Comprehensive Assessment of Existing Copy Move Forgery Detection Discussing the Trends and Challenges

Varsha Thakur[1*] and Rohit Agarwal[2]

[1,2]GLA University, Mathura,India
[*1]varshavbn@gmail.com

Abstract. Because of the impactful picture editing instruments, images are available to a few controls; in this manner, their genuineness is becoming problematic particularly when pictures have compelling power, for instance, in an official courtroom, news articles, as well as protection rights. Image forensic approaches decide the trustworthiness of pictures by applying different super advanced mechanisms created in the previous work. In this article, the pictures are broke down for a specific sort of imitation where a locale of a picture is reordered onto a similar picture to make a copying or to hide a few prevailing items. To recognize the copy-move forgery attack, pictures are primary categorized into overlapping square blocks as well as DCT constituents are implemented as the block representations. Because of the great lay-ered feature of the element space, Gaussian RBF kernel PCA is functional to accomplish the condensed dimensional feature vector depiction that likewise superior the proficiency at the time of the feature matching. Investigational trials are conducted to assess the suggested strategy in contrast with cutting edge. Thus, this paper offers the several proposed procedure gives a computationally effective and de-pendable method of copy-move forgery detection (CMFD) that builds the believability of pictures in proof centered applications.

Keywords: Forgery, Deep Learning, RSNET50, VGG, Feature Extraction, Transfer Learning.

1 Introduction

Recently, Internet service providers and social platforms like Instagram, Facebook, Snapchat, and Reddit have grown, affecting digital information flow. The International Telecommunication Union (ITU) said that 53.6% of the world population accessed the Internet in 2019, giving 4.1 billion people access to this technology and many online capabilities. The community material is mostly original or edited for enjoyment, but it may be manipulated for propaganda or disinfor-mation, which may have forensic or political consequences, such as using false data in an illegal inquiry.

Video and photo manipulation involves manipulating digital data using applications like PILR, GIMP, Adobe Pho-toshop, or AI. The copy-move method copies and re-inserts picture segments [1]. As editing technology improves, fake photos become indistinguishable from real ones. Post-processing alterations including Scaling,

brightness and JPEG com-pression may reduce manipulation remains and complicate identification [3].

Handcrafted and machine learning methods are used in the CMFD [2]. Block-based, key point-based, and hybrid techniques are the main types. Custom designs provide more applications without preparing or refining pre-existing struc-tures like VGG-16 [4]. Block-based methods employ finite elements such the Tetrolet transform [7], DCT [5, 6], and Fouri-er Transform. Since forging is identified by a matching interaction, they want to reduce execution time when replicated content is resized or rotated [8]. Key point-based methods, such as SURF (Speed-Up Robust Features) and SIFT (Scale In-variant Feature Transform), are more resilient to rotation and illumination, but they must identify fakes in uniform intensi-ty regions, misclassify naturally similar objects as false duplicates, and rely on authentic key points in the image [6]. Only for a particular dataset, a hybrid method produced more consistent recall (R), precision (P), and F1 score [11].
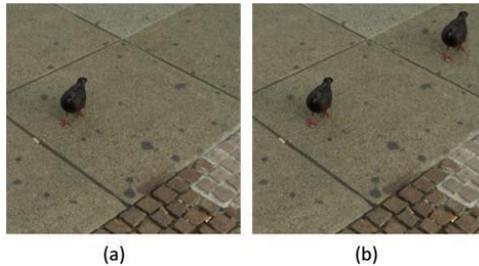

(a)   (b)

Fig. 1. An example of Copy Move Forgery where (a) is the original image and the (b) is forged image, in the (b) diagram one bird is copied from (a) and pasted in (b) forged.

