e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
Volume:02/Issue:05/May-2020 www.irjmets.com

# IMAGE FORGERY DETECTION USING DIGITAL IMAGE PROCESSING

**Abishek R B *[1], Karthick kumar R *[2], Sriram Dharsan S *[3], Tapas Bapu *[4]**

[*123] UG Scholars, Department of ECE, S.A Engineering College, Chennai-600077,TamilNadu,India

[*4] Professor, Department of ECE, S.A Engineering College, Chennai-600077,TamilNadu,India.

## ABSTRACT

Duplicate move fraud is one of the most normally utilized controls for altering computerized pictures. Keypoint based location strategies have been accounted for to be extremely powerful in uncovering duplicate move proof because of their strength against different assaults, for example, enormous scope geometric changes. Be that as it may, these strategies neglect to deal with the situations when duplicate move frauds just include little or smooth areas, where the quantity of keypoints is extremely constrained. To handle this test, we propose a quick and viable duplicate move phony discovery calculation through various leveled include point coordinating. We first demonstrate that it is conceivable to produce an adequate number of keypoints that exist even in little or smooth districts by bringing down the difference edge and rescaling the information picture. We at that point build up a novel hierarchical coordinating system to take care of the keypoint coordinating issues over countless keypoints. To decrease the bogus alert rate and precisely restrict the altered areas, we further propose a novel iterative limitation procedure by abusing the vigor properties (counting the predominant direction and the scale data) and the shading data of each keypoint. Broad trial results are given to exhibit the unrivaled presentation of our proposed conspire regarding both effectiveness and precision.

**KEYWORDS:** Copy-move, forgery detection, hierarchical feature matching, iterative localization.

## I. INTRODUCTION

With the improvement of present day picture altering delicate products, for example, Photoshop and Gimp, computerized pictures can be manufactured at an extremely minimal effort. This brings a major risk for the dependability of computerized pictures. Duplicate move imitation is one regular control among different computerized picture falsifications, where one or a few districts of a picture are stuck somewhere else in a similar picture so as to cover up or copy objects of intrigue [1]–[7]. Such procedure might be with revolution, resizing, pressure and commotion expansion to make the last frauds all the more persuading. Distinguishing them at times

The creators are with the Department of Computer and Information Science, Faculty of Science and Technology, University of Macau, Macau 999078, China (email: yb57410@umac.mo; jtzhou@umac.mo). Computerized Object Identifier 10.1109/TIFS.2018.2876837

**Fig-1:** Two Examples of the duplicate move falsification. Left to right: unique pictures, produced pictures through duplicate move activities, and duplicate move districts.

It tends to be exceptionally testing, particularly when the duplicate move phony just includes little or smooth locales, or when the produced regions have been prepared by some extreme assaults, for example, enormous scope resizing and overwhelming commotion expansion. Two models are appeared in Fig. 1, where the duplicate move forgeries are directed over just smooth or little areas. In the ongoing years, many picture duplicate move imitation detection techniques have been proposed, which can be generally ordered into two gatherings: 1) thick field (or square based) approaches [1], [2], [6], [8]–[13] and 2) inadequate field (or then again keypoint-based) approaches [3], [5], [14].

For the thick field duplicate move phony identification draws near, the info pictures are first isolated into covered and ordinary squares; at that point the fabrication restriction method is performed through square coordinating. To improve the strength against some normal mutilations, for example, geometric changes, different systems have been utilized to plan the square highlights, for example, Discrete Cosine Transform (DCT) [1], Discrete Wavelet Transform (DWT) [2], Principal Component Analysis (PCA) [8], Singular Value Decomposition (SVD) [9], and different procedures [10], [11]. The thick field approaches were demonstrated to be more precise than the keypoint-based ones at the expense of higher unpredictability [6]. All the more as of late, Cozzolino et al. [12] proposed a productive thick field duplicate move imitation location technique, where the handling time was profoundly decreased by falling back on the PatchMatch calculation—a quick rough closest neighbour search conspire . Unfortunately, all the current thick field plans experience the ill effects of certain assaults, for example, scaling, revolution and commotion expansion. This can be completely approved by the test results to be introduced in Section VI.

