FAKE IMAGE IDENTIFICATION

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ABSTRACT: Recently fake images are more and more realistic with high-quality, even hard for humaneyes to detect. Due to these fake images many fields like forensics are facing problems, evenin social media also it became a problem because of the fake images. Many forensics peopleare trying to overcome this problem. As new types of fake images are emerging fast, thegeneralization ability of detecting new types of fake images is absolutely an essential task,which is also very challenging. In this project, we explore this problem and use machinelearning and image preprocessing to overcome this problem. In this project we are designingLBP Based machine learning Convolution Neural Network called LBPNET to detect fakeface images. Here first we will extract LBP from images and then train LBP descriptorimages with Convolution Neural Network to generate training model. Whenever we uploadnew test image then that test image will be applied on training model to detect whether testimagecontainsfakeimageor non-fakeimage

INTRODUCTION

Local binary patterns (LBP) is a type of visual descriptor used for classification in computervision and is a simple yet very efficient texture operator which labels the pixels of an imageby thresholding the neighborhood of each pixel and considers the result as a binary number.Due to its discriminative power and computational simplicity, LBP texture operator hasbecome a popular approach in various applications. It can be seen as a unifying approach tothe traditionally divergent statistical and structural models of texture analysis. Perhaps themost important property of the LBP operator in real-world applications is its robustness tomonotonic gray-scale changes caused, for example, by illumination variations. Anotherimportant property is its computational simplicity, which makes it possible to analyze imagesinchallengingrealtimesettings.TheLBP featurevector,initssimplestform,iscreatedinthefollowingmanner:Dividethe examinedwindowintocells(e.g.16x16pixelsforeachcell).

For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise orcounter-clockwise.Wherethe centerpixel'svalueisgreaterthantheneighbor'svalue,write

"0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted todecimal for convenience). Compute the histogram, over the cell, of the frequency of each"number" occurring (i.e., each combination of which pixels are smaller and which are greaterthanthecenter).Thishistogramcanbe seenasa256-dimensionalfeaturevector.3Optionally normalize the histogram. Concatenate (normalized) histograms of all cells. Thisgives a feature vector for the entire window. The feature vector can now be processed usingthe Support vector machine, extreme learning machines, or some other machine learningalgorithm to classify images. Such classifiers can be used for face recognition or textureanalysis. A useful extension to the original operator is the so-called uniform pattern,[8] whichcan be used to reduce the length of the feature vector and implement a simple rotationinvariant descriptor. This idea is motivated by the fact that some binary patterns occur morecommonly in texture images than others. A local binary pattern is called uniform if the binarypattern contains at most two 0-1 or 1-0 transitions. For example, 00010000 (2 transitions) is auniformpattern, but01010100 (6transitions) isnot.In thecomputation of theLBPhistogram, the histogram has a separate bin for every uniform pattern, and all non-uniformpatterns are assigned to a single bin. Using uniform patterns, the length of the feature vectorfor a single cell reduces from 256 to 59. The 58 uniform binary patterns correspond to theintegers 0, 1, 2, 3, 4, 6,7, 8, 12, 14, 15, 16, 24,28, 30, 31, 32, 48, 56,60,62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 207, 223, 224, 225,227, 231, 239, 240, 241, 243, 247, 248,249, 251, 252, 253, 254 and 255.

EXISTINGSYSTEM

Biometric systems are useful in recognizing person’s identity but criminals change theirappearance in behaviour and psychological to deceive recognition system. In this can’t solvetheproblem.

PROPOSEDSYSTEM

Now-a-days biometric systems are useful in recognizing person’s identity but criminalschange their appearance in behaviour and psychological to deceive recognition system. Toovercome from this problem we are using new technique called Deep Texture Featuresextraction from images and then building train machine learning model using

CNN(ConvolutionNeuralNetworks)algorithm.ThistechniquereferasLBPNetorNLBPNetasthis technique heavily dependent on features extraction using LBP (Local Binary Pattern)algorithm.

SYSTEMIMPLEMENTATION(Modules**)**

• GenerateNLBPNetTrain& TestModel

• UploadTestImage

• ClassifyPictureInImage

MODULESDESCRIPTION:

Generate NLBPNet Train & Test Model: In this module we will read all LBP images fromLBP folder andthen trainCNNmodelwithallthoseimages.

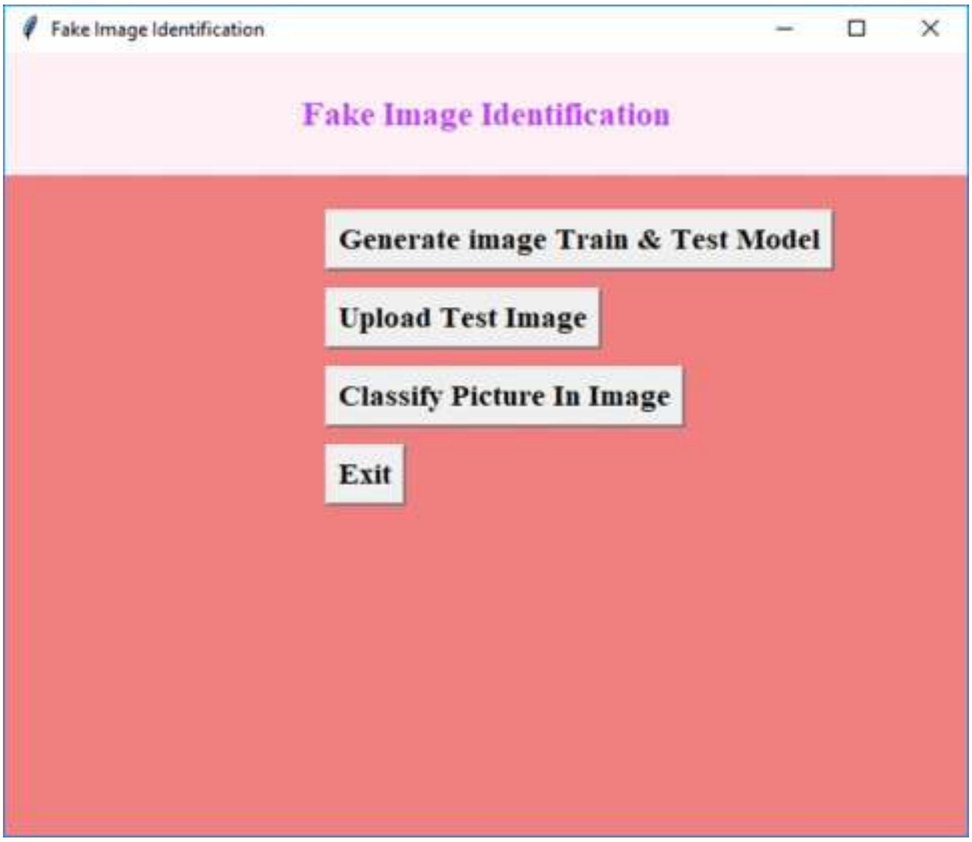
Upload TestImage:

