An Enhanced Technique for Detecting Spliced Images using Median Filter Residual Textural Analysis

Priyanka C G[1] and Shihabudeen H[2]

[1,2]College of Engineering Kidangoor, Kottayam, Kerala, India

[1] priyankacgopi@gmail.com, [2]shihabudeenh@ce-kgr.org

Abstract.
A spliced image is one that has been forged using various tools and manipulated by cut and paste method. In image forensics, it is extremely difficult to detect cut and paste manipulation. This research employs the classification technique of the image, which is spliced to identify picture forensics. It has five feature vectors for classification, that are morphological erosion and opening image of local entropy and local range, and entropy-based edge. Calculation of the entropy information on the spliced image can extract the feature set for the ground truth mask. The proposed algorithm categorizes the Cut and Paste region in a differently altered spliced image utilizing classifiers employing texture analysis on the MFR of the spliced image. And discovered that, which classifier is the most accurate and efficient by comparing different classifiers. Utilizing Median Filter Residual Textured Analysis, U-Net is an efficient method for enhancing the method for irregular background spliced image identification.

1.Introduction

In the today's world, because of the rapid advancement of digital image processing technology as well as the growing use of digital recording devices, digital image processing has become a very straightforward procedure even for untrained users. Using contemporary digital image processing tools, any person may alter digital photos in such a manner that it is nearly hard to visually differentiate a fake from the real data. Because of this authenticity of digital images has become a source of contention [1]. Due to this required an accurate method to find faked data, but Several techniques for manipulating images to create fakes exist, such as copy-and-paste, cut-and-paste, and double compression of an image etc [2]. Figure 1 shows different types image forgeries.

Some counterfeiters choose the Cut and Paste technique since it creates a new composite image fast from several separate photographs. One of the methods for cutting and pasting utilize median filtering (MF), which provides the benefit of keeping picture borders. Because of this, MF is widely employed in the creation of fake images consequently. [3] Therefore, median filtering detection (MFD) is critical in picture forensics. The relationship between pixels is statistically prepared or the image's spatial and frequency domains are examined in standard image forensics detection. [4] In picture forensics, the median filtering is frequently used, and attribute definitions are required to identify spliced regions. The median filter residual is primarily performed in the pre-processing stage of the questionable image in the spliced image forensics detection. This work proposes detection strategy to identify forensically spliced images by employing texture analysis of the photograph of its own and outperforming current techniques. Additionally, the group feature vector or mixture features increases length of the feature descriptor for improved performance. [5]

Mainly, two types of classifier used to detect the spliced image, SVM and KNN. The differences between SVM and KNN classifiers will be compared in this paper and U-Net used to improve the result. SVM belong to the group of supervised learning algorithms. It can be used for outlier detection, regression, and classification. Linear SVM classifier functions generate a distinction between two classes in a straight forward manner. As a result, each data point on either side of the line corresponds to a category, and the other side represents a different category. [6] This implies that there are an unlimited number of lines from which to choose. SVM algorithm selects the appropriate line to classify data points, making it superior to some other algorithms like k-nearest neighbours. It selects the line that divides the data and is as far from the nearest data points as it can be. A cubic SVM classifies as more accurate and requires less processing power [7].

Another classifier that is used in this work is KNN .and it is the simplest machine learning algorithm. After storing all the previous data, a new data point is categorized using the KNN algorithm based on Euclidean distance [8]. This shows that when fresh data appears in a category that makes sense for it, the KNN method can quickly classify it. The KNN algorithm works well in classification and regression problems associated with data science applications. U-Net is used to get the enhanced result of the SVM classifier output. A potent form of CNN for effective image segmentation is U-Nets. In order to produce a full-resolution semantic prediction, a U-Net adds an associated expansive path to the standard CNN architecture. That is to create feature extraction images that draw attention to elements and objects in the image. The output images typically possess a similar size (dimensions) as the input images and are created per level using colour values. [9]