Container and Lyu [14] spearheaded the work on utilizing keypoint coordinating for vigorous duplicate move imitation recognition. Helped by the Scale Invariant Feature Transform (SIFT) highlight, their technique was demonstrated to be powerful against geometric changes, where the parameters were estimated by the RANdom SAmple Consensus (RANSAC) calculation. A to some degree comparative plan was proposed by Amerini et al. [3] to identify various copied districts, where the coordinated correspondences may follow distinctive geometric changes. Right now, worldwide the RANSAC estimation over all the coordinated sets doesn't work any more. To handle this issue, [3] recommended to utilize the various level agglomerative bunching calculation [25] to gather the coordinated keypoints into isolated groups dependent on their areas in the picture plane, and afterward apply the RANSAC estimation over every two coordinated groups. Instead of grouping the keypoints, proposed to bunch the coordinated matches in a theoretical space. For curtness, we call such keypoint based systems including bunching techniques as keypoint-grouping based calculations. Rather than utilizing the bunching calculations to assemble the coordinated keypoints, some different scientists proposed to initially section the entire picture into non-covered little fixes; the coordinating procedure was then directed between every two fragmented areas [5]. In our work, we call those keypoint-based procedures including division procedures as keypoint division based calculations. Other than the SIFT descriptor, SURF , LBP and some other nearby highlights [15] were likewise considered in the ongoing literatures. Despite the fact that the keypoint-based duplicate move fabrication recognition techniques have been concentrated from different viewpoints, they were shockingly demonstrated to be less precise than the thick field ones [6], [12], and the presentation hole was very huge when the duplicate move imitation just includes little or smooth areas as appeared in Fig. 1. The fundamental downsides of the current keypoint-based duplicate move phony location strategies can be abridged as follows:

1) They neglect to create an adequate number of keypoints (henceforth coordinated sets) in those little or smooth duplicate move districts, causing location disappointment;

2) It is troublesome (even difficult) to discover an all around great bunching/division calculation and related parameters appropriate for all pictures. This is on the grounds that the duplicate move areas can be of any sizes, and can be exceptionally different from the surfaces. Moreover, the quantity of duplicate move areas is commonly obscure; appropriately playing out the grouping right now troublesome;

3) The existing keypoint-based strategies absence of dependable relative lattice approval and inliers choice, as in certain anomalies could be treated as inliers by the existing homography estimation systems (e.g., RANSAC), causing a high bogus alert rate.

Right now, propose a productive and exact keypoint-based technique for picture duplicate move imitation location and limitation, accomplishing reliably great execution regardless of whether the duplicate move fabrication just includes smooth or little locales, or the fashioned pictures have been prepared by some serious assaults (e.g., huge scope resizing and overwhelming commotion addition). Fig. 2 presents the structure of our proposed picture imitation identification plot, which follows the exemplary work process, in particular, 1) highlight extraction; 2) include coordinating; and 3) phony limitation. Our principle commitment lies in planning novel and advanced answers for all these three stages. At the primary stage, we structure a basic yet compelling approach to separate an adequate number of SIFT keypoints, even in smooth and little areas, by bringing down the complexity edge and rescaling the information picture. At the subsequent stage, a novel various level point coordinating methodology is proposed to take care of the keypoint coordinating issues over an enormous number of key-focuses. At the third stage, a novel iterative homography esti-mation and a duplicate move confinement method are recommended, without including any bunching and division techniques. By completely misusing the power properties (counting the predominant direction and the scale data) and the shading data of each keypoint, our proposed strategy accomplishes exceptionally exact location results at significantly brought down computational cost. Broad test results show that our proposed conspire prompts a higher True Positive Rate (TPR) and a lower False Positive Rate (FPR) simultaneously in the greater part of the cases, contrasted and both the current thick field and keypoint-based methodologies.

