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Frequency based Digital Image Forgery Detection Through Optimal Threshold Using SOELTP

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Abstract

INTRODUCTION: Image forgery detection is a very challenging task now a day. Latest tools and applications make it easy. Artefact change our thought and perceptions.
OBJECTIVES: A forgery detection system is a need of time to detect image forgery.
METHODS: We proposed a blind image forgery detection technique. Optimal threshold-based Enhanced Local Ternary Pattern (OELTP) technique implemented on smoothed image. Features are extracted in the form of frequency to implement Discrete Wavelet Transform (DWT) on the chrominance component of the image. Support Vector Machine is used for classification.
RESULTS: The accuracy of the forgery detection on the proposed technique is better than some of the previous states of work.
CONCLUSION: Image forgery detection system performance has been improved by better localization of the forgery. Performance of the global threshold improved by using the latest technique, and reducing the operational complexity.

Keywords: YCbCr, DWT, SOELTP, ELTP, Accuracy.

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1. Introduction

Image forgery is not a current-day problem, it's happened from decay ago. The latest software tools and techniques make it easy as fingertips. Now a day sharing of information through images is widespread. The number of social networking sites plays a significant role in spreading fake news. Post-processing is implemented on images for their better appearance, but people do this to spread fake news and fill their desire through wrong evidence. Directly or indirectly, people are misusing these tools. As per research, it is found that the effect of image on the mind is very long-lasting compared to others. It changes our perceptions about what we should eat, wear, etc. If we observe, then we will find a lot of fake images surrounding us. These fake images change our perceptions to see our past and affect our present and future also. So need to develop such a system that detects the image's forgery to verify the authenticity of the image. Image forgery is categorized into two groups, Active and Passive shown in fig. 1. In active, images are prevented by watermarks or digital signature. In passive, it's further divided into two groups copy-move and splicing. In copy-move forgery, a single image is used to copy some part of the image and pest some ware in the same image. In splicing, number of different images is used to copy and paste some ware in another image. Splicing technique is also known as blind because there is no previous information about the image. Number of operations performed on images like resampling, filtering, contrast enhancement for mainly two purposes, first to hide traces of the image, and second for retouching. In this paper, we proposed an image splicing forgery detection technique to detect the forgery of the image. Two operations are performed on them, Training and Testing. In training, features of the original and forged image have been extracted through the feature extraction technique and trained the system after classifying it. In testing, features are extracted by original and forged images such as training, and it test to find the image is forged or not with the classifier. Fig. 2 shows the image splicing detection technique.