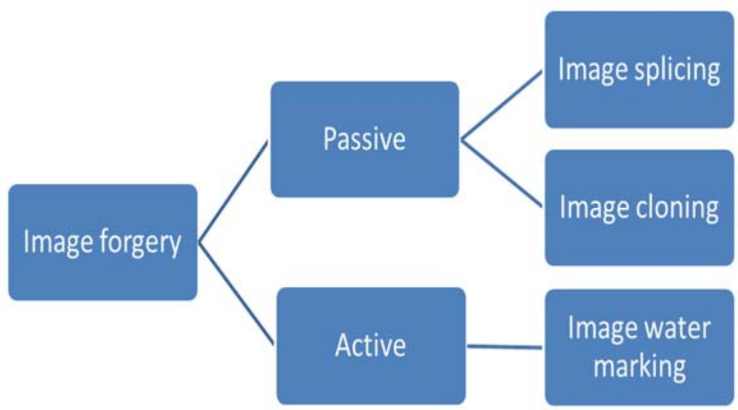

Figure 1. Types of image forgeries

1.1. Key Highlights:

The paper proposes a new spliced image detection method based on the features collected by applying texture analysis to the MFR. As a result, the suggested technique possesses the traits of pattern analysis and image filtration. The method is very effective to detect spliced image.

This paper’s primary contribution is as follows:

a. The entropy and range of the median filter residual from the spliced image are processed, and their patterns assessed to look for an unidentifiable state.
b. Morphological opening and erosion are performed on the spliced image to distinguish the cut-paste potion in the altered image.
c. Any altered areas of the image can be found using the proposed detector.
d. By contrasting various classifiers, one can determine which is the most accurate and effective.

The paper has the following structure:

Section 1. depicts the introductory part of spliced image detection, Section 2 depict literature review. Section 3explains proposed system for image detection. The results and discussions are presented in Section 5 , and finally, the conclusion is presented in Section 6.

2.Literature Review

The usage of the SIFT method has been emphasized in most studies given in recent years [10]. In addition, most methods detect copy-and-move fraud when the recreated region is neither scaled nor rotated, and most algorithms do not investigate the effects of changing the image nature. Most algorithms with the highest accuracy employ a highly complex method to detect forgeries [11-13]. In image forensics detection, the pre-processing phase of the dubious image is where the median filter residual (MFR) is most frequently used (IFD) [14]. Chen et al. [15] first used the CNN algorithm to detect median filtering the structure used was simple and performance is not well in which MFR is performed by the first CNN layer. Kang et al. [16] used an auto regressive (AR) model to examine the median filter residual, which is the changes in the value of the actual image and the MF image, to obtain AR coefficients as the extracted features for MFD. They investigated the MFR AR of an image and discovered that it could reduce image data that could interfere with the MFD.

2D MFR model developed by Yang et al uses a combination of residuals created by median filter, average filter and Gaussian filter for training SVM. The method performs well with the detection of spliced images. [17] SVM is employed along with features collected by applying statistical analysis spatial domain, uses of Canny and prewitt algorithm, and hue invariant moments. The model can detect forgeries like cut-paste and re-altered images. [18] The MFR AR and MFR 2D-AR are mostly used in all the traditional approaches for detecting spliced images that use statistical algorithms for detection. In this paper, a scheme is proposed to surpass these methods by using texture analysis of the picture itself. The use of ensembled feature vectors or combinations of features increases the length of the feature but provides improved performance, whereas other models fail in investigative detection.

3.Proposed System

The Cut and Paste zone of a spliced image should be classified by mage forensics detection. Each region differs from the neighbouring pixels in terms of correlation, attributes, and validation. Specifically, the alignment of hue changes and periodicity in an image is referred to as texture analysis. In this regard, the proposed schemes cut and Paste region was classified using a texture analysis. Local entropy and range of the MFR of the spliced image is obtained by applying texture analysis is utilized for further processing. There are five steps in the suggested plan.Figure 2 shows the design flow of proposed algorithm. The suggested methodology's flow consists of the phases listed below