A CMFD is a passive tampering identification in forgery recognition in which minimum single locale has been reorganized inside the alike picture as shown in Fig. 1.. Common motivations of these frauds include hiding a constituent for the image (for exam-ple steganography) or emphasizing a certain item (for example a crowd of demonstrators). In CMFD, the general manipu-lated regions in the picture are viewed as fabric, greenery or grass [12]. Such regions are not difficult to mix with the foun-dation because of similitudes in the color and texture.
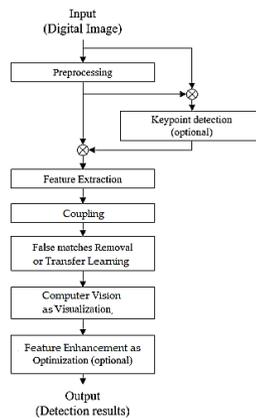
Fig. 2. Architectural diagram of a CMFD Model

Numerous methods are available for CMFD (Fig. 2). This array of tactics is categorized into one of three classes: block-based techniques, key point-based strategies, or segmentation-based strategies. The block-based approaches partition the information image into non-overlapping blocks, which are then compared to identify regions that are nearly identical [13]. The difference among various block-based methods is in the criteria used to align the blocks . Key point-based approaches iso-late features from the overall image and correlate these points to identify similar regions [14].

2   Related Work

Analysts have created numerous digital picture CMFD detection methods. These strategies are split into key point and block-based methods. Block identification divides the picture into non-overlapping or overlapping parts. Each block un-dergoes feature extraction (FE). The block-based method requires Euclidean distance, hash value, radix sort, K-d tree, and lexicographical ordering for block feature matching [15]. CMFD was accomplished via robust matching, auto-correlation, accurate block matching, and exhaustive block search. This method detects counterfeits but mismatches huge textured photos.

Pacloviet al. [16] formed non-overlapping chunks of the picture utilizing multiracial variations for feature extraction and metaheuristic organization. This method does not detect geometric transformation frauds. A. Diwan et al. [17] limited im-age copy-move using LPP. They clearly defined and limited fabrication in AWGN and JPEG. They reduce computer com-plexity by not sorting picture feature vectors like earlier block-based techniques. QPCETM-based sub-sampled picture methods were suggested by Hosny et al. [18]. The pre-FE analysis of the picture is intriguing, but it may not work for smooth textures or images with a thick surface. Zhong et al. [19] retrieve and analyze picture information using two-stage hashing.

Before applying the hash function, the normalized moment transform extracts block properties. Gani et al. [20] Use cellular automata for each picture DCT block. Approach temporal complexity is high. Block-based methods are computationally

intensive. They are also susceptible to blurring, 180-degree flips, and geometric alterations. Key point-based methods may solve these issues. [21]. this method detects forgeries using key image spots. Experts have utilized several key point-based forgery identification systems. Warif et al. [21] addressed rotation and scaling using SIFT and mirrors SIFT. They use LoG to cut computing expenses. Muzaffer et al. [22] proposed binary SIFT, where each component works together.

CNNs extract and characterize features in current methods [22]. A CNN with nine convolutional layers and a fully connected (FC) layer were suggested [14]. The framework was independently trained on CASIA v1 and CASIA v2 datasets to 98.04% and 97.83% accuracy. A comparable research as shown in Table 1 used a custom architecture with six convolutional layers and three fully connected layers, dropout in the fully connected levels (save the last layer), and batch normalization across all con-volutional layers. Internal validation of this design using the CoMoFoD dataset yielded 95.97% accuracy [15]. Less complicated custom design uses two completely linked and two convolutional layers [16]. The scientists trained and validated the framework using one, two, and three datasets, earning 90%, 94%, and 95% F1 scores. They simplify, but both datasets are uneven, with one having a 2:1 ratio for counterfeit and legitimate photos and the other 2:3. CNN-based data-driven lo-cal descriptors had CoMoFoD F1 scores between 0.5 and 0.7 [17].

Table 1. FT with six variations in CMFD and their developments.

