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Image Splicing Detection with Markov features and PCA

Rachna Mehta[1], Navneet Agarwal[2]

PhD Scholar, Department of ECE , CTAE, MPUAT, Udaipur, India [1]

Assistant Professor, Department of ECE , CTAE, MPUAT, Udaipur, India [2]

Abstract: Image splicing is exceptionally normal and central in picture altering. Along these lines, picture splicing detection has pulled in increasingly more consideration as of late in digital image forensics. grey pictures are utilized straightforwardly, or colour pictures are changed over to grey pictures before be handled in past picture splicing detection algorithms. Be that as it may, most forged pictures are can be color or grey pictures. So as to utilize the grey data in pictures, a classification algorithm is upgraded which can utilize grey pictures with Spatial, DCT and DWT features directly. In this paper, an algorithm dependent on Markov chain with spatial, DCT and DWT area is proposed for picture splicing detection. As a matter of first importance, grey data is generated from blocked pictures to build DCT and DWT in an entire way, and the DCT and DWT coefficients of blocked pictures can be obtained. Furthermore, the expended Markov features created from the Transition probability matrix in spatial, DCT and DWT area can catch the intra-block, yet additionally the Inter block correlation between's blocked DCT and DWT coefficients. Then we use PCA for reducing the dimensionality of pictures and enhancing the correlation among pixels. At long last, ENSEMBLE classifier is used to classify the Markov feature vector. The final results show that the proposed algorithm not just utilize grey data of pictures, yet in addition can yield significantly better detection results in contrasted to previous work for splicing detection methods applied on same equivalent dataset

Keywords: Image DCT, DWT, Markov Chain, PCA, Ensemble Classifier.

I. INTRODUCTION

In the present digital world, Digital Image Forensics is profoundly a difficult locale. Digital Image Forensics [1] is a moderately hot research zone targeting gathering data on the historical backdrop of a picture. In current computerized period, the advanced media or advanced picture has assumed a significant job in the present ordinary life. So we can express uncertainty about the unwavering quality of computerized visual data. With the spread of digital pictures and because of the accessibility of simple touse media-controlling devices, for example, Photoshop, which can be found anyplace on the computerized frameworks or web has progressed toward becoming progressively simple to control pictures to adjust content and importance. Any individual can control the data of their computerized record so as to achieve their expectation without leaving any intimations that are conspicuous by others. The decisive capability of visual media and accessibility of their, stockpiling, obtaining, and dissemination is with the end goal that they are increasingly more preferred position to convey the data. Because of that, presently a days pictures and recordings assumes an indispensable job as a proof for the two preliminaries and regular daily existence contention. Some video cuts in TV program or news is commonly perceived as an accreditation of the validity of that program or news. Likewise, a CCTV recordings can be a piece of central trial material in a trail.In combination with irrefutable increases, the accessibility of computerized media drives a significant entanglement.

The researchers in Image can easily adjust the content of a picture. By and large, with the expansion of ease and easy to understand photograph altering toold, the technique for changing and duplicating the realize information is not any more controlled. Henceforth digital image forgery detection is a hot research field which center at the accuracy of the creativity of pictures by recapturing the realities about the history. There are a few cases including media fraud displayed and examined [2]. In a few papers, they exhibited the detail characterization and brief overview on Image forgery detection [3][11][16]. This article characterizes the procedure of splicing and after that looking feature extraction with markov chain and co-occurance matrix and classify them with ensemble classifier.

II. LITERATURE SURVEY

Picture splicing, which incorporates solidifying no less than at least two pictures into another photo, is a champion among the most surely understood sorts of picture counterfeiter identification. Most of the research into splicing location relies upon the way that the photo splicing procedure can cause disconnection along boundary and corners. These unpredictable advances are a fundamental sign in the check of picture's validity. Early undertakings to distinguish altered pictures concentrate on diversity in the overall quantifiable qualities caused by sudden disconnection in the altered pictures [4– 7]. In any case, the minute based splicing identification strategies are compelled in that the quantifiable minutes for an entire picture don't capably distinguish the area disconnection caused by a splicing operation. Splicing perceiving strategies that are prepared for finding adjacent changes caused by joining that have been presented in picture locale. One of these systems is the run length-based splicing recognizable proof approach [8– 10]. Using this methodology, we can take out neighborhood changes caused by splicing distortion. Run length-based splicing Identification procedures have achieved surprising recognizable proof sign with few features. Regardless, the accuarcy rates of these computations are not impeccable in light of the way that the finishing up features are isolated from the snapshots of various run length frameworks. Other promising splicing detection techniques that use neighborhood changed features with Markov techniques. Markov-features are sensibly useful for the distinguishing proof of changed pictures that have been altered.