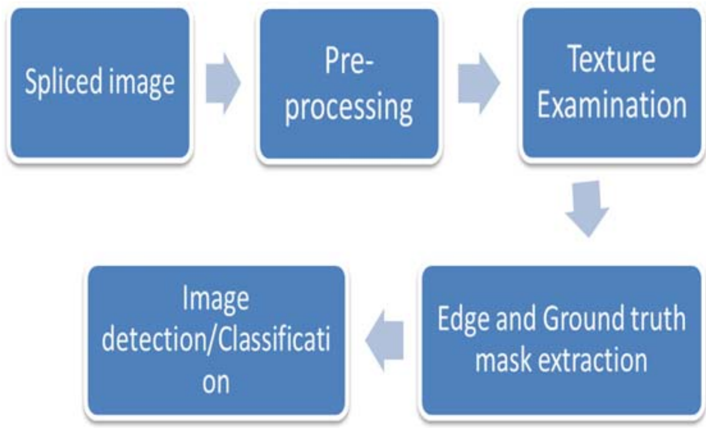

Figure 2. Design Flow

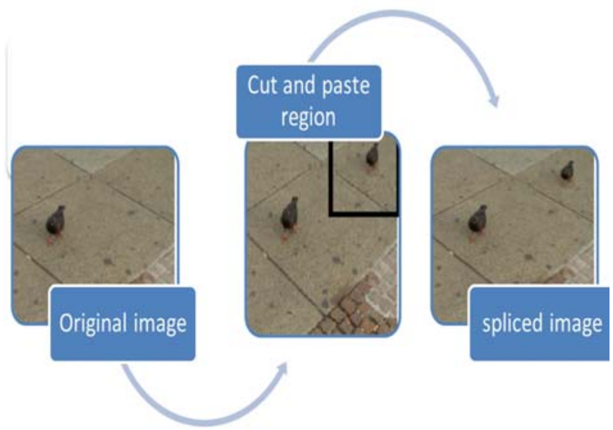

Figure 3. Spliced Image

Spliced Image: In the original image, a forger chooses the areas to be changed. The altered region it is transformed region. Five transformations applied to that region:

- Median filter form of an image (3x3)
- Median filter form of an image (5x5)
- Double compression
- Average filter form of an image

Spliced image acquired from the Comofod site were used in this investigation. 200 spliced images used for Training purpose and 50 used for Validation. Figure 3 shows an example of the Spliced image