Researcher(s)	Method	Merits	Demerits	Explanations
Singh et al. (2022) [22]	DWT SIFT	Blurring, noise, rotation, scaling, and JPEG compression-re sistant.	Geometrical issues.	Using DWT and SIFT involves tentacle matchong of same features extracyed from each points.
Sadhu et al.(2022) [23]	SURF BRISK	Works on Geometric transforms	Further needs improvement for keypoints and descriptors.	SURF and Brisk features are used with the HierarchicalAgglomerative Clustering(HAC)
Shankar et al. (2022) [24]	DWT	Less Accuracy time	If the image has gone through the transforming attack then weak performance.	DWT is used with DCT along with correlation.
Gani et al. (2020) [25]	DCT	Robust against noise and JPEG compression	Incapable to recognize scaling and rotation in copy move forgery.	Uses the DCT with cellular automata, kd tree nearest neighbour searching is used.
Chennamma et al. (2023) [26]	DCT SURF	Robust to JPEG compression.	Computational complexity	DCT is used along with SURF methods.

Kumar et al. (2023) [27]	SIFT	Robust against blurring and JPEG compression.	Post processing transformation.	Improved saliantkeypoint method with KAZE keypoints.
Diwan et al. (2024) [28]	CenSurEkeypoint detection	Works on Image with various textures	Only works for copy move forgery.	CenSurEkeypoint detection with the hybrid model of CNN.
Wang et al. (2024) [29]	Keypoint with FQGPCET –GLCM Features	Handles various post processing issues with high precision.	Computation complexity is more.	Simple linear iterative clustring and k multiple means is used.

3   Block-Based FE Approaches

By and large, the FE methods for block-based are as frequency transform, dimension reduction, log polar transform, mo-ment invariant, intensity as well as texture as well as others. The subtleties of the FE procedures are deliberated as follows.

3.1   Frequency transforms (FT)

FT is the most famous FE methods for block-based, maybe because of its vigor to noise as well as distinctness of the translational/rotational parts. A few upgrades, in view of Wiener Filter Wavelet, Dyadic Wavelet Transform (DyWT), fast Walsh-Hadamard Transform (FWHT), Discrete Wavelet Transform (DWT), FT and Discrete Cosine Transform (DCT), have been suggested to further better the results. With the transform functions, DCT is broadly utilized in CMFD. [30] DCT is recognized for its sturdiness in contradiction of JPEG compression and noise expansion. Generally, the improvements of FT functions are centered on the decrease of feature aspects that prompts small computational intricacy in future examination. Their CMFD exhibitions are strong in contradiction of the picture with post-processing activity and insufficient with transitional task.

3.2   Intensity and Texture

Intensity as well as texture occur in environmental conditions like ground, tree, cloud as well as grass, picture characteristics, for example, coarseness, smoothness and consistency address the texture matters. Their intensity, texture as well as fore can be used as features to discover the similitudes in the false picture. In CMFD, intensity as well as texture are estimated and classified through color info, intensity/pattern. Moreover, MLBP depicts an additional benefit of sturdiness to brilliance varieties. RGB, gray value, spatial color as well as illumination are the essential parts in

addressing the color data. Such parts are separated via the similarity measurement, color quantification and color space. The color data is invariant regarding rotation, translation and scaling. However, a mixture among the Tamura texture as well as average gray value will bring about further advantages, for example, vigorous to JPEG compression as well as Gaussian noise with less time intricacy. In the interim, Ardizzoneet al. acquainted the bit plane assessment with categorize gray scale texture in the picture data [32].

3.3   Dimension lessening

Dimension lessening strategies are regularly utilized with area features to diminish the picture dimensionality as well as have better intricacy. Such methods are Singular Value Decomposition (SVD) and Locally Linear Embedding (LLE). The SVD is usually steady, attains rotation invariance and scales for both geometric as well as algebraic features. SVD lessens computational intricacy and is vigorous to different tasks especially revolution, scaling, filtering and Gaussian noise. On the other hand, LLE can be executing to lessen dimensionality in high-dimensional dataset. LLE tracks down the topologi-cal correlation between nonlinear dataset and map high-dimensional information to low-dimensional information deprived of altering the comparative areas. In correlation with Principal Component Analysis (PCA), LLE has the capacity to track down the pre-owned edge that conceals the follows in produced picture, yet PCA verified a quicker handling time. Among these two procedures, SVD has a greater by and large execution of vigor to different tasks and computational intricacy.

