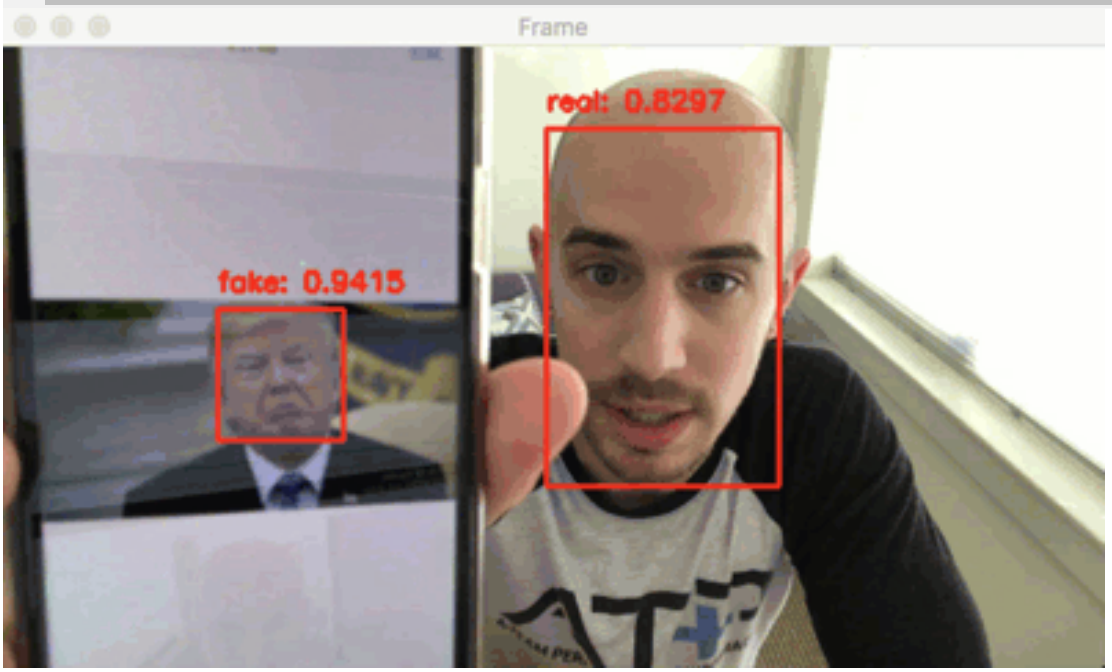
From there, open up a terminal and execute the following command:

liveness Detection with OpenCV

Shell

```
1 $ python liveness_demo.py --model liveness.model --le le.pickle \
```

```
        --detector face_detector
Using TensorFlow backend.
[INFO] loading face detector...
[INFO] loading liveness detector...
[INFO] starting video stream...
```



Here you can see that our liveness detector is successfully distinguishing real from fake/spoofed faces.

I have included a longer demo in the video below:

Limitations, improvements, and further work

The primary restriction of our liveness detector is really our limited dataset — there are only a total of **311 images** (161 belonging to the "real" class and 150 to the "fake" class, respectively).

One of the first extensions to this work would be to simply **gather additional training data**, and more specifically, **images/frames that are not of simply me or yourself**.

Keep in mind that the example dataset used here today includes faces for only *one* person (myself). I am also white/caucasian — **you should gather training faces for *other* ethnicities and skin tones as well.**

Our liveness detector was only trained on spoof attacks from holding up a screen — it was *not* trained on images or photos that were printed out.

Therefore, **my third recommendation is to invest in additional image/face sources** outside of simple screen recording playbacks.

Finally, I want to mention that *there is no silver bullet* to liveness detection.

Some of the best liveness detectors incorporate *multiple* methods of liveness detection (be sure to refer to the *"What is liveness detection and why do we need it?"* section above).

Take the time to consider and assess your own project, guidelines, and requirements — in some cases, all you may need is basic eye blink detection heuristics.

In other cases, you'll need to combine deep learning-based liveness detection with other heuristics.

Don't rush into face recognition and liveness detection — take the time and discipline to consider your own unique project requirements. Doing so will ensure you obtain *better, more accurate* results.

Summary

In this tutorial, you learned how to perform liveness detection with OpenCV. Using this liveness detector you can now **spot fake fakes and perform anti-face spoofing in your own face recognition systems.**

To create our liveness detector we utilized OpenCV, Deep Learning, and Python.

The first step was to gather our real vs. fake dataset. To accomplish this task, we:

1. First recorded a video of ourselves using our smartphone (i.e., "real" faces).
2. Held our smartphone up to our laptop/desktop, replayed the same video, and then *recorded the replaying* using our webcam (i.e., "fake" faces).
3. Applied face detection to *both sets of videos* to form our final liveness detection dataset.

After building our dataset we implemented, "LivenessNet", a Keras + Deep Learning CNN.

This network is *purposely* shallow, ensuring that:

1. We reduce the chances of overfitting on our small dataset.

2. The model itself is capable of running in real-time (including on the Raspberry Pi).

Overall, our liveness detector was able to obtain **99% accuracy** on our validation set.

To demonstrate the full liveness detection pipeline in action we created a Python + OpenCV script that loaded our liveness detector and applied it to real-time video streams.

As our demo showed, our liveness detector was capable of distinguishing between real and fake faces.

I hope you enjoyed today’ s post on liveness detection with OpenCV.