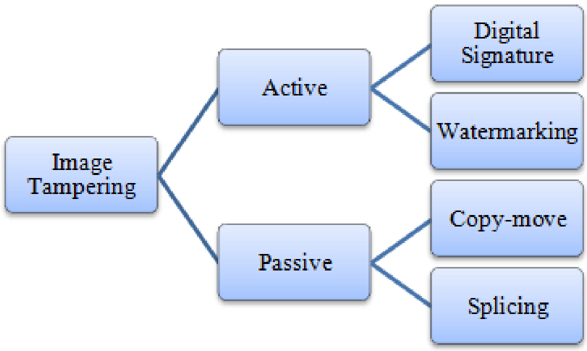

Figure 1. Image Tampering Detection Techniques

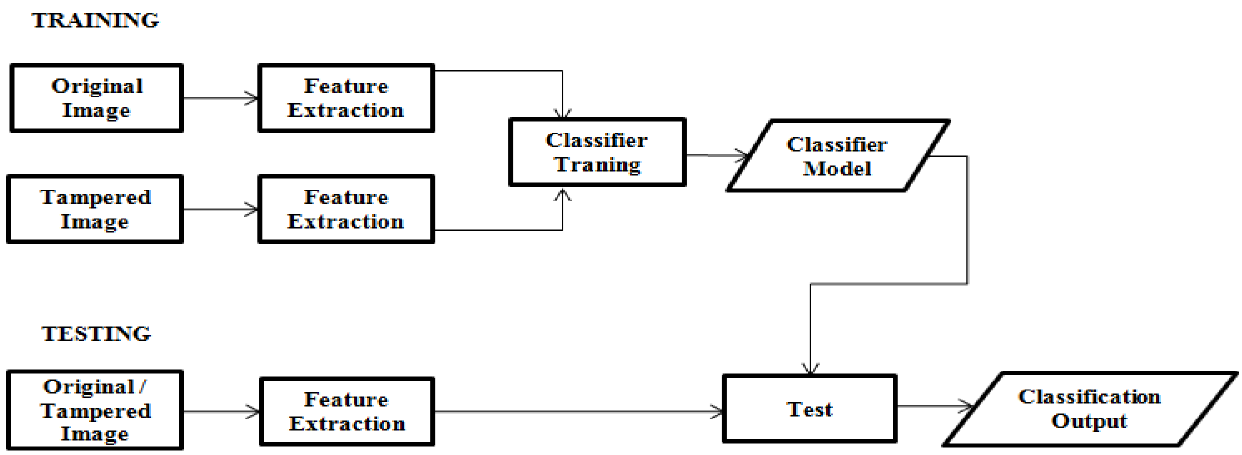

Figure 2. Architecture of Image Splicing Detection Technique

2. Literature Review

Image forgery is very common now. Different techniques are implemented on images to generate forged image based on feature extraction through various approaches like illumination, JPEG compression, camera-based property or limitations, and so on. In Paper, Alahmadi et al. [1] have discussed, chrominance colour component of YCbCr colour channel is much more feasible for forgery detection. Features are extracted through LBP by DCT. Features are classified by SVM. In paper, P. Cavalin et al. [2] had implemented, texture descriptor-based local binary pattern (LBP) technique on traditional gray level co-occurrence material (GLCM). CNN and multi-scale patch-based recognition were used as a fisher vector. In paper, Cortes C, Vapnik V [3] had defined, SVM as a very simple to use and reliable classifier. It's works like a learning machine used for classification. SVM is following the linear mapping technique, implemented over a very high dimensional feature vector. It's also reliable to implement over non-separable training data. Dong J et al. [4] represent the features of the CASIA images data sets and inform their versions. How it becomes effective to use as a database. In paper, Goh J, Thing VL [5] has proposed, a hybrid framework used to develop the best feature set for existing all possible features of the image tampering. In paper, Hakimi et al. [6] had detected, image forgery identifies to implement LBP in DCT. The chrominance component of the colour is used to identify the non-overlapping blocks. Frequency-based features extraction technique is implemented using K-Nearest Neighbour (KNN) algorithm to classify the image. In paper, Hakimi et al. [7] use the chrominance colour component to divide the non-overlapping block. To extract features from the overlapping block, LBP is implemented with wavelet transform through principal component analysis (PCA). SVM is used for classification to identify an image is forged or not. In paper, He Z et al. [8] had proposed, the run length is detected by an edge gradient-based matrix. DWT is used to find more feature. With the help of the approximation coefficient (Low-Low) band, more features are extracted in DWT. Features are classified by support vector machine (SVM) to identify forgery. In paper, He et al. [9] used the Markov approach to identify the image forgery, a Block-based feature extraction technique implemented through DCT coefficient on intra-block and inter-block. In Paper, Hsu, Chang et al. [10] had defined that every camera has different intensity, generating geometry invariants of the pixels. The noise of camera used as a fingerprint to identify image splicing, and used to generates a difference between pixel intensity. In paper, Muhammad et al. [11] is used the chrominance colour component of the image to extract the feature through LBP histogram by steerable pyramid transform (SPT). Features are classified by support vector machine (SVM). In paper, Kanwal, N. et al. [12] had used Otsu-based optimal threshold by mean absolute deviation to extract the feature of the image. The energy of the OELTP is used as a primary feature of each block for dimensionality reduction. In paper, Ojala et al. [13] had implemented rotation invariant technique to the excess uniform pattern over grayscale image to quantize the regular space for special resolution. Multiple operators are used for multi-resolution analysis. Shah A, El-Alfy ES [14] has proposed a novel approach for forgery detection to implement multi-level LBP on DCT. In paper, Cortes, Tan, Truggs [15] has proposed three value codes (0, 1, -1) to implement LTP on image. The LBP is used two value codes (0, 1) to excess the feature in depth. The performance of LTP is reliable compare to LBP in noise sensitivity. In paper, Yao et al. [16] has discussed, noise has been generated on the image after post processing operations which generate an important role in forgery detection. Noise level function (NLF) is used to characterize noise. Image intensity is used to generate a relation between NLF and camera response function (CRF) for forgery detection. Image intensity differences have defined image splicing. In paper, Yuan JH et al. [17] had discussed the advanced LTP approach in the form of ELTP technique. The complete enhanced local ternary pattern (CELTP) concept is used for feature extraction. Threshold has been generated through auto adaptive strategy on behalf of traditional gray value of the central pixel.