4   Block-Based Matching Approaches

Matching strategy is a procedure to track down among at least two features in the picture. The procedure is conducted after every component in the picture is estimated as well as extricated to characterize the manipulated region. From the prior research work, the matching strategies for block-based can be separated into Euclidean distance, hash, sorting, relationship and others.

4.1   Sorting

It organizes characteristics into a framework. Sorting is a common block-based matching strategy. Radix, KD-Tree, and Lexicographical are used for block-based matching. Lexicographical sorting is the most common block-based approach.
The last option is a nearest neighbor (NN) looking through method that sort's exhibit of blocks. In the first place, the method portions the exhibit into two sections recursively with various aspects. At the point when the exhibit size is more modest or equivalent to the local inquiry size, the iterative cycles are ended. At last, the area is examined and contrasted with a limit with characterize the conceivable copied region. This strategy has the capacity for a proficient reach questions in multi-faceted information for examination of block closeness.

4.2   Correlation

It is a geometric estimation of at least two factors to demonstrate the degree of variation. The relation coefficient is normally utilized to characterize the copied areas after sorting is performed. Be that as it may, the relationship can be conducted freely without sorting to discover the resemblance criterion in the picture. The most usually sent relationship strategy in CMFD is phase correlation. Regularly, the phase relationship recognizes the format matching in two comparative pictures (Table 2). This comparability is addressed by a substantial peak that reaches somewhere in the range of 0 and 1. Afterward, the stage relationship is embraced to track down the matching inside one picture.

4.3   Euclidean distance

It is an estimation of distances among two vectors in Euclidean space. Like correlation, Euclidean distance is in many cases concluded in the manipulated region after the sorting system. It computes the distance between comparable blocks distin-guished by the arranging strategy to recognize the copying in a picture. Muhammad et al. work out the distance among in-distinguishable blocks and wipes out the sorting system. A picture is associated with been messed with in the event that the two blocks is close to one another with a comparable area.

Table 2. Comparison between CMFD Techniques

Work	Technique	Explanations	Accuracy
Zheng (2022) [33]	SIFT	SIFT along HSV color model	95.83%
F Akar (2008) [34]	Hybrid FAST and SURF	FAST and SURF methods combined	0.7475%(F1 Score)
Kashyap and Joshi (2013) [35]	Lexicographic classification and SVD	Validity against compression, noise and blur filters	Notavailable
Gan, Y., Zhong, J., &Vong, C (2022) [36]	Improved SIFT	SIFT is improved wioth the feature label matching and HSM	92.11%
Devika, A. D., &Rajan, B. K. (2022) [37]	SIFT with Two stage filtering	SIFT is used with two stage cluster filtering to find out forged regions	90.79%

5   Key Point-Based Method

The key point feature abstract the particular local elements like edges, blobs, as well as corners from the picture. Every feature is given a descriptor set created with in a locale around the features. The descriptor assists with expanding their obligation of the elements to the comparative variation. Then, at that point, the two features as well as descriptors in the image are characterized as well as matched to one another to discover the duplicate/false locales in the CMFD. We found various research papers on key point-based techniques distributed and filed in WOS.

5.1   Key point-based FE approaches

Three main point-based approach FE techniques are Speeded Up Robust Features (SURF), Scale-Invariant Feature Transform (SIFT), and Harris Corner Detector.

