Digital Image Forgery Detection using Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG)

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Abstract - *The detection of accurate forgery in digital images plays an exceedingly substantial role in the field of forensics and medical forgery. As forgery in images is a sensitive issue, utmost security and caution must be maintained while safeguarding it. This paper proffers an approach in order to detect authentic and tampered images by incipiently implementing the LBP (Local Binary Pattern) descriptor on the image and then the HOG (Histogram of Oriented Gradients) descriptor is applied on the extracted LBP features and finally they are classified into the two different classes: Authentic Images and Tampered Images, adopting the Support Vector Machine (SVM). The structured model implemented on the CASIA 1 and CASIA 2 databases signifies 92.3% and 96.1% rate of detection respectively. The time complexity is also considerably reduced and the method is found to be functioning well under diverse illuminating variation conditions.*

***Key Words*: Digital Image Forgery, Digital Image Authentication, Local Binary Patterns, Histogram of Oriented Gradients, Support Vector Machine, CASIA.**

1. INTRODUCTION

In the recent times, the interest in digital image forensics has grown exponentially with the ingress of new sophisticated cameras, smartphones and tablets. Social media such as WhatsApp, Facebook have further contributed to their extensive applications. Consequently, the editing tools like Photoshop, Picasa, and smartphone beautify apps for digitally manipulating digital images have also increased greatly, hence making it very trivial to easily manipulate the images. Several methods have been avowed to discern diverse manipulations in digital images, that encompasses resampling detection, detection of copy-move, object removal and splicing, machine learning, JPEG artifacts differentiating and deep learning techniques [1]. In [2], Farid and Popescu proposed a statistical method to determine fragments of image resampling and discrete cosine transform (DCT). Further, convolutional neural network (CNN), that shows excellent results in computer vision problems, has also been applied to detect various image distortions. Stamm and Bayar in [3] displayed excellent performance with CNN in detecting various image manipulation. Cozzolino et al. in [4], subsequently put forwarded a system network that provide significant detection performance in image forensics while making use of a small image training set through a local descriptor. These techniques, however, only apply to certain image manipulations and file formats and are limited to detecting manipulations in uncompressed images and do not reflect the real-world image forgery, where various image manipulations and superimposed compression occur. No previous study, as far as our knowledge and studies is concerned, has considered fusion of LBP and HOG descriptors in digital image forgeries even though they are widely used in Recognition of Facial Expression (FER) task and Face Recognition (FR) task [5]. In this paper, we contemplate fusing the LBP-HOG descriptors followed by Linear SVM [5] and performed on the CASIA 1 and CASIA 2 datasets [6] which outperforms many existing methods [7,8]. The system in [7] works on an image noise map, by applying a regression filter on the image noise map, and then feeds the output to the fusion of support-vector-machine (SVM) based and extreme-learning (ELM) based classifiers. Kim et.al in [9] proposed a two-stream neural network approach for image forensics, based on Convolutional Neural Network (CNN) and Markov characteristics.

The rest of the paper being systematized as follows. Section 2 illustrates our proposed method. Results and their Discussions are narrated in Section 3. Conclusion being asserted in Section 4.

2. PROPOSED METHODOLOGY

The system we proposed, encompass three functional blocks. The elemental function is to select the input frame from the database. The succeeding function block is to acquire the features using LBP descriptor and then applying HOG on the LBP extracted features. The SVM classifier training and classification constitute the endmost function step. Figure.1 shows schematic overview of our proposed system for detection of forgery in digital images.

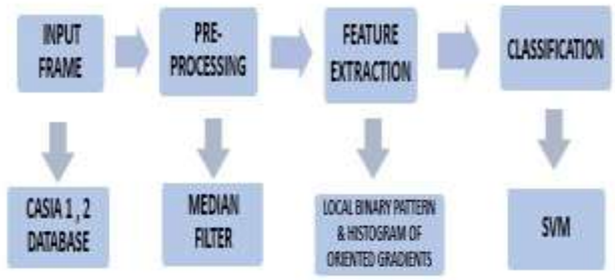

Figure -1: The Proposed Method of Forgery Detection

2.1 LOCAL BINARY PATTERN

Local Binary Pattern (LBP) [10] is primarily a texture measure operator which is gray-scale invariant. Initially, it was found to be a powerful feature for texture classification, but its application became widespread also in the fields of facial expression recognition, face recognition, etc. In LBP based descriptions, features can be efficiently derived and then combining the textures, the shape and all the dynamics in a feature vector. The first step of LBP descriptor modelling is converting the image to the grayscale. For every grayscale image pixel, the LBP operator, thresholding the 3×3 neighborhood with the center value, forms certain labels for the image pixels and considering a binary number as the result. The LBP coding of a pixel is done as following equation:

$$LBP^{K,R}(x_c,y_c) = \sum_{i=0}^{K-1} s(g_i^{K,R} - g_c)2^{(i-1)}$$

where, g_c is the gray scale value of the current pixel and g_i is the gray scale value of the i^{th} neighbour pixels.