3. Proposed Technique

The block-based feature extraction technique has been proposed in this paper. It's an advanced image splicing detection technique due to its local feature extraction ability. In this proposed work Overlapping block-based feature extraction technique is used to extract the feature. Three different open-access data sets, CASIA v1.0, CASIA v2.0, and Columbia are used to implement the proposed work. The chrominance colour component of YCbCr colour image is used to extract the feature because Cb and Cr are highly reliable in forgery detection [18]. The effect of the chrominance component is shown in Fig. 3. The discrete wavelet transform (DWT) technique is implemented on the image to hold the feature in the form of frequency. DWT break the image component into four frequency band (LL, LH, HL, HH). It gives satisfactory results in texture classification and edge detection [19]. We proposed a unique features extraction technique, Smoothing Otsu-based Enhanced Local Ternary Pattern (SOELTP) to identify the feature of the image. In this proposed work, before implementing OELTP on the image, a smoothing technique was implemented over the image's approximation coefficient (LL band). The otsu-based dynamic threshold value is used to generate the effect of ELTP on images for feature extraction. The architecture of the proposed technique is shown in Fig. 4. The enhanced local ternary pattern (ELTP) is used ternary values (0, 1, -1) to find the difference in the intensity of the neighbor pixels. In this proposed work, the 3x3 image mask is used to implement the proposed work. DWT generates the frequency-based features, and novel features are extracted after applying the OELTP technique over smoothing images. It's normalized by K-fold technique and classified by SVM to know the image is forged or not.