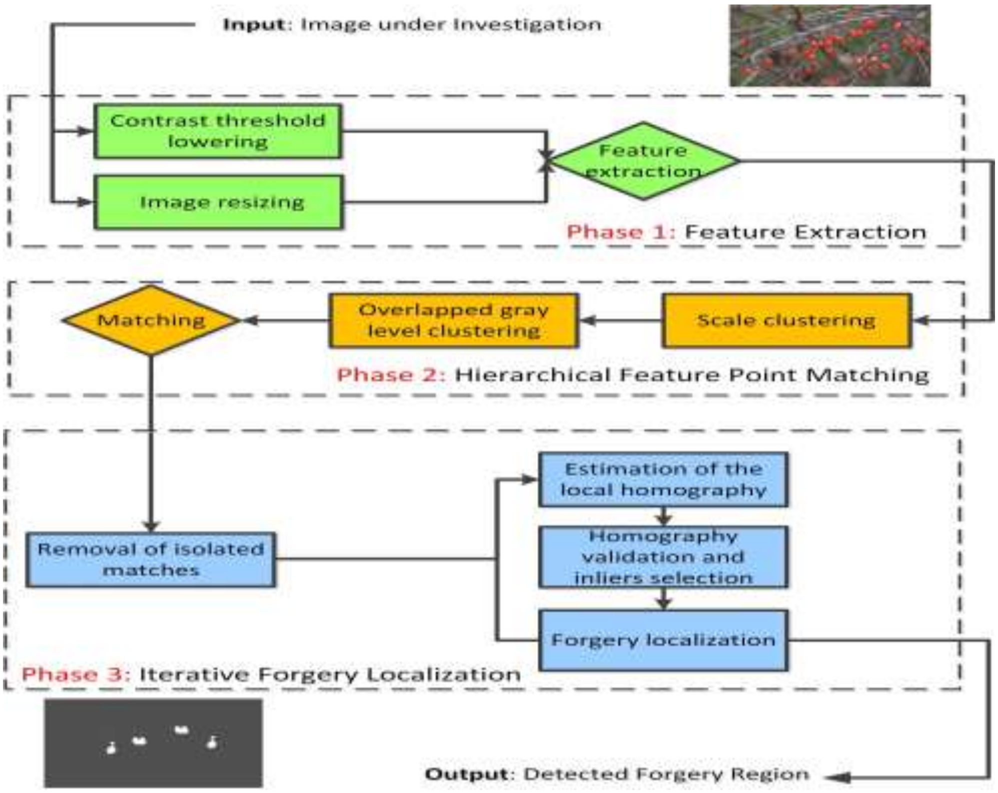



**Fig-2:** Proposed algorithm framework

Contrast from the Conference Version: parts of the work introduced straight away recently showed up in [21] as a gathering adaptation. We've got significantly refined the paper as so much as each specialised and trial elements. The essential enhancements are often half-length as follows. particularly else, we tend to cautiously gift the technique to settle on inliers utilizing the prevailing knowledge in Section V-C, and that we implant another Section V-D to introduce the phony limitation in thick fields by misusing the size knowledge and also the shading knowledge of every keypoint. Besides, in Section VI, we tend to distinction our calculation and lots of best in school plans to fully exhibit the predominant discovery execution. Further, we tend to lead the procedure many-sided nature correlation with show the high proficiency of our set up. To wrap things up, another Section VI-D is given to assess the strength against numerous changes. We tend to exhibit that the planned conspire accomplishes higher recognition execution at each the image level and also the picture element level, considerably below some troublesome conditions (e.g., huge scope resizing).

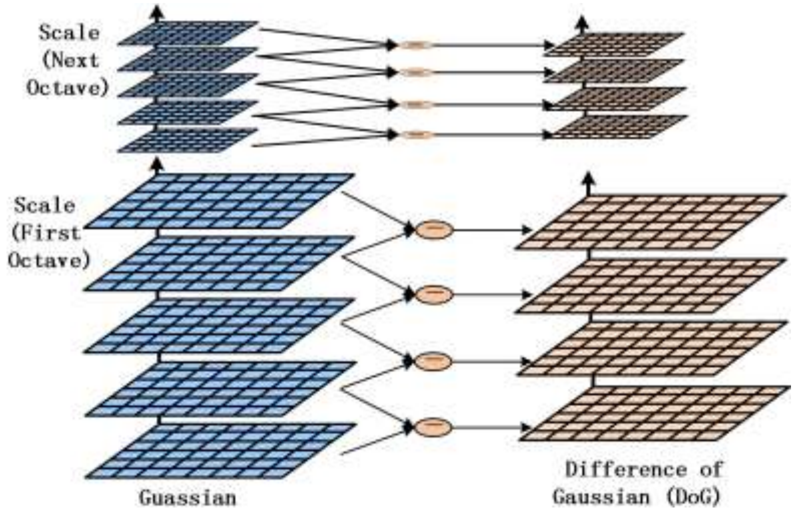



**Fig-3:** The schematization of Gaussian-blurred images (left) and DoG images (right).

The rest of this paper is sorted out as follows. phase II offers a terse presentation of the SIFT calculation. phase III portrays the part extraction methodology, and Section IV clarifies the assorted leveled embody purpose coordinating set up. A tale fraud restriction calculation is definite in Section V. wildcat outcomes on the duplicate move fraud location area unit introduced in Section VI, and a brief finish is at long last attracted Section VII.

## II. INTRODUCTION TO THE SIFT

As one of the most well known calculations in PC vision to extricate and portray picture nearby highlights, the SIFT [23] has been demonstrated to be brilliantly vigorous against clamour bending and geometric changes [26], [27]. Right now, quickly audit the SIFT highlight age and coordinating calculation.