In 2012, He et al. [11] show Markov-features in both discrete cosine transform (DCT) and discrete wavelet transform (DWT) domain, and they perceive picture splicing as demonstrated by the cross-space Markov-features. This procedure achieved a accuracy rate of 93.55 % on Colombia grey-scale picture data file [11]. Regardless, this strategy required up to 7290 features. In this way, feature reduction strategies, for instance, recursive feature end (REF) was indispensable. An enhanced Markov state selection procedure [13] was represented decreasing the number of features. This approach analyzes the anticipated coefficients for change area and maps endless coefficients with limited expresses that have coefficients in light of various inferred work models. In any case, to reduce the number of features,

El-Alfy et al. suggested a forgery detection technique for picture splicing by using Markov-features thatincorporate into both spatial and DCT-domain [14]. They furthermore utilized principal component analysis (PCA)to pick the most vital features. They achieved a accuracy rate of 98.82 % with a more straightforward testingcondition (they utilized ten times cross-verification, while most extremes utilized six times cross-verification). In 2015, a photo splicing detection technique [15] using a two-dimensional (2D) non-causal Markov technique was introduced. In this technique, a 2D Markov model was associated in the DCT area and the discrete Meyer wavelet transform domain and the cross area features were considered as the closed features for classification. This technique achieved an accuracy rate of 93.36 % on Colombia diminish picture data file; nevertheless, up to 14,240 features were required

III. SUGGESTED WORK

The benefaction of this work is centered on redesigning of feature extraction and classification methods for digital image forensics. Figure 1 demonstrates the flowchart of the proposed work for Splicing detection in image forensics domain.

Feature Extraction

In this paper, Splicing detection is considered a two-class image detection problem. That is, a given test picture should be delegated either a spliced picture (with forged information) or an original picture (without forged information). Along these lines, feature extraction is a important part in the Splicing detection. In this section, we initially divide the pictures in 8x8 non-overlapping blocks using BDCT. With this BDCT we define the 2-D array for each picture, after finding the 2D- array we find the difference 2-D array along various directions i.e. horizontal, vertical, major diagonal and minor diagonal. We at that point propose to extract the features using Markov process. As indicated by the hypothesis of a random process, the transition probability matrix can be utilized to describe the Markov process. Our proposed features are extracted from the transition probability matrix. So as to accomplish proper stability between Splicing and computational problem, we utilize the well known one-step transition probability matrix in this work. So as to additionally minimize the computational cost by decreasing the dimensionality of features, we resort to a thresholding procedure [20]. Then for further feature selection process, we use so-called principal component analysis (PCA) for selecting the most correlated features.

Spatial Domain based Difference array

This difference array strategy can catch the Splicing relics which emerge by the diverse assortments of picture content by Splicing. For difference array method we expected to subtract the pixel values from its neighboring pixel values in each situation to get the edge pictures [20, 21] by using Eqs. (1– 4).

$$S_h(r,c) = I(r,c) - I(r+1,c); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c \tag{1}$$

$$S_v(r,c) = I(r,c) - I(r,c+1); \quad 1 \le r \le U_r, 1 \le c \le U_c - 1 \tag{2}$$

$$S_{md}(r,c) = I(r,c) - I(r+1,c+1); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c - 1 \tag{3}$$

$$S_{mj}(r,c) = I(r+1,c) - I(r,c+1); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c - 1 \tag{4}$$

where I(r,c) ∀r,c is the source picture in the spatial domain and Ur, Uc shows the dimensionality of the spatial picture.

