A State of Method for detecting forged images based on SVM Classifier

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Abstract –In the modern era of social media, the general public is exposed to a lot of visual imagery and stands to get easily affected by it. In such a world, detecting forged images is a prime concern. A forged image might cause riots, wars, change election results, or malign an individual forever. In this paper, a method is proposed to identify images in which tampering or forgery has occurred. Feature sets are extracted from a standard database and SVM classifier is used for classification purpose. The features are extracted using sub-pixel edge detection and GLCM features. The edge image is converted into feature vector using HOG descriptors.

Keywords –Forgery Detection, SVM, Sub-pixel Detection, Glcm features.

1. Introduction

In cyber-crime investigations, computer forensics is used to gather proofs which can be admissible for establishing the crime. One such aspect of computer forensics is forgery detection in images. Since there is a lot of powerful image processing software such as Photoshop, Corel Draw available to everyone, identifying the authenticity of forgery images is becoming a daunting task.In recent years, a lot of methods have been proposed for the detection and localization of digital image forensics [1]. There are three main areas in digital image forensics–

Image Source Identification to identify the device which was used to acquire the image,

Discrimination of Computer-Generated Images to detect if an image is natural or synthetic

Image Forgery Detection to detect if an image was tampered. There are different ways in which an image can be tampered such as photo compositing, retouching, enhancing etc.In image retouching, some features of the image are improved for visual aesthetics. One of the most difficult kinds of tampering to detect is the copy-move forgery [4] in images. In copy-move forgery some part of the image is copied and then replicated over some other part.

Digital image forgery detection methods use different mechanisms but in almost all method one thing which is common is the feature extraction. The feature can be extracted for all the pixels which would be computationally expensive and is known as dense-field features. Other than that,we can calculate features for selected pixels also known as key points. These features are known as sparse-field features. The first robust keypoints -based algorithm was proposed in [2], where SIFT features are used to deal with different kinds of invariance. Other than that, the key points characterized by other descriptors such as SURF [4], LBP [5], and DAISY [6] have also been used in image forgery detection .In order to improve the overall accuracy of the classifier, we are also taking dense-field features based on texture.

A forgery detection methodology uses minute inconsistencies within the edges and intensity of the images for its operation. So, by extracting edge-based and texture-based features it is possible to detect forgery in images. An SVM classifier is used for training the classifier. The database used in this paper is a standard database – the COMOFOD database.

In the proposed methodology, subpixel-basededge detection techniques are used.Edge detectors can be based on gradient or second derivative. Gradient operators generate high peaks at edge locations. In order to generate proper edges, the gradient operator is followed by thinning operation or maximum detection step to reduce redundancy in edges.Second derivative operators give a response of zero-crossing on edge locations.

2. Proposed Methodology

The proposed method is an area of digital image forensics. In order to provide additional security, we have used the AES algorithm. To access the system, the password has to be provided which is stored in AES encrypted format. To extract the sparse-field features, we are using asubpixel edge detector. The edge features are stored used HOG (Histogram of Oriented Gradient)

descriptors. The dense-field features are extracted using GLCM (Gray Level Cooccurrence Matrix). The final feature set is given for training using SVM (Support Vector Machine) classifier.

2.1 AES Algorithm

AES algorithm is used because it is a secure encryption algorithm and it also has high speed. It encrypts data in terms of 128-bit blocks in 10, 12 and 14 rounds.The steps involved in AES encryption are as such

1. Initialize state array and add the initial round key to the starting state array.
2. Perform Usual round 1 to 9
3. Execute final round

The round function consists of four steps

1. Subbytes: substitute every byte of the state with an S-box entry.
2. Shiftrows: cyclically left shift every row $i$of the state matrix by i, $0 \leq i \leq 3$
3. Mixcolumns: multiply each column, taken as a polynomial of degree less than 4 with coefficients in range 0 to 256, by a fixed polynomial, modulo $x^4 + 1$
4. AddRoundKey: xors the r-th round key into the state.

In the final round, the mix column step is not executed.