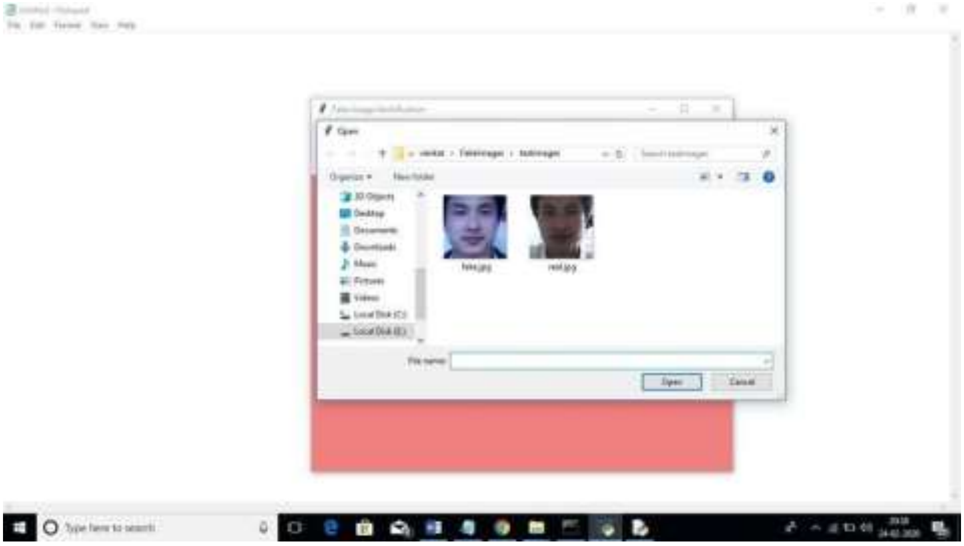
Inthis modulewewilluploadtestimagefrom‘testimages’folder.Applicationwillreadthisimageandthenextract DeepTexturesFeatures fromthisimageusingLBP algorithm.

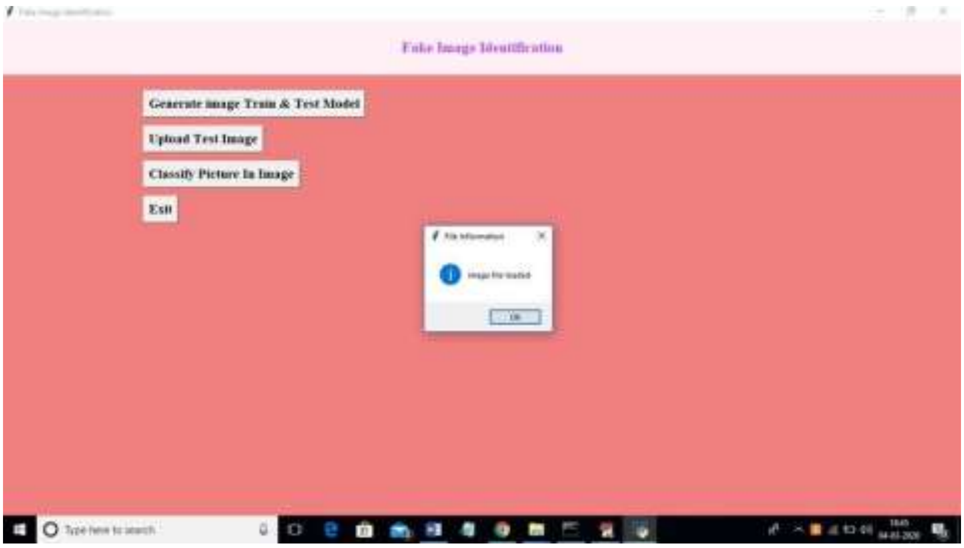
ClassifyPictureInImage:

Thismoduleapplytestimageon CNNtrainmodeltopredictwhethertestimagecontainsspoofor non-spoof face.

SAMPLESCREENS






Fake Image Identification
Generate image Train & Test Model
Upload Test Image
Classify Picture In Image
Exit


Fake Image Identification
Upload Test Image
Exit

CONCLUSION

We are designing LBP Based machine learning Convolution Neural Network called LBPNETto detect fake face images. Here first we will extract LBP from images and then train LBPdescriptorimageswithConvolutionNeuralNetworktogeneratetrainingmodel.Wheneverweupload newtestimagethenthattestimagewillbeappliedontrainingmodeltodetectwhethertestimagecontainsfak eimageornon-fakeimage.

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