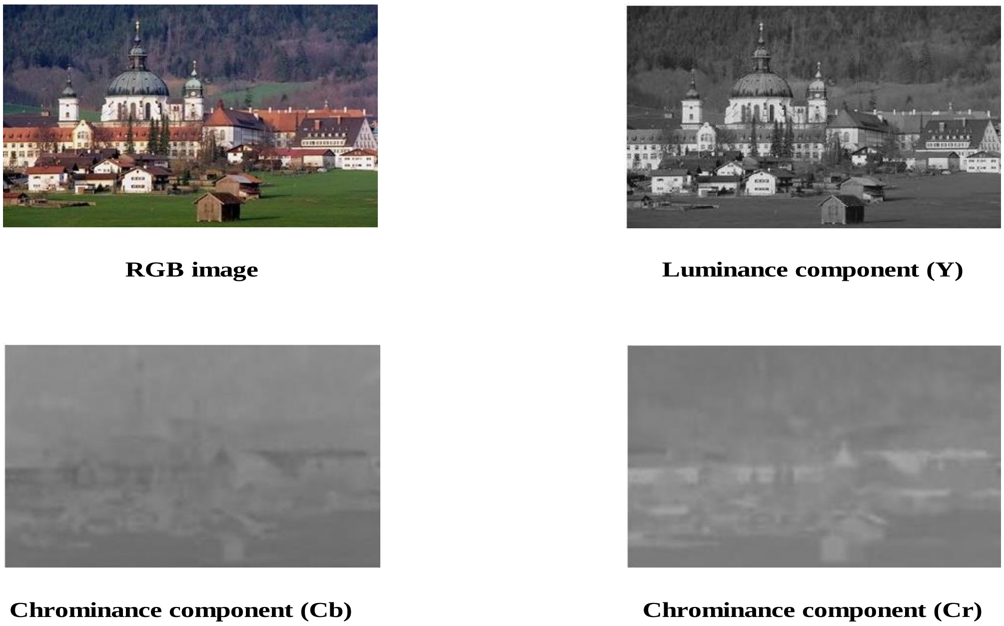

Figure 3. RGB Image and Corresponding Luminance and Chrominance Component

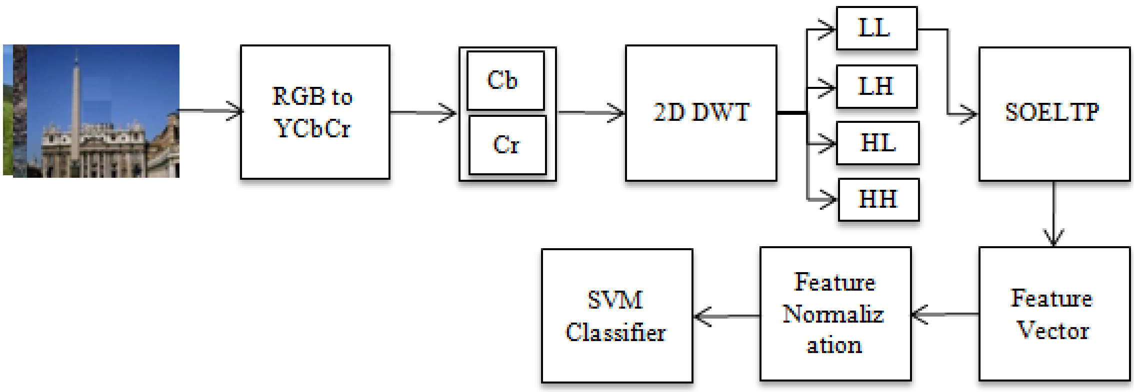

Figure 4. Architecture of the Proposed Model

3.1 Enhance Local Ternary Pattern (ELTP)

In LTP constant threshold value concept is used, which is not entirely invariant. A dynamic threshold concept is used in enhance local ternary patterns (ELTP) [17]. A predefine mean absolute deviation (MAD) concept is implemented to generate the threshold of a block. After implementing the ELTP technique on an image it gives better results compared to LBP [25] and LTP. The intensity of the central pixel (I^e_C) and threshold value (ts^e) of ELTP define in equation 1.

$$M = I_i \mid i = 0,1,2,3\ldots.8 \mid$$
$$I^e_C = \mathrm{Mean}(M) \qquad (1)$$
$$ts^e = \mathrm{MAD}(M)$$

In the above equation, M is used to represent the 3x3 matrix of the image. The intensity of the surrounding pixels is represented by I_i. The intensity of the central pixel depends on the mean of the matrix, and the threshold value is based on the value of mean absolute deviation (MAD) of surround pixels. ELTP ternary matrix is generated by equation 2.

$$S^e(I_i, I^e, ts^e) = \begin{cases} 1 & I_i \geq I^e{}_C + ts^e \\ 0 & I_i - I^e{}_C < ts^e \\ -1 & I_i \leq I^e{}_C - ts^e \end{cases} \quad (2)$$

Fig. 5 represents the ELTP matrix generation process. First, we take 3x3 image matrix to assign -1, 0, 1 as per equation 2. Upper case (+) and Lower case (-) segmented of the ELTP matrix have been used to find the decimal code of the ELTP matrix,[20] as per Fig. 5. ELTP code of the pixel at coordinate (x,y) [17,18] is represented by equation 3.