DCT domain based Difference array

In DCT domain based difference array we first take DCT for 2D array then we take the absolute of this 2D array which shortened the values to fixed value then we subtract the DCT coefficient with neighbouring values [9, 20, 21] in the same way as we have done for spatial domain as shown in eqn (5-8).

$$D_h(r,c) = D(r,c) - D(r+1,c); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c \tag{5}$$

$$D_v(r,c) = D(r,c) - D(r,c+1); \quad 1 \le r \le U_r, 1 \le c \le U_c - 1 \tag{6}$$

$$D_{md}(r,c) = D(r,c) - D(r+1,c+1); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c - 1 \tag{7}$$

$$D_{mj}(r,c) = D(r+1,c) - D(r,c+1); \quad 1 \le r \le U_r - 1, 1 \le c \le U_c - 1 \tag{8}$$

where D(r,c) r,c is the absolute value of BDCT 2D array.

DWT domain based Difference array

For DWT based feature [21] we calculate the wavelet transform on pictures I(r,c) by utilizing y(=0,1,2,...,y) decomposition level as given below.

$$V_x^{y+1}(r,c) = DWT\left(V_{LL}^y(r,c)\right); \quad x \in (LL, LH, HL, HH) \tag{9}$$

LL = Low frequency subband; LH = Horizontal position; HL = Vertical Position;HH = Digonal position, Where $V_x^{y+1}(r,c)$ is the group of four wavelet subbands in the j + 1-th level, DWT(l) is the DWT on l, and x demonstrates the position of the wavelet subband. A altered image I(r,c) is presented as I(r,c) = . $V_{LL}^0(r,c)$. Subsequent to applying DWT on suspicious picture we adjusted the all coefficient of DWT to closest whole number and take the highest values. Like other techniques that use investigative features, we moreover subtract the values in the wavelet domain as shown in equations (10-16).

$$DV_{LH}^y(r,c) = \left[V_{LH}^y(r,c) - V_{LH}^y(r+1,c)\right] \tag{10}$$

$$DV_{HL}^y(r,c) = \left[V_{HL}^y(r,c) - V_{HL}^y(r,c+1)\right] \tag{11}$$

$$DV_{HH}^y(r,c) = \left[V_{HH}^y(r,c) - V_{HH}^y(r+1,c+1)\right] \tag{12}$$

Since the LL subband has no directional data, we calculate the rounded maximum difference value as given below.

$$DV_{LL}^y(r,c) = \max\left(\mathrm{D}V_{LL}^{yh}(r,c), DV_{LL}^{yv}(r,c), DV_{LL}^{yd}(r,c)\right) \tag{13}$$

Where

$$DV_{LL}^{yh}(r,c) = \left[V_{LL}^y(r,c) - V_{LL}^y(r+1,c)\right] \tag{14}$$

$$DV_{LL}^{yv}(r,c) = \left[V_{LL}^y(r,c) - V_{LL}^y(r,c+1)\right] \tag{15}$$

$$DV_{LL}^{yd}(r,c) = \left[V_{LL}^y(r,c) - V_{LL}^y(r+1,c+1)\right] \tag{16}$$

Thresholding

For reducing the dimensionality of features we use thresholding technique. In this, we adjust the values of the features between –E to + E. Where, E shows the specific threshold value which is selecting by us [20, 21, 27]. If we have the features greater than E then it will be adjusted to E and if we have features smaller than –E then it will be adjusted to –E. This results in reducing the dimensionality by using equation (17).

$$E(r,c) = \begin{cases} +E & H(r,c) \ge +E \\ -E & H(r,c) \le -E \\ H(r,c) & Otherwise \end{cases} \tag{17}$$

where H(r,c) represents for S_h(r,c), S_v(r,c), S_{md}(r,c), S_{mj}(r,c), D_h(r,c), D_V(r,c), D_{md}(r,c), D_{mj}(r,c), and $DV_{LL}^{yh}(r,c), DV_{LL}^{yv}(r,c), DV_{LL}^{yd}(r,c)$, Hence, the values of the difference array of DCT,DWT coefficients and spatial domain, are constrained to the range (-E, E) with only(2E + 1) feasible values.