### A. SIFT Feature Generation

The SIFT calculation can be generally separated into four stages:

1) Applicant keypoint recognizable proof through the scale space extrema discovery; ii) keypoints refinement as indicated by the complexity and edge limits; iii) predominant direction relegate ment of each keypoint; and iv) highlight descriptor age. Fig. 3 shows the development of the scale space. At stage I), the up-and-comer keypoints are distinguished at various scales. Given an info picture I, progressive Gaussian-obscured pictures are produced by more than once convolving I with Gaussian channels at various scales. At that point, the up-and-comer SIFT keypoints are chosen as neighborhood extrema inside a 3 × 3 × 3 shape of the Distinction of Gaussians (DoG) area. In particular, the DoG picture at scale σ is given by

$D(x, y,\sigma) = L(x, y, k\sigma) - L(x, y,\sigma)$, (1)

where k is a predefined consistent and $L(x, y,\sigma)$ means the Gaussian-obscured picture determined by

$L(x, y,\sigma) = I(x, y) \otimes G(x, y,\sigma)$. (2)

Here $G(x, y,\sigma)$ is the Gaussian piece. At stage ii), all the applicant keypoints are additionally refined as per a difference limit and an edge. This method assumes a key job for dismissing unsteady extrema in the SIFT calculation. At stage iii), a predominant direction is allocated to each endure keypoint to accomplish revolution invariance. For each point $(x, y,\sigma)$, its direction is figured as

$\theta(x, y,\sigma) \tan^{-1} dy$ , (3)

dx

where dy and dx are the vertical and even angles of $(x, y,\sigma)$. A direction histogram is then developed by social occasion the angle direction data of focuses in a neighbourhood window focused at the SIFT keypoint. The top in the direction histogram relates to the prevailing orientation. At stage iv), a 128-dimensional descriptor is determined by encoding the encompassing data in a neighbourhood (16 estimated in the scale space) focused at the SIFT keypoint. Through the over four stages, a rundown of n key-focuses k1, k2, ... , kn and their comparing descriptors f1, f2, ... , fn are produced for a given picture I. Leave k alone a nonexclusive SIFT keypoint, which is spoken to as a four dimensional vector

k = (xk , yk, σk , θk ), (4)

where (xk , yk) are the directions in the picture plane,

σk indicates the scale and θk fills in as its prevailing direction.

For more insights concerning the SIFT, it would be ideal if you allude to [23].

### B. SIFT Feature Matching

To locate a dependable match (may not exist however) of the keypoint k, essentially assessing the separations with the other (n 1) keypoints against a worldwide limit doesn't perform well in the high dimensional component space [3], [23]. The generally utilized coordinating calculation was proposed in the first SIFT paper [23], where the coordinating strategy is led by assessing the proportion of the nearest separation to the second-nearest one. The justification behind is that for those bogus matches, there will probably be a few other bogus matches with comparative separations. This is on the grounds that the separations are com-puted in the high dimensional element space. In particular, let vector d d1, d2, ... , dn 1 record the Euclidean separations between the keypoint k and the rest of the (n 1) keypoints in an expanding request, i.e., d1 d2……… dn 1. At that point, the keypoint k is coordinated with one of the other (n 1) keypoints if and just if

$d_1/d_2 < t$, (5)

where t (0, 1) is a predefined parameter commonly set as 0.6. ∈

**Fig-4:** (an) Original picture; (b) manufactured picture through duplicate move tasks, where the keypoints are gotten by setting C 4; (c)fashioned picture through duplicate move activities, where the keypoints are acquired by setting C 0.1; (d) and (e) show how the differentiation limit and rescaling factor influence the quantity of key points, separately.

## III. FEATURE EXTRACTION

Because of its brilliant power against the clamor twisting and geometric changes, the SIFT calculation [23] is likewise utilized right now the element extraction. As discussed in Section I, one basic issue for the keypoint-based methodologies (counting SIFT-based ones) is that they can't produce an adequate number of keypoints in smooth or little districts, hence prompting second rate identification execution [6], [12], [28]. Right now, propose two basic yet successful systems to produce a considerably more number of SIFT keypoints, even in smooth or little districts, to be specific, 1) bringing down the complexity limit and 2) resizing the information picture.