2.2 Subpixel Edge Detection

Optimized Filtering

The derivative of any image provides with anumber of insignificant edges. These edges have to be removed by usingthe filtering process. The filtering process will be based on the optimization of SNR (signal to noise) ratio, edge localization, and nonmultiplicity of the process.To do this, we use a spatial gradient which is a first, second or third order IIR (Infinite Impulse Response) filters.The first order operator is given as

$$g(x) = ce^{-\alpha|x|}$$

$$f(x) = sign(x)\, de^{-\alpha|x|}$$

The function g(x) is the impulse response of the regularization filter and f(x) being the impulse response of the derivative filter. After sampling and normalization, the function can be given as

$$F(z) = (e^{-\alpha} - 1).(z^{-1} - z).\frac{1}{1 - e^{-\alpha}z^{-1}}.\frac{1}{1 - e^{-\alpha}z}$$

$$G(z) = (1 - e^{-\alpha})^2.\frac{1}{1 - e^{-\alpha}z^{-1}}.\frac{1}{1 - e^{-\alpha}z}$$

The α is the width of the filter. If the filter has a larger width, the filter will only perform smoothing instead of edge detection. $f[k]$ and $g[k]$ are the corresponding sampled impulse responses.

Subpixel Gradient Estimation

If $e[k]$is the initial discrete signal, its interpolated version can be given by

$$e(x) = \sum_{k=-\infty}^{k=\infty} u[k]\, \beta^n(x - k)$$

Where $\beta^n(x)$is a B-spline function of order n and where the interpolation is such that: $e[k] = e(x)|_{x=k}$.The impulse response f(x) is decomposed on a p-order B-spline basis as

$$f(x) = \sum_{k=-\infty}^{\infty} h[k]\beta^p(x - k)$$

The figure shows the cubic B-spline interpolation of a discrete step.

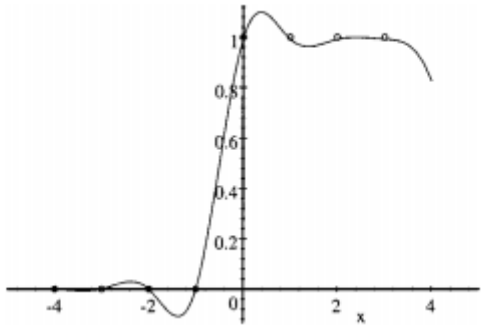


Figure 1 Cubic B-spline interpolation of a discrete step

For a continuous gradient estimation, we use the function s(x) which is computed in two steps. The first one consists in discrete convolution products

$$v[k] = \left(e * f * b^{n}_{-1} * b^{p}_{-1}\right)[k]$$

The second step is the summation for a given x, on a finite number of integer values weighted by the masks defined by B-spline functions of the order $n + p + 1$.

$$s(x) = \sum_{k} v[k]\beta^{n+p+1}(x-k)$$

The interpolation must be done to the closest pixel. In case of the 2D images, this gradient estimation expression is given a separable manner

$$\nabla_x e(x,y) = \sum_{l=-\infty}^{\infty}\sum_{c=-\infty}^{\infty} v[l,c]\beta^{n+p+1}(x-c) \times \beta^{n+p+1}(y-l)$$

Here $v[l,c]$ is obtained by separable filtering of input signal following

$$\frac{V(z_1,z_2)}{E(z_1,z_2)} = \frac{F(z_2)G(z_1)}{B^n(z_1)B^p(z_1)B^n(z_2)B^p(z_2)}$$

Interpolation masks $\beta^{n+p+1}(x-c)$ and $\beta^{n+p+1}(y-l)$ are applied separately on rows then on columns.

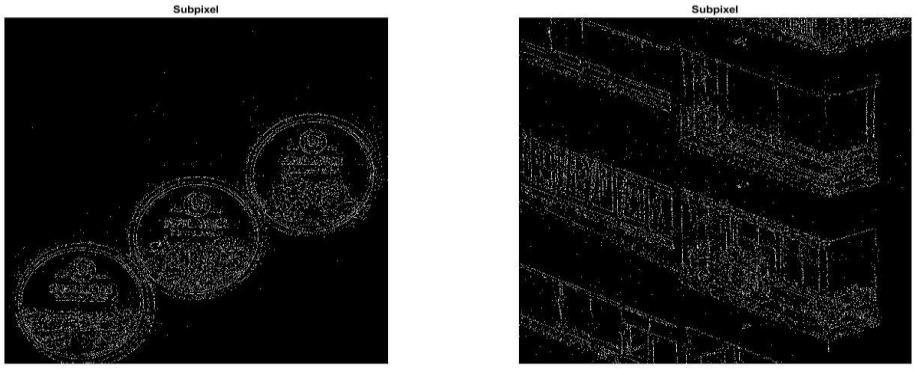


Figure 2 : Sub-pixel results for some of the images.