Markov based Transition Probability Matrix

We propose to extract the Markov features with above-defined difference 2D array and thresholding technique using Markov random process. As per the hypothesis of the random process, the transition probability matrix can be utilized to define the Markov procedure. There are well-known one-step transition probability matrix and n-step transition probability matrix [19, 20, 21, 22]. So here for maintaining the balance between Splicing and computational

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complexity, we use one step transition probability matrix which helps in finding the correlation between neighboured pixels. With this thresholded arrays we extract the markov features using transition probability matrix and we calculated the dimensionality of these features is (2T+1)× (2T+1). Finally, the calculation of these markov features with transition probability matrices along horizontal, vertical, major diagonal and minor diagonal is given by

$$\Pr\{E_h(r+1,c)=m|\mathrm{E_h}(\mathrm{r,c})=\mathrm{n}\} = \frac{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c}\delta(E_h(r,c)=m, E_h(r+1,c)=n)}{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c}\delta(E_h(r,c)=m)} \tag{18}$$

$$\Pr\{E_v(r,c+1)=m|\mathrm{E_v}(\mathrm{r,c})=\mathrm{n}\} = \frac{\sum_{r=1}^{U_r}\sum_{c=1}^{U_c-2}\delta(E_v(r,c)=m, E_v(r,c+1)=n)}{\sum_{r=1}^{U_r}\sum_{c=1}^{U_c-2}\delta(E_v(r,c)=m)} \tag{19}$$

$$Pr\{E_{md}(r+1,c+1)=m|\mathrm{E_{md}}(\mathrm{r,c})=\mathrm{n}\} = \frac{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c-2}\delta(E_{md}(r,c)=m, E_{md}(r+1,c+1)=n)}{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c-2}\delta(E_{md}(r,c)=m)} \tag{20}$$

$$\Pr\{E_{mj}(r,c+1)=m\big|\mathrm{E_{mj}}(\mathrm{r,c})=\mathrm{n}\big\} = \frac{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c-2}\delta(E_{mj}(r+1,c)=m, E_{mj}(r,c+1)=n)}{\sum_{r=1}^{U_r-2}\sum_{c=1}^{U_c-2}\delta(E_{mj}(r+1,c)=m)} \tag{21}$$

Where

$$\delta(F=m,G=n)=\begin{cases}1 & F=m,\ G=n\\ 0 & otherwise\end{cases}$$

$$\forall F,G\in\{-E,-E+1,\dots\dots\dots.-0,E-1,E\}$$

In result, we have (2E+1)×(2E+1) features for all these four transition probability matrices and overall we have 4×(2T+1)×(2T+1) features and these all of them are considered as markov features for Splicing detection. So, we can say we have 4×(2T+1)×(2T+1)- D features for Splicing detection. Plainly we ought to pick a threshold E value for good Splicing detection with reasonable computational complexity

Feature selection with PCA

The most discriminative features are selected by using the principal component analysis (PCA). It converts the feature vectors into a lower - dimensional space by means of taking the Eigen values from the covariance matrix [20]. The final features are the ones which have the highest contribution within the variance in the data. for example, while E = 3 and E = 4, the range of Markov features are 392 and 648, respectively. the usage of PCA, we have decreased those numbers to 30, 50, 100 and 150 dimensions.

Ensemble Classifier

A new research idea has been innovated in supervised learning for building the classifier which is based on the gathering of information from each classifier based on their weighted vote for prediction and that classifier is known as ensemble classifier. Ensemble classifier [28, 29] are learning algorithm that creates a strategy of classifiers whose singular predictions are joined together and after that arrange them by taking the weighted vote of their predictions. The basic disclosure is that gatherings of information from the classifiers are fundamentally more right than the prediction taken by individual classifier like Support Vector Machine (SVM) [26] and this property of ensemble classifier affects them to up among other classifiers.

Generally, The support vector machine is the machine tool [26] which is most commonly used for classification in forgery detection. But with SVMs the computational complexity has been increased very rapidly with the increasing dimensionality of features. The Principal component analysis is the standard methodology that handles and reduces the high dimensional features. While such strategies help in decreasing the dimensionality, in any case, one disadvantage is that the new features can be hard to interpret, thusly making it difficult to relate with original features. Thus for removing this disadvantage, we use co-occurrence matrix which enhances the correlation among pixels. Also with ensemble classifier, we can reduce the computational complexity of SVM which has been arrived by the hyper plane equations.