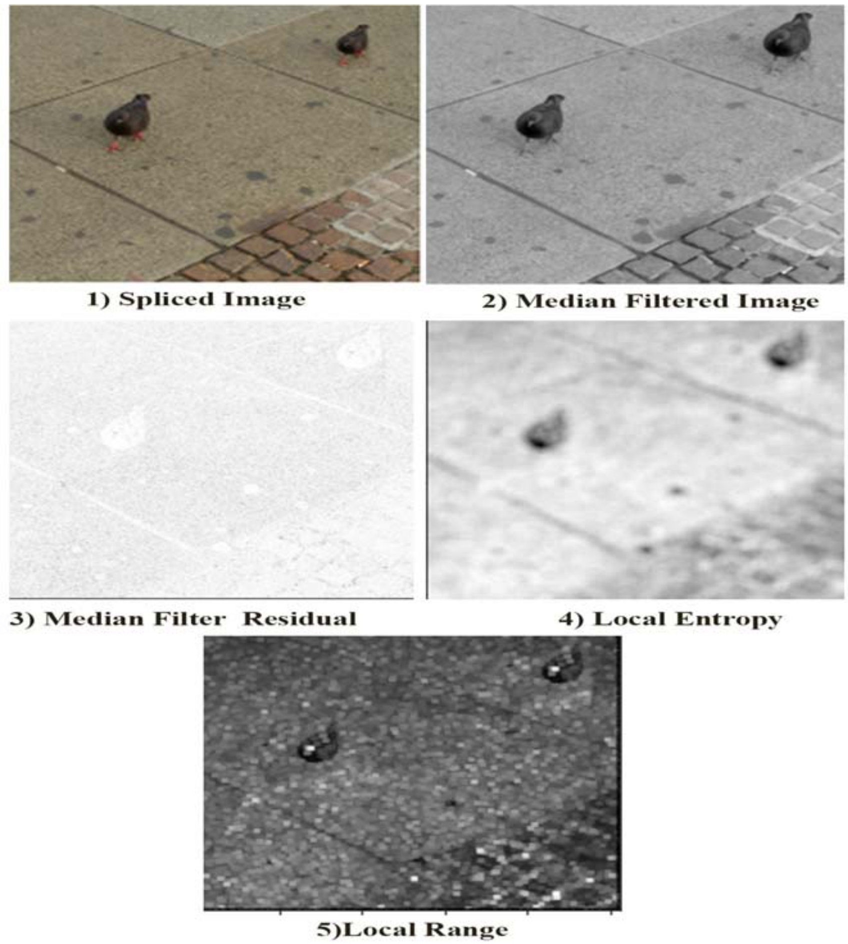

Figure 4. Pre-processing stage

Pre-processing: This is the first stage of the procedure.Figure 4 shows the pre-processing stage. Median filtering of the spliced image is performed to collect features for detection. The difference of the features from the spliced and the median filtered version is taken as median filter residual [19]. MFR is mainly considered as a pre-treatment in the identification of median filtering. The equation for the median filter residual c is Equation is given below

$$c\,(i, j) = Median_w\,(y\,(i, j)) - y\,(i, j) = z\,(i, j) - y\,(i, j) \quad (1)$$

Where (i, j) is a pixel coordinate, w is the median filter window size, and median is median filtering.

Texture Information: The process of classifying areas of an image based on their texture content is known as texture analysis [20]. It makes an effort to calculate the subjective qualities" such as roughness, smoothness, silkiness, or bumpiness" as a result of the spatial variation in pixel intensity. From this perspective, an approximate mean to variance in the grey levels is taken into account [22]. Numerous applications, such as environment monitoring, smart inspection inspection, and the processing of medical and military images, among others, use texture examination, which is a texture classification, can also be used to locate the texture border edges. When the texture of an object in a picture is more accurate than its luminosity and the current cutoff point techniques are ineffective, texture assessment is crucial. Statistics are used in texture segmentation to categorise textures. It is capable of detecting item perimeters that are more prominently displayed by tone/texture than by luminosity. [22] Entropy filtering on the gray scale image determines the entropy of the region surrounding the linked pixel and assigns that value to the last pixel taken into consideration. Additionally, the range filtering technique, which identifies regions of photos with a lot of texture. Each pixel of the texture contains the range value (maximum - minimum) of the area surrounding the corresponding pixel in an image. [23]

$$\text{Entropy value } H(k) = -\sum p(k) \log_2 p(k) \qquad (2)$$

Where the picture area's brightness histogram H (k) is derived, and p (k) is then normalized and whose attributes can be evaluated. If a luminosity value is K (K = 0, 1, 2... K- 1), by first dividing each luminosity value's frequency by the overall frequency (a pixel number of the image area), and then normalising the outcome, the total number of pixels will be determined. Smoothness is required in the transformed image (Examples include JPEG compression, average filtering, and median filtering.), the gray-level values show little variation when compared to an untouched image. As a result, an untampered picture has much texture, and the range values of the pixels are higher.

Statistical measurements are employed in texture Examination. With this technique, it is possible to accurately detect an object's border using a texture instead of an image's contrast. Since the Cut and Paste region can be used to classify the difference in entropy in spliced images, texture analysis will be used in this paper.

Edge and Ground Truth Mask Extraction: The two images that the texture analysis is drawing are the entropy Le and the range Lr of the Median filtering residual image. Le and Lr are expressed as (3) and (4), respectively, in the equation

$$Le = E\,f(MFR), \text{where } E\,f\text{: entropy filter (corresponding neighborhood pixel).} \qquad (3)$$

$$Lr = Rf\,(MFR)), \quad \text{where } Rf\text{: range filter (max. − min. value).} \qquad (4)$$

Using five ground truth masks, the Cut and Paste region of the spliced image is identified (GTM). Several times, the GTM feature set was retrieved using morphological open and morphological erosion methods. The first characteristic is FGM (Find Maxima of the Gray level.) The second and fifth attributes are extracted: two photos of morphological openness and two images of morphological degradation (open and erosion).The formula for the FGM is Eq (5)

$$\text{FGM} = reg\_max(\overline{rec(\overline{Id},\overline{Ir})}) \qquad (5)$$

reg_max refers to regional maxima.

Je â† me (Lr, r), Je. Stands for morphological-erosion image.

Jr â† rec (Je, Lr), Jr. Stands for reconstruction image.