$$ELTP_{x,y} = ELTP\_P_{x,y} * (x + 2) - (ELTP\_P_{x,y} * (ELTP\_P_{x,y} + 1)) / 2 + ELTP\_N_{x,y} \quad (3)$$

Where

$$ELTP\_P_{x,y} = \sum_{i=0}^{N-1} e(S^e (I_i, I^e{}_C, ts^e), 1)$$

$$ELTP\_N_{x,y} = \sum_{i=0}^{N-1} e(S^e (I_i, I^e{}_C, ts^e), -1)$$

$$e(X, Y) = \begin{cases} 1, \text{ if } X = Y \\ 0, \text{ if } X \neq Y \end{cases}$$

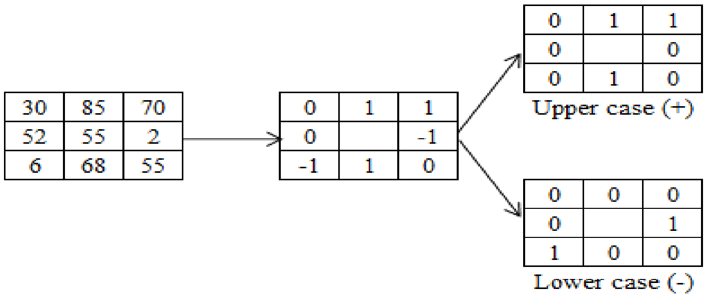

Figure 5. Process of ELTP Matrix Generation

3.2 Effect of DWT and SOELTP on Image

In the proposed work, a digital filtering technique on the image is implemented by DWT to obtain time scale depiction. DWT is implemented of the image to find features in the frequency domain [22, 23]. The threshold of the digital image has been improved by implementing the smoothing technique on the image. Otsu technique is used to enhance the performance of the histogram of the image. The performance of the Otsu has been represented by Fig. 6.

After implementing the Smoothing technique on the image the performance of the threshold has been improved. The performance of the histogram is shown in Fig. 6(e). represent image after smoothing. The effect of the Otsu is shown in Fig. 6(f), after implementing the smoothing on the image. Fig. 6(a) shows the noise of the image, and Fig. 6(b) represents the histogram of the noise image. The Otsu effect is represented in Fig. 6(c), and the smoothing technique effect is shown in Fig. 6(d).