### A. Lowering the Contrast Threshold

As expressed in Section II (stage ii), the complexity sift old indicated by C, is predefined to dismiss those precarious extrema with low difference values.1 Typically, for each point x = (x, y,σ) in the scale space, its differentiation esteem is given b

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
Volume:02/Issue:05/May-2020 www.irjmets.com

y D(xˆ) = D + 1 . ∂ D ΣT xˆ, (6)

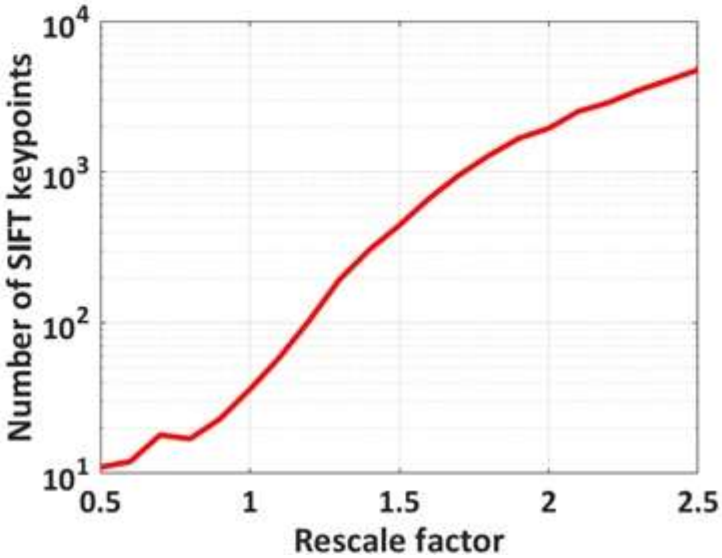
where D is characterized in (1), and x is the refined area of x in the nonstop space [23]. Any extremum with differentiate esteem littler than C is dismissed to be a last SIFT keypoint.

In any case, we find that in smooth locales, the difference estimations of extrema will in general be low. As an outcome, few or even no extrema can pass the differentiation refining technique lastly get by as SIFT keypoints. Fig. 4 gives a model, where a piece of the moon is produced. When setting the complexity limit C 4 (a typical setting for the VLFEAT execution), only one keypoint can be identified.

To guarantee that an adequate number of keypoints can be produced in smooth districts, we propose to bring down the differentiation edge C in the SIFT calculation, permitting loads of extrema with low complexity esteems to be endure. Be that as it may, we need likewise to abstain from embracing an exceptionally little C (e.g., C 0 in the outrageous case), as it will trigger an excessive number of shaky keypoints, accordingly prompting numerous inconsistent matches. What is more regrettable, a little C will likewise disturb the keypoint coordinating issues (to be examined in Section IV-A). So as to locate a decent tradeoff, we first physically select 100 pictures containing smooth districts, for example, sky, glass, desert, moon and so forth., from the datasets list in Section VI-A. At that point for each chosen picture, we extricate 5 smooth patches with sizes extending from 100 to 500. Difference is the paradigm for the fix choice. For instance, to separate the fix of size 100 from a specific picture, we first gap it into covered patches of a similar size, and afterward extricate the one with the base fluctuation. By rehashing comparable tasks, we at long last acquire 500 smooth patches. Leave Si alone the size of the I - th fix. By considering the way that the RANSAC estimation needs at any rate 4 right matches, and the duplicate move patches are commonly no littler than 1200 pixels [12], we can pick another complexity limit C by taking care of the accompanying improvement issue.

### C. Resizing the Input Image

Exclusively bringing down the differentiation limit can't completely tackle the issue of producing an adequate number of keypoints, when the duplicate move imitation is directed on little areas. Our integral procedure is to resize the information picture by a factor of s before computing SIFT keypoints. We have led broad analyses, demonstrating that augmenting the information picture will exceptionally build the quantity of keypoints. The bend in Fig. 4(e) exhibits that an a lot bigger number of keypoints are produced as the scaling factor s increments. As two extraordinary cases, s 1 and s 2 compare to the cases that SIFT keypoints are determined from the octaves 0 and 1, separately. Despite the fact that a bigger s triggers more keypoints, it will cause the keypoints to firmly group in the picture plane, compounding the keypoint coordinating issues (to be discussed in Section IV-A). In our trials, we set s 2 to accomplish a decent trade off. Through the over two methodologies, the quantity of keypoints can be altogether expanded, even in smooth or little districts. In any case, such countless keypoints additionally cause some basic coordinating issues (Section IV-An) and furthermore increment the chance of bogus coordinating. On account of the proposed coordinating methodology (Section IV-B and IV-C) and the new fraud restriction system (Section V), such issues can be incredibly moderated.




## IV. HIERARCHICAL FEATURE POINT MATCHING

In the duplicate move falsification location situation, the component point coordinating activity plans to distinguish comparable neighborhood areas in the picture. Right now, first clarify the issues of the point coordinating over countless keypoints. A tale various leveled highlight point coordinating plan is then proposed to lighten such issues.