Jd â† rec (Jr, r), where Jd is represents reconstruction image

A morphological operation's radius pixels are represented by the letters r and rec (.) is the reconstruction image. The border used to categorise the various texture properties is called the entropy-based edge, or EbE

$$EbE = mo \cdot me \cdot Le \tag{6}$$

$$\mathrm{MOI}(r)ME = mo(Le,r), \text{where } r = 4or5. \tag{7}$$

$$\mathrm{I}(r) = me(Lr,r), \text{ where } r = 4or5. \tag{8}$$

Eqs. (7) and (8), which represent MOI and MEI, respectively Features are obtained by using the above equations and this is the input of the classifier[19].

Image Detection and Classification: Detection block is made up of five components. Using the classifiers classify any component of the picture that is altered. Two different types of classifier used to detect the splice image forensic, SVM and KNN.U-Net also used to improve the Result of the SVM. And discovered that, which classifier is the most accurate and efficient by comparing these classifiers

Support Vector Machine: A support vector machine classifies the input vector x and maps to different category named a hyper plane in multidimensional space. A cubic SVM classifies as more accurate and requires less processing power. [24] Inner product as presented by the kernel is as follows:

$$\mathrm{k}(x_i,x_j)=(x_i{}^T x_j+1)^d \tag{9}$$

Classification of classes 1 and 2 is shown in Figure 5, where d is polynomial degree and input pixels (x) are mapped by kernel function k.

KNN: The KNN can be understood using the following algorithm: Determine the K-number of neighbours' Euclidean distances from one another after choosing the neighbours' K-number. Determine the number of data points in each category between the K nearest neighbours using the Euclidean distance estimation. Then, place the new data sets in the segment with the largest number of neighbours [25]. Finally, model is complete and Figure 6 gives an overview KNN algorithm.

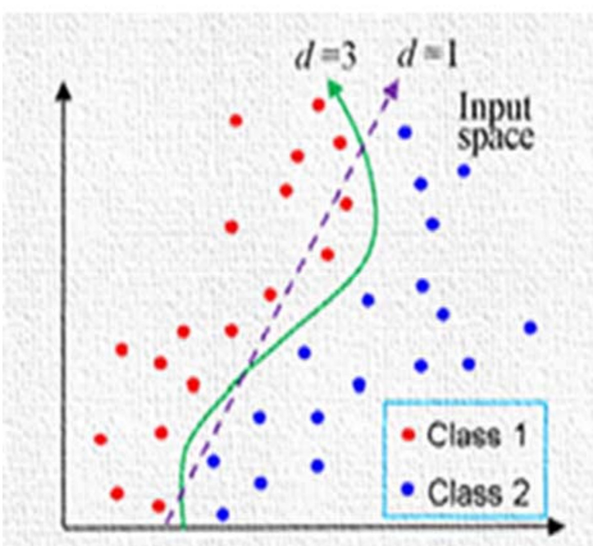

Figure 5. SVM Classifier Model [19]