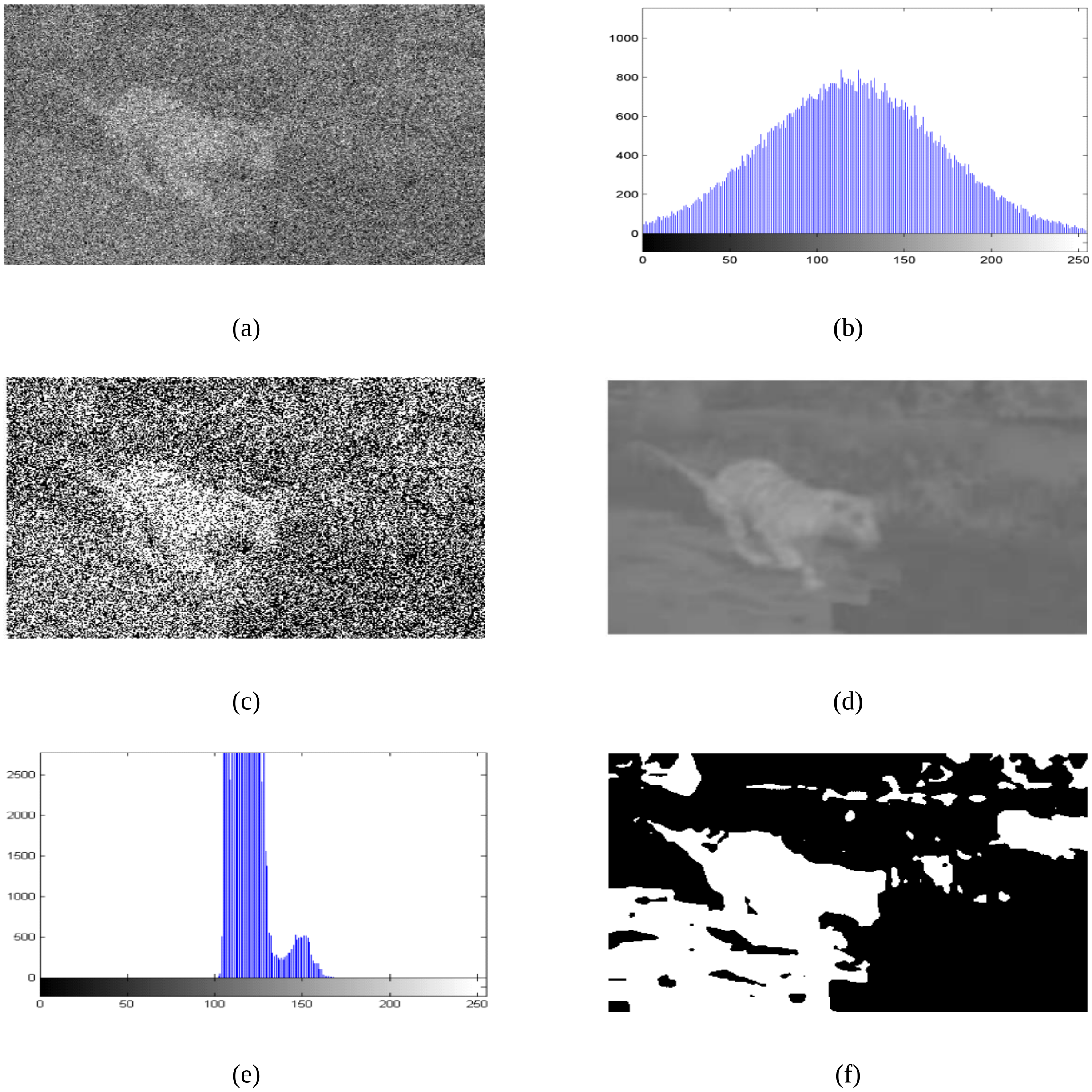

Figure 6. (a) Image Noise (b) Histogram of the Noise Image (c) Otsu's effect on Image (d) Effect of Smoothing on Noisy Image using 3x3 Averaging Mask (e) Histogram of Smoothed Image (f) Otsu effect on Smoothed Image

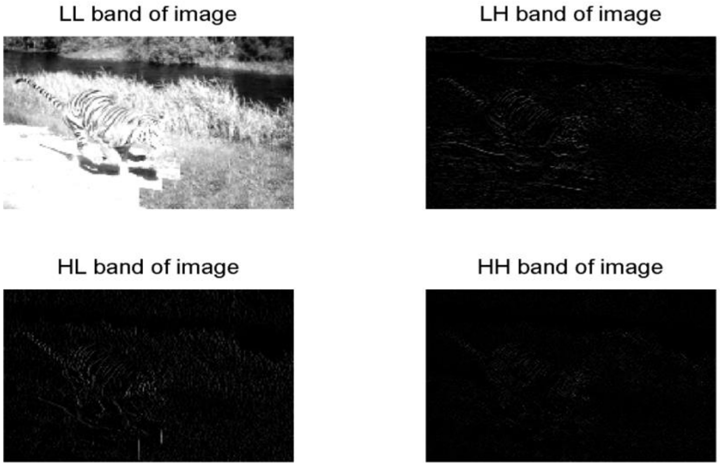

Figure 7. DWT Frequency Representation

In the proposed forgery detection technique, ELTP is implemented through the Otsu optimal global threshold to improve the performance of the image feature. SOELTP is a new feature descriptor. The matrix of the SOELTP technique is generated as per the ELTP technique. In SOELTP, matrixes are extracted as per the ELTP matrix extraction technique. Discrete wavelet transform is implemented over the chrominance component of the image to access the feature in frequency. We prefer the wavelet transform due to its simplicity and accurate result. It provides satisfactory results in texture classification, and edge detection. Image decomposed into four coefficients after implementing DWT on the image. Approximation coefficient (Low-Low), Horizontal coefficient (Low-High), Diagonal coefficient (High-Low), and Vertical coefficient (High-High) are the four coefficients. The effect of the coefficient is shown in Fig. 7. The frequency of the image reduces the complexity of the forged image. Features of the image are classified by SVM to detect the forgery.