The binary encoding function s(x) is defined as follows:

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

When the center pixel's value is larger than the neighbor's value, "0" is assigned, otherwise, a "1" is being assigned to it. For calculating the center pixel's LBP value, we can proceed in clockwise or counter-clockwise from any arbitrary neighboring pixel. This results in a binary number of 8-digit, converted to decimal. The endmost step is histogram computing over the LBP array. In our structured method, we used a 3 × 3 LBP operator on the input image and we obtain a feature vector.

2.2 HISTOGRAM OF ORIENTED GRADIENTS

Since HOG features are quite sensitive to object deformations, we propose to apply it. In 2005, Dalal and Triggs proposed "Histogram of Oriented Gradients" (HOG) [11]. HOG [11], is widely used in various object detection fields, predominantly in detection task of pedestrian.

HOG computes in an image the emergence of the gradient orientation in a local patch. The idea is to evaluate the local intensity and orientation distribution that could depict the local object shape and appearance [11]. The HOG can be computed in the basic five steps as follows:

1. Gradient Computation: At first, the LBP encoded image is being convoluted with the 1-D Sobel filters [-1, 0, 1] and $[-1,\ 0,\ 1]^T$ for forming respectively the horizontal gradient map and vertical gradient map.

2. Magnitude and Orientation Computation: Using the horizontal and vertical gradient maps, we can compute the magnitude and orientation map.

3. Image division: The features are divided into cells of size 10×10 pixels.

4. Quantization: Each cell orientation value is being quantized in histogram form using 8 orientation bins, where the values of magnitude represent voted weights.

5. Normalization: A block forms from four adjacent cells with each block having 50% overlapping with the adjacent one. The orientation histograms of each of the blocks are being normalized locally and then concatenated into a feature vector of 1-D. We resize the LBP feature vector to 50% of its original size and repeat the HOG steps on them. After that we concatenate the both the obtained HOG features and then we normalize them.

2.3 SUPPORT VECTOR MACHINE

Support Vector Machine [12] finds wide applications in the domain of pattern recognitions. In separating the various classes, the SVM achieves a separation level which is near optimum. In our study, by using the extracted features we train the SVM to perform the classification of the images i.e. Authentic or Tampered. The SVM, in general, separates the high-dimensional space by building a hyperplane. As the interspace between the data of training-set of any of the classes and the hyper plane is the largest, it is termed as the ideal separation. Given labelled samples of a training set:

$$D = (X_i, y_i) | x_i \in \{-1, 1\}_{i=1}^{p}$$

The SVM tries to acquire a hyper plane that distinguishes the samples having the smallest errors.

$$w.x - b = 0$$

For x_i ,an input vector, the classification process is achieved by evaluating the distance from x_i , the input vector to the hyper plane. The actual SVM is a binary classifier. However, for performing the multi-class classification, here we take the one-against-rest strategy.

3. EXPERIMENTAL RESULTS

In order to appraise our proposed approach, we make utilization of the two customarily used datasets: The CASIA 1 and CASIA 2 databases [8].