2.3 HOG Descriptors

HOG is a window-based detector used locally to detect keypoints. The window is centred upon the keypoint and divided into a regular square grid. Inside each section of the grid, frequency histogram is computed to represent the distribution of edge orientations inthat section. The edge orientations are calculated as arctans and then quantized into a fixed number of bins. The HOG representation is inspired by the SIFT descriptor proposed by Lowe [15]. It is created by dividing the tracking regions into non-overlapping grids and then calculating the orientation histogram of the image gradient of each grid. Let $I \in \mathbb{R}^{mxn}$ denote an image of width $m$and height$n$, and $I(x,y)$denote the pixel intensity in position (x,y).The HOG descriptor can be calculated as follows:

1. The image I is filtered with a symmetric low-pass Gaussian filter of size w_g with standard deviation σ_g. Then we compute the image gradient along the x and y-direction by a one-dimensional centred mask
   $g_x(x,y) = I(x+1,y) - I(x-1,y) \quad \forall x,y$
   $g_y(x,y) = I(x,y+1) - I(x,y-1) \quad \forall x,y$
2. The magnitude $m(x,y)$and orientation $\theta(x,y)$of the image gradient is computed by
   $$m(x,y) = \sqrt{g_x(x,y)^2 + g_y(x,y)^2}$$

$$\theta(x,y) = tan^{-1}(g_y(x,y)/g_x(x,y))$$

3. The image is partitioned into $s_w \times s_h$non-overlapping grids. For each grid, the orientation $\theta(x,y)$ for all pixels is quantized into s_b orientation bins weighted by its magnitude$m(x,y)$.
4. Each feature is normalized by the sum of all features to generate the HOG descriptor of the image.

In conclusion, it can be said that HOG is used so that the image can be characterizedin terms of local appearance and shape.

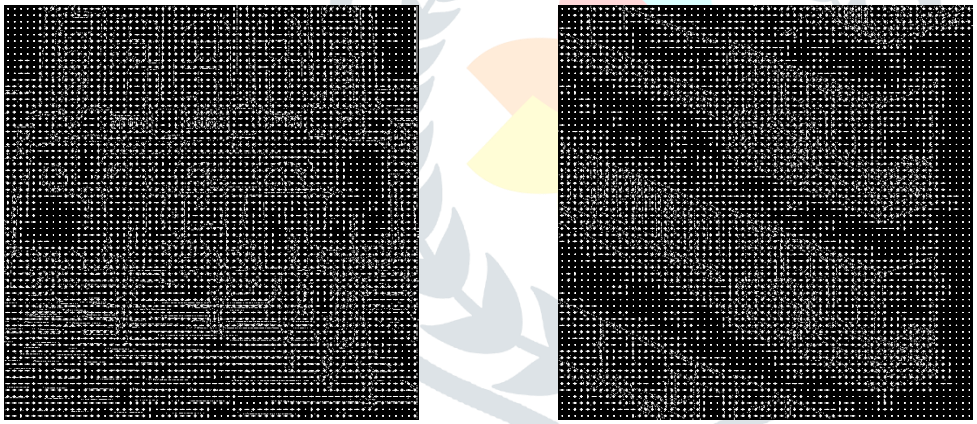


Figure 3 HOG Values of database images

2.4 GLCM Features

Texture Feature extraction can be used for dense-field features as it reduces a large amount of data required to represent the images. The texture is an important characteristic of an image. In the proposed method GLCM is used to obtain the statistical texture features. In GLCM, texture features are calculated from the statistical distribution of observed combinations of intensities at fixed positions with respect to each other in the image. According to the number of pixels in each combination, features are classified into first-order, second-order and higher-order features. The GLCM is used to extract second-order features .A GLCM matrix has the same number of rows and columns as the number of gray levels in the image. The matrix element$P(i,j|\Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance $(\Delta x, \Delta y)$, occur within a given neighbourhood, one with intensity 'i' and the other with intensity 'j'. The matrix element $P(i,j|d,\theta)$ has the second order probability values for changes between gray levels i and j. Using a large number of intensity levels will make the matrix size larger.So the number of gray levels is often reduced.The features used in the proposed method are:

1) Contrast

It represents the variance in the gray level

$$contrast = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i-j)^2P(i,j)$$

2) Homogeneity

It is high when the local graylevel is smooth.

$$homogeneity = \frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}P(i,j)}{1+(i-j)^2}$$

3) Angular Second Moment (ASM)

It is also known as uniformity or energy. It is the sum of squares of entries. When pixels are very similar, ASM value is very high.

$$ASM = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}P_{ij}^2$$

4) Dissimilarity

It is similar to contrast and it is high if the region has high local contrast

$$dissimilarity = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i-j)P(i,j)$$

5) Mean

$$\mu_{ij} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}ijP(i,j)$$

6) Variance

$$\sigma_{ij} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(1-\mu_{ij})P(i,j)$$

7) Entropy

It represents the amount of data from the image which is required for the image compression. Itquantifies the loss of information or message in a transmitted signal and also measures the image information.

$$entropy = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}-P_{ij} * logP_{ij}$$

8) Maximum Probability

It is the largest value found in the GLCM matrix.

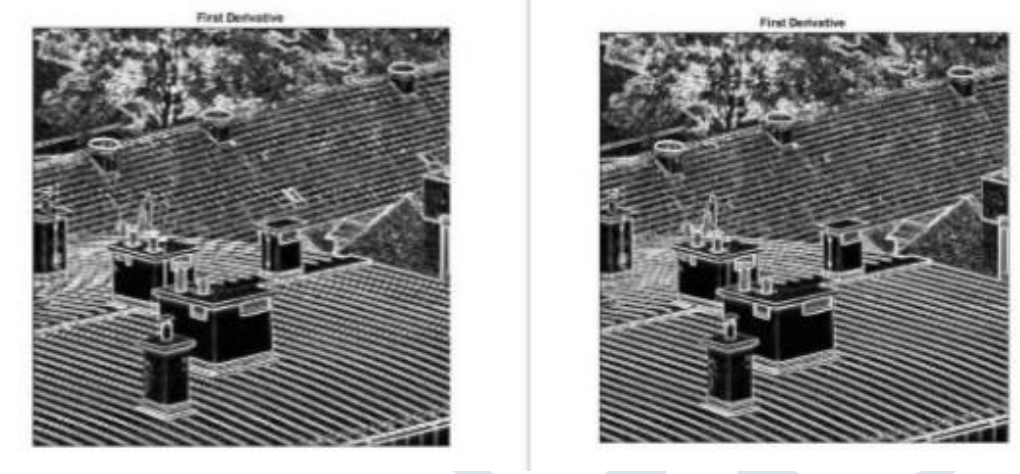
2.5 SVM Classifiers

The set of features obtained in the previous section is used to train an SVM. It is employed for image forgery detection because it is a two-class problem. SVM is a machine-learning classifier which involves testing and training stages.With the two-class problem, training patterns (a_i, b_i) are given where $i = 1, 2, \ldots M$, $a_i \in R_d$,$b_i \in \{-1,1\}$. Here a_i is a feature vector of the training set, b_i is the class label, -1 and +1 point of the two classesC_1 and C_2. The final aim is to create a classifier from the existing features which reduce the probability of misclassification of a new feature. This is done by creating an optimal hyper-plane