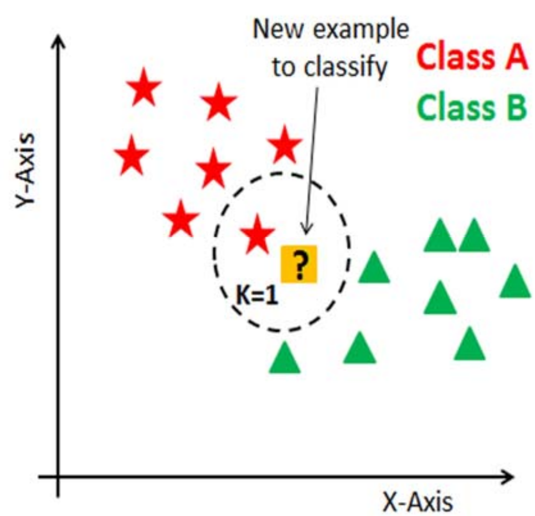

Figure 6. KNN Classifier model

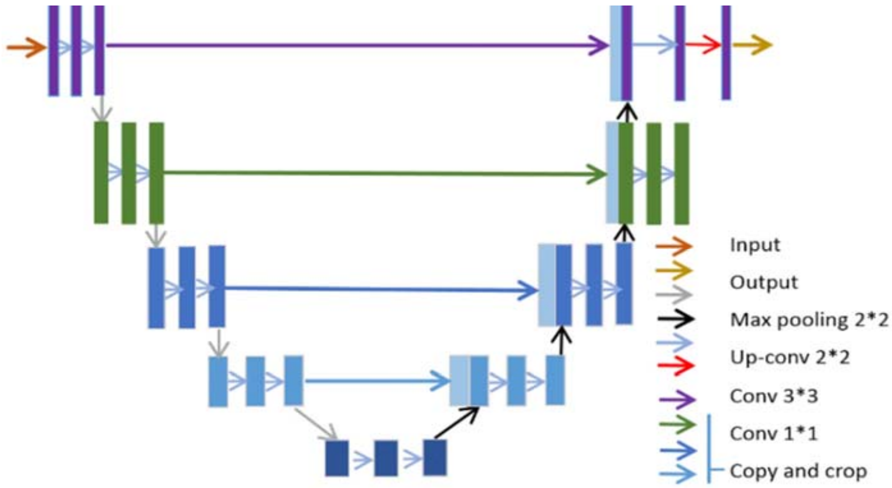

Figure 7. U-Net Architecture

U-NET: U-Net is a semantic segmentation architecture. There are two paths: one that contracts and one that expands. The contracting path follows the common design of the CNN model. To reduce the number of features, two 3x3 convolutions (un-padded convolutions) are applied multiple times with a stride of 2, and a 2x2 max pooling is performed. When the Re Lu is performed with the down sampled features and passes to the next layer, the number of feature channels is doubled before every down sampling step. Prior to each step in the expanding route, a 2x2 convolution is applied to the feature map, two 3x3 convolutions, halving the number of feature channels, each being followed by a Re LU, linear combination and a similarly well-trimmed feature map from the contracting path. Cropping is necessary since every convolution result in border pixel loss. There is 23 convolutional layers and by using a 1x1 convolution, every 64-component feature set is mapped to the few classes in the last layer. [26] U-Net is a successful method for enhancing Median Filter Residual Texture Analysis's method for irregular or contour background spliced image forensics detection.

4.Result and Discussion

This study used a median filter residual-based method to identify and categorise spliced images and used different classifier to test the accuracy of each classifier. The proposed models were written in the Python programming language and training were carried out using Google Co-laboratory. Here 20% of the spliced photos are utilised for validation, while 80% are used for training. For training, 200 photographs are used, and for testing, 50 images are used. For this experiment spliced image converted into gray scale image. Proposed model extracted the five types features from the image database; features are used for training of both SVM and KNN classifiers. Utilize the one component and the five criteria specified by IFD right now. The spliced image's cut-and-paste border is described by the "EbE" element, and the five features are extracted from it. The cut and paste locations in the spliced image is now recognised using the suggested IFD approach. Table 1 shows the classification accuracy analysis of proposed model. The suggested spliced image detection and classification Result by using SVM +U-Net is given Figure 8. Inside the Square box we can see the Blue coloured texture. That is the predicted region. The suggested spliced image detection and classification Result by using KNN is given Figure.9.

Table 1. Classification Accuracy Analysis

Classifier	Training data	Testing data	Accuracy	Characteristics
SVM	200	50	87.5%	Good Accuracy Ability to locate forgery detection Poor efficiency with non-uniform background
KNN	200	50	70%	Good Accuracy Ability to locate forgery detection Not work well for region classification
SVM+U-NET	200	50	95.5%	Highly accurate Ability to locate forgery detection

Figure 8. Spliced Image Detection Using SVM+U-Net Figure 9. Spliced Image Detection Using KNN

5. Conclusion

Cut & Paste spliced image forensics has become a popular technique for photo editing because to how simple it is to utilise. Every forgery detection algorithm strives for precise and reliable detection. Implementation of the method used in this study to categorise the Cut and Paste portions in a spliced image using pattern recognition of the image processing. The approach offers exceptional high specificity to distinguish the Cut and Paste portion thanks to the carefully designed Ground Truth Mask and the entropy-based edge. The SVM +U-net classifier model performs flawlessly for spliced images with non-linear backgrounds and irregular shapes.

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