By falling back on the methodologies proposed in Section III, an a lot bigger number of SIFT keypoints are created. One maybe clearly feels that the quantity of coordinated sets would likewise be profoundly expanded as needs be. Tragically, we tentatively acquire a contrary outcome. Fig. 5 gives a model, where we can see, through bringing down the differentiation edge and developing the information picture, in excess of multiple times bigger number of keypoints are produced; be that as it may, the quantity of matches drops from 5 to 1. The purpose for is that subsequent to bringing down the complexity limit, more keypoints are created at the close by areas or even a similar area (yet in various scales).

Review that all SIFT keypoints are recognized in the scale space, where the Gaussian pictures are assembled by octave as appeared in Fig. 3. When bringing down the complexity edge C and augmenting the info picture, the keypoints recognized at various scales would be firmly grouped. This irritates the keypoint coordinating issue I. Right now, arrangement is to maximumly isolate the grouped keypoints identified at various scales. To this end, we propose to lead the coordinating system inside each single octave of lower scales independently, while together inside various octaves of higher scales. The justification is two-folds: 1) the quantity of keypoints in higher-scale octaves is substantially less than that of lower-scale ones, and consequently don't experience the ill effects of the keypoint coordinating issues; 2) mutually coordinating the keypoints in higher-scale octaves accomplishes the heartiness against enormous scope resizing assault.

## V. EXPERIMENT RESULTS

Right now, assess the proposed duplicate move falsification discovery technique. The identification execution is estimated at both the picture level and the pixel level. At the picture level, we center around the capacity that a picture can be accurately recognized as manufactured or veritable; at the pixel level, we investigate the exhibition for falsification limitation precision. To grasp the idea of reproducible research, the code of our paper is accessible at https://github.com/YuanmanLi/FE-CMFD-HFPM. The initial two estimates are True Positive Rate (TPR) and Bogus Positive Rate (FPR)

### A. Datasets

Six test datasets, i.e., FAU GRIP[12], MICC-F220 [3], MICC-F600 [16], CMH [15] and Inclusion [34] are utilized to show the adequacy of our plan. Note that the altered patches from FAU and GRIP are not additionally prepared, while the ones from the other four datasets could be applied with various assaults (changes) in a practical design, for example, rotation, scaling, or a mix of them.

**B. Detection Results on Six Datasets**

We initially assess the proposed conspire under plain duplicate move assault, to be specific no further assault is performed on the duplicate move areas. The analyses are led over FAU and GRIP datasets. Two models are delineated in Fig. 8, where the principal push and the subsequent line show the cases that the duplicate move fabrications are directed in little districts and smooth areas, separately. For the produced picture demonstrated, the proportion of the littlest duplicated district over the entire picture is about 0.27%, and the fluctuation of the replicated area is about 3.9.

To our best knowledge, these are the best results ever reported. Besides the detection accuracy, we also present the average CPU-time for each algorithm in Table I. To make a fair comparison, all the methods operate in single-thread modality. We can see that the keypoint-clustering-based technique [3] is the most efficient. Its high efficiency is mainly due to the following two factors: 1) it doest not deal with the forgery localization problem, and hence, it can only give the image level detection results; and 2) the number of features extracted is often very limited without specifically handling smooth or small copy-move forgeries. Clearly, it would make the matching procedure very efficient even without any speed- up strategies; but at the cost of severe performance degra- dation, as can be seen from Table I. By resorting to the proposed hierarchical feature point matching and the iterative localization strategy, our method is also very efficient, and the computational efficiency gains over the other methods (except [3]) are quite remarkable, especially when images are of high resolutions. For example, our method is over 50 times faster than [5], 30 times faster than [6], 10 times faster than [15], and 5 times faster than on FAU dataset.

Evaluating the connection map is a mainstream algorithm for keypoint-based strategies to restrict the fashioned districts [14], [16]. Relationship based calculations as a rule require to initially process relative lattices, and afterward apply geometrical changes overall picture. In any case, these techniques are probably going to cause bogus alerts when the picture contains numerous comparative examples and periodical changes. For our strategy, in every cycle, we first develop suspicious areas by abusing the scale data of keypoints, and afterward refine the guide utilizing the shading data. This makes our technique not just strong against the impedance of comparative examples, yet additionally extremely effective. To approve this, we supplant the confinement methodology in Section V-D with the connection based calculation ZNCC proposed in.

**C. Performance of Challenging Copy-Move Forgery Detection**

In this Section, we show some challenging examples of the copy-move forgery detection. Figs. 12(a1)-(g1) depict the results when the copy-move forgery only involves smooth regions, where the variance of the copied region is about 9.0. As can be expected, all the previous keypoint-based algorithms [3], [5], [14] fail completely in this case, due to the lack of keypoints.