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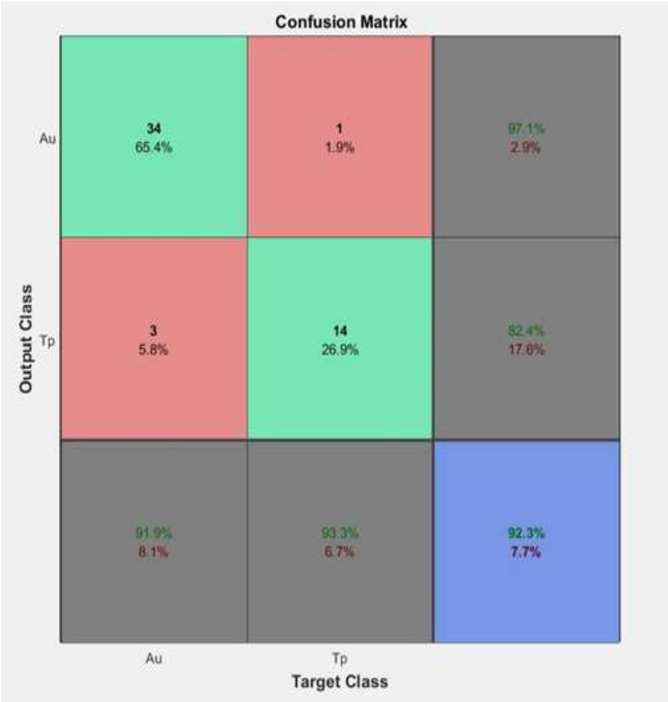

Figure -2: Accuracy Plot for CASIA-1 Dataset

The images here are resized to 256×256. When the input image is fed, at first, we apply the 5×5 median filter. Subsequently the techniques of the proposed method are applied for acquiring the features. The CASIA 1 and CASIA 2 datasets contains images of different subjects like animal, art, archaeology, nature, etc. of two classes: Authentic and Tampered images. Of all the various subjects of the two datasets, from each one of the datasets of Authentic and Tampered images, we selected randomly the images of each of the two categories to constitute the training set and also the test dataset. Finally, in the training set, there were 321 images and the test data set have 58 images. Then, we train the SVM on the train dataset and subsequently check the result by enquiring an image from the test dataset to check if the enquired image is correctly recognized. The plot of the confusion matrix of CASIA 1 and CASIA 2 are shown in Fig.2 and Fig.3 respectively.

Table-1: Comparison Table

METHOD	RECOGNITION RATE
SVM + ELM [7]	84.3%
FCID [8]	85.37%
CNN + Markov [9]	86.11%
PROPOSED METHOD	96.1%

Table-1 gives a comparative study of our structured proposed method to existing methods. Our method worked siginificantly and has a high accurate rate of detection irrespective of rotation and scaling.

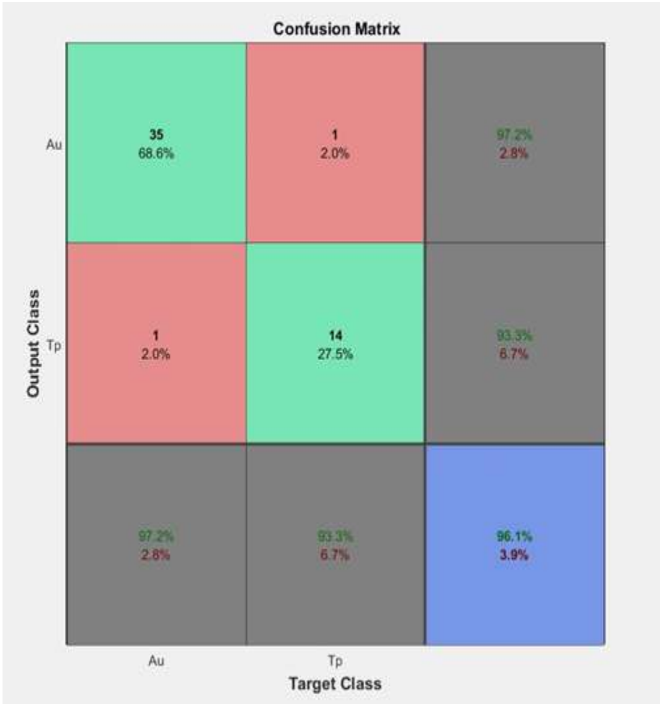

Figure -3: Accuracy Plot for CASIA-2 Dataset

4. CONCLUSION

We propose an effective method in this paper to handle the problem of Digital Image Forgery Detection. Forgery in digital images like copy-move forgery, leaves little traces of spikes or edges. These subtle spikes or changes are described by the LBP and HOG features, that are very sensitive to the shape of objects. The features are then used to train an SVM classifier. Experimental results on the CASIA 1 and CASIA 2 database signifies that the proposed method consummates a significantly good accuracy, the accuracy being respectively 92.3% and 96.1%. Also, the method we proposed here consumes much lesser time. The task of forgery detection is very exacting. More efforts to improve the recognition accuracy is to be necessitated for vital applications. Our future work objective is improving the performance accuracy of the method in the medical images and in multimedia (video) applications.

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