4. Result and Discussion

We use the accuracy of the forgery detection as a performance evaluation. Accuracy estimation is based on percentage with TP, TN, FP, and FN parameters, represented by equation 4.

$$\text{Accuracy} = (TP + TN) \times 100 / (TP + TN + FP + FN) \tag{4}$$

Where

TP : True Positive, No. of fake image identify as fake.

TN : True Negative, No. of original image identify as original.

FP : False Positive, No. of original image identified as fake.

FN : False Negative, No.

The result of the SOELTP is compared with the previous state of work [1, 5, 9, 11, 12] in terms of accuracy of the forgery detection. A K-fold cross technique is implemented to classify with an SVM classifier. The result of the proposed technique is based on three different open-access data sets, CASIA v1.0, CASIA v2.0, and Columbia [4]. The average accuracy rate on CASIA v1.0 is 99.02%, on CASIA v2.0 is 98.35%, and at the end 97.85% on Columbia [26], it compare with previous techniques like LBP, and OELTP showed in Fig. 1. The performance of the SOELTP is better than LBP, and OELTP. The performance of the proposed technique is compared with the previous state of work, shown in Table 1.

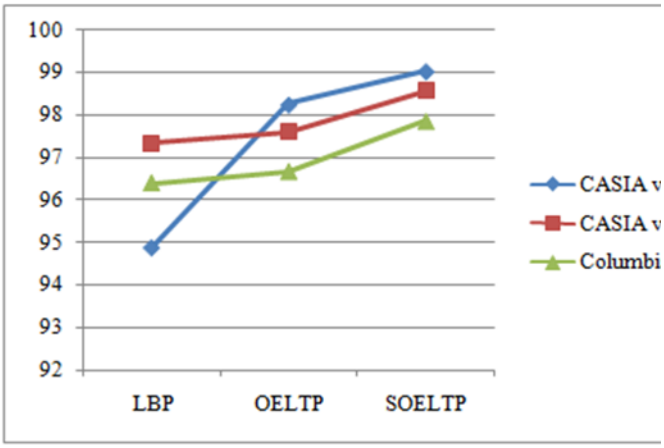

Figure 8. Performance Evaluation of Proposed Technique Using LBP, OELTP, SOELTP Accuracy

Table 1. Proposed Method Performance of Accuracy in Percentage Comparison with Previous State of work

Techniques	CASIA v1.0	CASIA v2.0	Columbia
He et al. [9]	89.76	89.76	–
Muhammad et al. [11]	94.89	97.33	96.39
Goh and Thing [5]	90.18	96.21	–
Alahmadi et al. [1]	97.5	–	–
Kanwal, N. et al [12]	98.65	98.01	97.23
Proposed	99.02	98.35	97.85

5. Conclusion and Future Scope

In this paper, a robust overlapping block-based feature extraction technique has been discussed to detect image forgery. In this proposed work DWT is implemented over the chrominance component of the image for accessing the feature in terms of frequency. Before implementing the OELTP feature extraction technique on the image we perform the smoothing technique to get a better histogram of the image. The accuracy of the proposed work gives a better result to the previous state of the work. The accuracy of the proposed technique is, 99.02% on CASIA v1.0, 98.35% on CASIA v2.0, and 97.85% on the Columbia dataset. In the future, the performances of the proposed work have been improved by localization of the forgery, and improve the performance of the global threshold using the latest technique, reducing the operation complexity, and deeply exploring the localization.

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