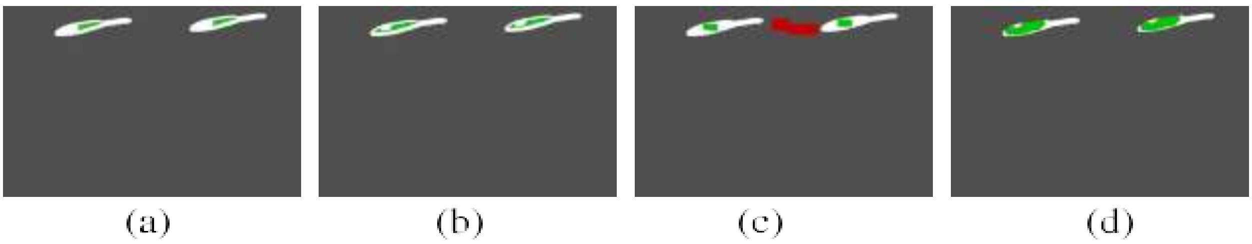



**Fig-5:** The localization maps obtained by different algorithms. The variance of the copied region is 2.13 (the average offset from the mean is about 1.46).(a) Bravo-Solorio and Nandi [31]. (b) Zernike [6]. (c) GoDeep [15].(d) Proposed.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
Volume:02/Issue:05/May-2020 www.irjmets.com

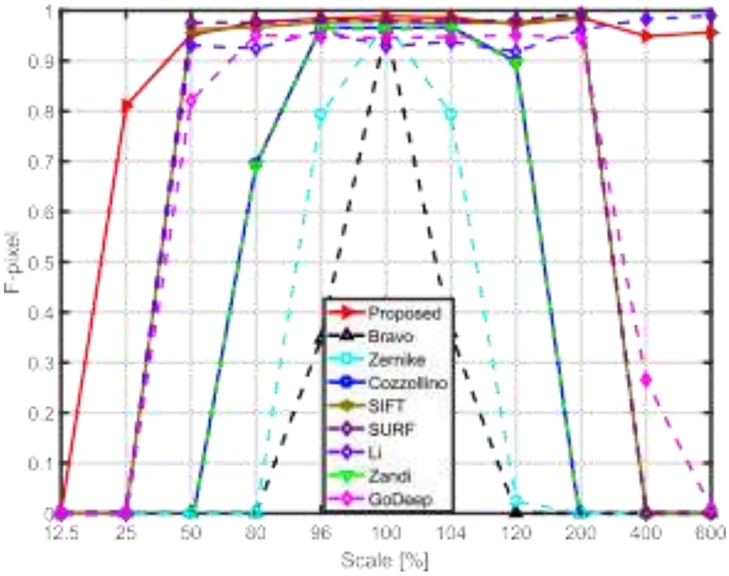



**Fig-6:** An example of copy-move forgery detections with extreme scaling factors. (a) The forgery image and (b) localization performance of copy-move forgery detections with respect to different scaling factors.

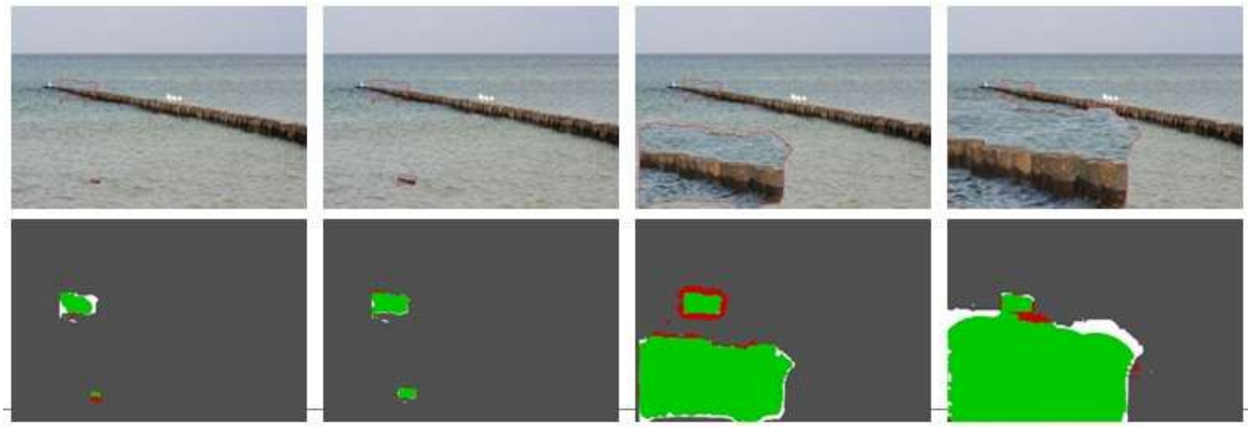


**Fig-7:** The localization maps obtained by our method when the copied region is resized by a factor of (a) 25%, (b) 50%, (c) 400% and (d) 600%.