There are no. of ensemble classifiers like Bagging and boosting. But we preferred one of the types of boosting algorithm is Adaboost algorithm. Which is more accurate and suitable for binary classification and also it is fast and less memory usage then others. Here we take a look how Adaboost ensemble classifier works. AdaBoost [28, 29] keeps up an arrangement of weights over the training features. In every iteration *i* the learning algorithm is conjured to limit the weighted error on the training set, and it restores a hypothesis h_i . The weighted error of h_i is calculated and applied to refresh the weights on the training features The effect of the adjustment in weights is to put more weight on training

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features that were misclassified by h_i and less weight on features that were accurately classified. In ensuing iterations h_i therefore, AdaBoost builds dynamically on more tough learning issues.The last classifier, $h_f(x) = \sum_I w_i\ h_i(x)$ is built by a weighted value of the single classifiers Each classifier is weighted by (w_i) as per its precision on the weighted training set that it was trained on updated research has demonstrated that AdaBoost can be seen as a productive algorithm for reducing a specific error function. To characterize this error function, assume that each training features is named as +1 for spliced images or on the other hand -1 for authentic images relating to the positive and negative images, Then the amount $m_i = y_i h(x_i)$ is accurate if h correctly classifieds x_i and negative in other case. This amount m_i is known as the margin of clasffieer h on the training features. AdaBoost can be viewed as attempting to

$$\sum_l -\exp(-y_l \sum_i w_i\, h_i(x_l)) \tag{24}$$

Minimize, which is the negative exponential of the margin of the weighted voted classifier

As we discussed above the process flow for the proposed work is shown in Fig 1.