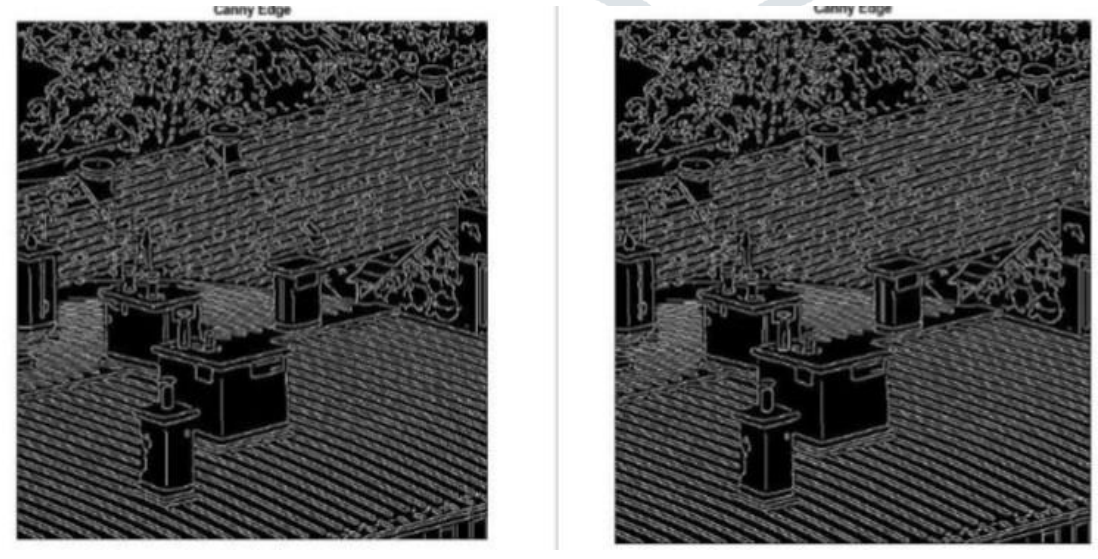
$g(a) = C^T x + C_0 = 0$ which locates the maximum margin for classification with better performance.The margin is the smallest distance between the nearest data points of each class and the hyperplane.

3. Results:

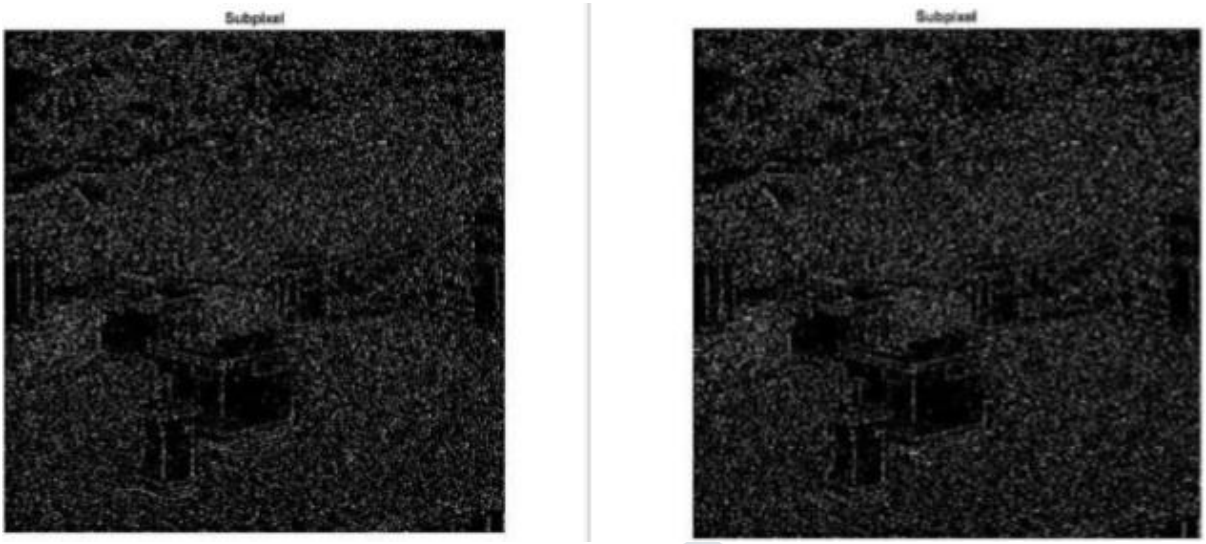
Figure showing orginal and froged images