## VI. CONCLUSION

Right now, have proposed a quick and successful keypoint-based duplicate move falsification recognition and limitation procedure. Via cautiously contemplating the keypoint extraction calculation (SIFT), we have first exhibited that it is possible to produce an adequate number of keypoints even in smooth or little areas, by bringing down the complexity edge and resizing the picture. At that point a novel progressive element point coordinating system has been proposed to reduce the basic coordinating issues. To decrease the bogus alert rate and accurately limit the replicated areas, we have additionally proposed a novel iterative confinement conspire without including any grouping and division methodology. By completely exploiting the vigor properties of the SIFT calculation (counting the predominant direction and the scale data) and the shading data of each keypoint, our proposed procedure accomplishes exceptionally high identification exactness. Broad exploratory outcomes have been given to exhibit the prevalent presentation of our proposed conspire.

## VII. REFERENCES

[1] G. Muhammada, M. Hussain, and G. Bebis, "Passive copy move image forgery detection using undecimated dyadic wavelet transform," Digit. Invest., vol. 9, no. 1, pp. 49–57, 2012.

[2] I. Amerini, L. Ballan, R. Caldelli, A. Del Bimbo, and G. Serra, "A sift-based forensic method for copy–move attack detection and transformation recovery," IEEE Trans. Inf. Forensics Security, vol. 6, no. 3, pp. 1099–1110, Sep. 2011.

[3] Y. Li, J. Zhou, A. Cheng, X. Liu, and Y. Y. Tang, "SIFT keypoint removal and injection via convex relaxation," IEEE Trans. Inf. Forensics Security, vol. 11, no. 8, pp. 1722–1735, Aug. 2016.

[4] J. Li, X. Li, B. Yang, and X. Sun, "Segmentation-based image copy- move forgery detection scheme," IEEE Trans. Inf. Forensics Security, vol. 10, no. 3, pp. 507–518, Mar. 2015.

[5] Y. Li, J. Zhou, and A. Cheng, "SIFT keypoint removal via directed graph construction for color images," IEEE Trans. Inf. Forensics Security, vol. 12, no. 12, pp. 2971–2985, Dec. 2017.

[6] A. C. Popescu and H. Farid, "Exposing digital forgeries by detecting duplicated image regions," Dartmouth College, Hanover, NH, USA, Tech. Rep. TR2004-515, 2004.

[7] J. Zhao and J. Guo, "Passive forensics for copy-move image forgery using a method based on DCT and SVD," Forensic Sci. Int., vol. 233, nos. 1–3, pp. 158–166, 2013.

[8] S.-J. Ryu, M. Kirchner, M.-J. Lee, and H.-K. Lee, "Rotation invariant localization of duplicated image regions based on Zernike moments," IEEE Trans. Inf. Forensics Security, vol. 8, no. 8, pp. 1355–1370, Aug. 2013.

[9] D. Cozzolino, G. Poggi, and L. Verdoliva, "Efficient dense-field copy-move forgery detection," IEEE Trans. Inf. Forensics Security, vol. 10, no. 11, pp. 2284–2297, Nov. 2015.

[10] X. Bi and C.-M. Pun, "Fast reflective offset-guided searching method for copy-move forgery detection," Inf. Sci., vols. 418–419, pp. 531–545, Dec. 2017.

[11] X. Pan and S. Lyu, "Region duplication detection using image fea- ture matching," IEEE Trans. Inf. Forensics Security, vol. 5, no. 4, pp. 857–867, Dec. 2010.

[12] E. Silva, T. Carvalho, A. Ferreira, and A. Rocha, "Going deeper into copy-move forgery detection: Exploring image telltales via multi-scale analysis and voting processes," J. Vis. Commun. Image Represent., vol. 29, pp. 16–32, May 2015.

[13] I. Amerini, L. Ballan, R. Caldelli, A. Del Bimbo, L. Del Tongo, and

[14] G. Serra, "Copy-move forgery detection and localization by means of robust clustering with J-linkage," Signal Process., Image Commun., vol. 28, no. 6, pp. 659–669, 2013.

[15] B. L. Shivakumar and S. S. Baboo, "Detection of region duplication forgery in digital images using SURF," Int. J. Comput. Sci., vol. 8, no. 4, pp. 199–205, 2011.

[16] J. Zhao and W. Zhao, "Passive forensics for region duplication image forgery based on harris feature points and local binary patterns," Math. Problems Eng., vol. 2013, Dec. 2013, Art. no. 619564.