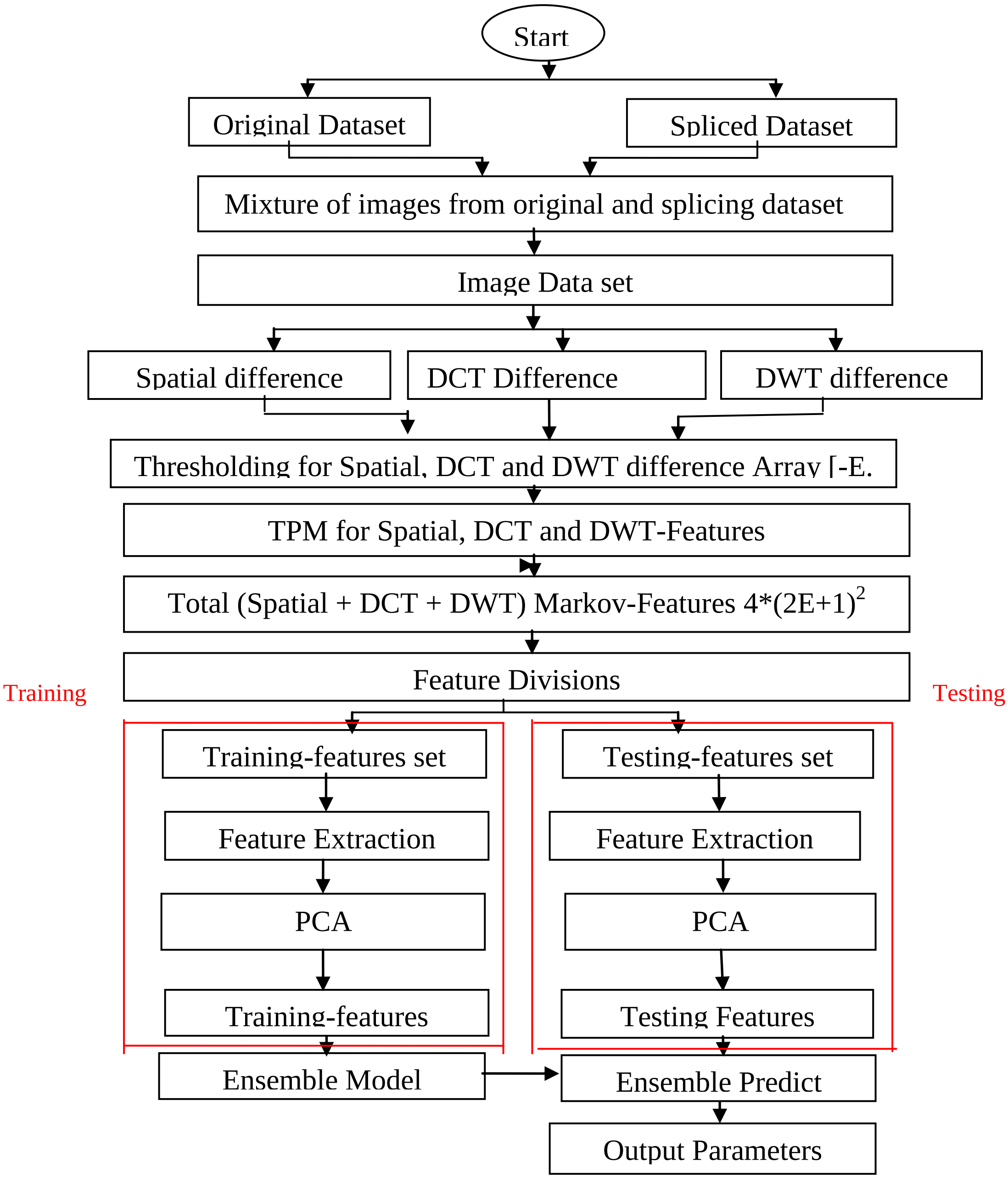

Fig.1. A Framework for splicing detection with PCA

IV. EXPERIMENTAL CONSIDERATIONS

For our proposed technique of Splicing detection, the markov features are ascertained and classified on a freely accessible and very much famous picture dataset, the Columbia Image Splicing Detection Evaluation Dataset. This dataset is made by Digital Video and Multimedia Lab (DVMM) at Columbia University. It comprises of 1,845 pictures of assorted content from which 933 are original and 912 are spliced pictures

- The proposed work starts with perusing the authentic and spliced pictures from the data file one by one. At that point, Difference arrays are ascertained for three Spatial, DCT and DWT-domains separately to calculate the connection between pixels with its neighbour.
- Then we set the values of difference arrays is in between threshold value [-E, +E] by thresholding technique and then the Markov-Features in all three domain are figured by tansition probility matrix (TPM) in all directions.The amounts of Markov-Features for Spatial, DCT and DWT domain are calculated separately for certain threshold value is appeared in Table 1 for various estimation of E. After calculating of Markov-Features we combine all these features.
- Then we apply an PCA for reducing the higher dimensionality to low dimension
- After this we apply an ensemble classifier [24].with Adaboost algorithm and 100 number of 'Tree' type weak learner. we used ten times cross-approval to survey the ensemble model parameters. In ten times cross-approval,

We randomly isolated each of the original pictures and the spliced pictures into ten proportional group. In each cycle, we used nine groups each from the real pictures and the modified pictures for training, while the remaining was used for testing. Along these lines, towards the consummation of ten emphasis, all the ten groups has been attempted. There is no overfitting probem has been found between the training set and the testing set in an iteration which is for the most part displayed in SVM classifier.

Performance Parameters

To assess the execution, we compute the true positive rate (TPR), the true negative rate (TNR), and the accurateness (ACC). The TPR is the rate of precisely distinguished credible pictures and the TNR is the rate of accurately distinguished altered pictures. The ACC speaks to the discovery rate, which is the normal of the TPR and TNR esteems. We likewise utilized the Receiver Operating Curve (ROC) and the Area Under the Curve (AUC) to plot the progressions in TPR and FPR

V. EXPERIMENTAL RESULTS

For extraction of features and classification we design functions and we show the output of user defined functions through GUI application of MATLAB in terms of of TPR, TNR and accuracy as shown in below figure 2.