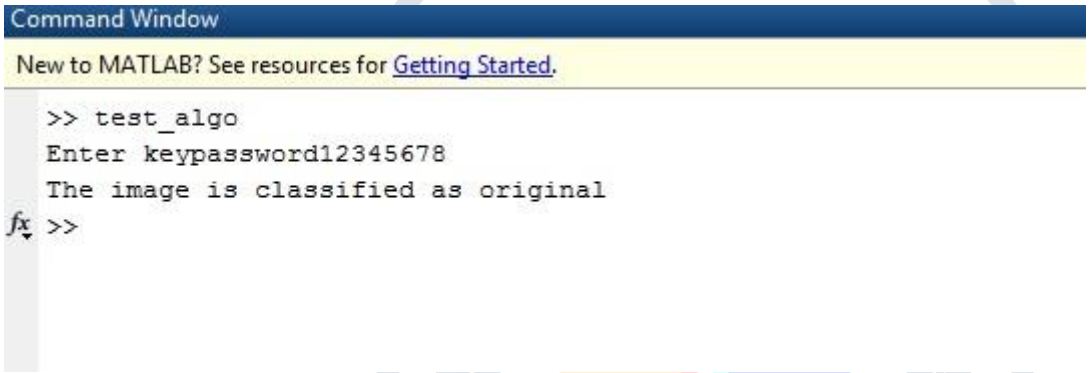
Figures showing first derivative of orginal and froged images



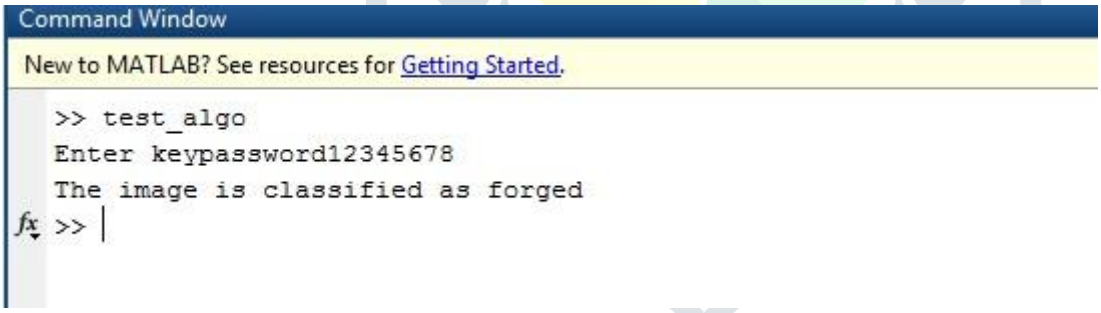
Figures showing canny edge detection of orginal and forged images



Figures showing subpixel edges of orginal and froged images



Our simulator classification for orginal image



Our simulator classification for froged image

Glcm feature comparison for orginal and forged datasets

Orginal database		Forged database		
Contrast	**5.688**	**2.3456**	**5.7046**	**2.3452**
Hommogenity	**0.7110**	**0.8661**	**0.7101**	**0.8658**
Angular second moment	**0.1741**	**0.2282**	**0.1731**	**0.2274**
Dissimilarity	**1.1958**	**0.5222**	**1.1997**	**0.5231**
Glcm_mean	**4.3286**	**4.3336**	**4.3327**	**4.3377**
Glcm_variance	**2.7999**	**2.7000**	**2.8021**	**2.7080**
Entropy	**2.3833**	**2.0138**	**2.3877**	**2.0167**
Maximum probability	**0.3758**	**0.4161**	**0.3744**	**0.4150**

4.Conclusions

For evaluation of the proposed method, we have used COMOFOD database. This database consists of five different kinds of tampering. The method is based on the derivation of dense-field and sparse-field features .For dense-field statistical texture features were used. For sparse-field HOG descriptor of the sub-pixel based edges is used. The results show that the proposed method is able to detect forgery in images with an accuracy of 80 percent. It is also noteworthy that the proposed method can be also used in other tampering operations detection.By using SVM, the proposed method is capable of identifying new forgeries without any previous knowledge. The proposed method has been tested on png images and in the future, we can analyze the effect of different file formats in the performance of the proposed method.

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