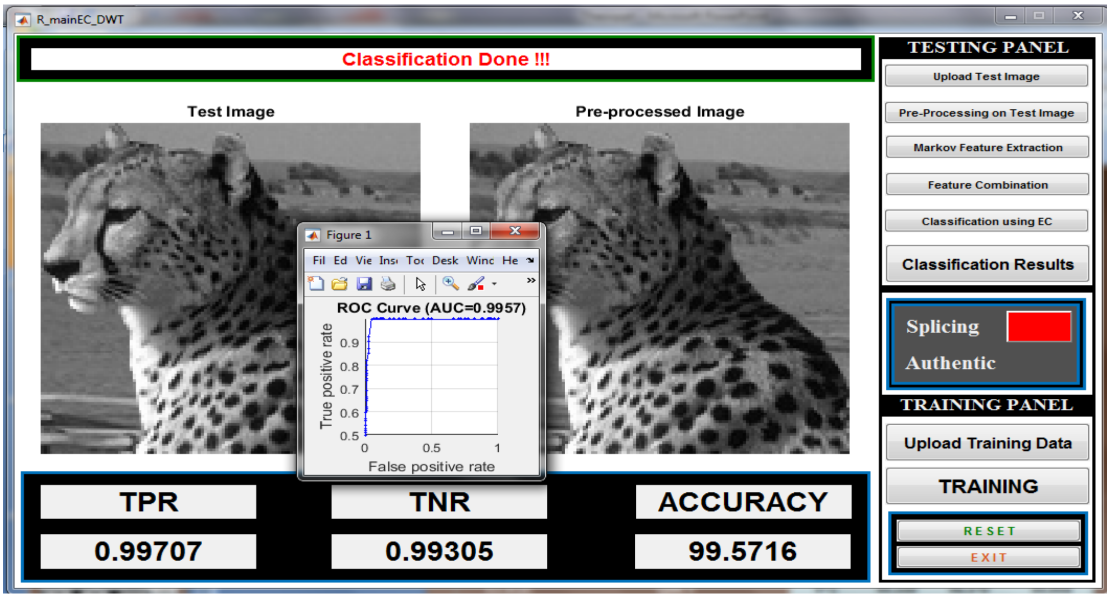

Fig.2. Experimental Results for Splicing detection with Markov Festures and PCA

Here, we show the comparison graph of output parameters in terms of True Positive Rate (TPR), True Negative Rate (TNR) and accuracy of our proposed method at different dimensionality of N = 30, 50, 100 and 150.are shown in below figure 3.and we compare these output parameter values with prior work with the same dimensionality which is shown in different colors and we found that our proposed work achieved best results in comparison to the prior results of EI-Alfy and He et. al. results

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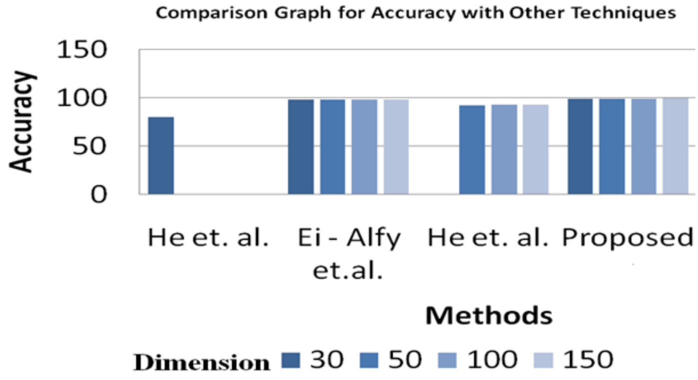

Fig.3. Comparison Results for Splicing detection with Markov Festures and PCA

VI. CONCLUSION

A novel passive forgery detection technique for picture splicing and its classification has been proposed and assessed in this paper. The thought is to combining all Markov-features from three domains i.e Spatial, DCT and DWT with PCA and classify them with an efficient ensemble classifier has been successfully implemented which is not yet been used in the prior work. The outcomes demonstrate that accuracy is enormously expanded with ensemble classifier for combined Spatial-Features, DCT and DWT based-features with PCA. The test outcomes approve the execution of novel technique with combining of all features in all three domains and classify them with Ensemble classifier and achieved best outcomes when contrasted with the most astounding detection accuracy achieved up till now from existing picture splicing detection techniques, which has been used SVM classifier with PCA on the same data file.The execution is evaluated and looked at as far as accuracy rate, true positive rate and true negative rate, and ROC curve. With 108 features or elements, the consolidated approach with ensemble classifier can accomplish 99.57 % accuracy, 99.70 % TPR, 99.30 % TNR and 0.9975 AUC .

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