i.   **SIFT:** The SIFT-based CMFD key point feature approach is the most prevalent. Lowe [14] presented SIFT to the object recogni-tion community and aimed to address rotation and scaling challenges. SIFT identifies significant points at various scales from the Difference of Gaussian (DoG) pyramid in scale-space representation. DoG operates on computational efficiency in picture extraction. The gradient orientation histogram in each SIFT feature is used to compute the rotation-invariant SIFT descriptor. CMFD endorses SIFT due to its provision of security for transitional and post-processing procedures. Four SIFT constraints in CMFD have been found. SIFT is computationally intensive because to the extensive quantity of element vectors derived from the picture. SIFT is unable to differentiate copy districts in flat regions with little visual distinction like solid boundary bounds. [39]

ii. **Harris corner detector:**Harris Corner Finder presents critical point techniques after SIFT. The locator eliminates zones' boundaries and corners for local auto-connection. Harris characteristics create textures in natural settings. CMFD explored the Harris locator and modified SIFT-based algorithms. The Harris identifier produces highlight focuses and joins suitable descriptor processes with the components. Improved Harris characteristics increase the focal points' reliability in detecting falsification.

iii. **SURF:**SURF reduces processing time and includes. By expanding Bay's methodology to 128 dimensions, researchers developed the SURF-based CMFD technology. SURF reduces erroneous matches, particularly for high-resolution pictures, although it is subject to modifications and post-processing.

5.2   Key point-based matching approaches

Likenesses amid the feature points in a picture can likewise be estimated utilizing NN. Although, because of the great computational complexity, distinguishing the imitation in an image is testing. Thusly, the NN procedures have been the topic of dynamic exploration. In this segment, the NN methods for key point-based method are isolated into four sorts, in particular: Best Bin First, g2NN, 2NN, and others.

i.   **Nearest Neighbor (NN):** NN analyzes the similitude among points by computing the distance of every point in vector space. The points are thought of as comparable on the off chance that the distances fulfill the threshold. There are four kinds of progress in NN method and they can be joined with different sorts to work on the exhibition. Key point features are generally listed utilizing Best Bin First, as well as the distance among every point is contrasted with a predefined Threshold eliminate misleading match [34] despite the fact that we see that thoroughly staying away from a bogus match is unimaginable.

ii. **Clustering:**CMFD uses Hierarchical Agglomerative Clustering (HAC) to cluster comparable items. Authors employ different linking methods to cluster estimates. Researchers showed object correlation via clustering rather than point matching. Weight Center of Mass Distance (WPGMC) connection group's vectors to

calculate object area then compares to a threshold. Thus, the duplicate with similar texture and shape may be legitimate.

6   Classification of Copied/Forged Areas

However there are some notable picture altering datasets for CMFD recognition accessible on the web, the greater part of them ordered the picture by activities engaged with the altering like scaling, scaling, rotation, compression and so on. MICC-F220 is a generally utilized dataset that involves 110 coy move pictures with various tasks [41]. This dataset has significantly helped the CMFD investigation community, regarding tracking down the tasks invariant methods.

6.1   Contextual

Contextual picture is characterized as the disparity among the objects as well as the environmental factors. This form refers the sights with varieties in brilliance as well as geometry situations rather than objects. The foundation can be a landscape, nature, surface or variety. Typically, homogenous foundations are been utilized to conceal the item showing up in the pic-ture. In this way, the prerequisite of surface examination including the force, examples, and variety is required.

6.2   Object

Essentially, an object is any physical structure i.e. genuine as well as conspicuous. Object in a picture incorporate design (e. g., construction), workmanship, lines, plant and shape. The object is replicated in the picture by and large for manipu-lating how much things while concealing the undesirable things. There is one domain in picture concentrates on which is recognized as acknowledgment as well as is effectively explored on at the hour of this composition.

6.3   Letter

The previous kind of duplicated areas is letter. In this, letter is a symbol of an alphabet set addressing a text or word. There are varieties of the letter in a similar alphabet in order. For example, computerized words have various textual styles alt-hough written by hand have assorted structures.

7   Limitations of CMFD Techniques

Many CMFD methods have been developed to eliminate district duplication. The study tries to improve picture depictions to identify duplicated locationsImage blocks are PCA-analyzed in [40]. On produce the component vector, singular value decomposition (SVD) is used on the less recurring parts of the image's four subgroups. The procedure is robust for JPEG compression up to 70 qualities. A reduction cycle reduces feature vector dimensionality in [41], improving DCT-based

forgery detection. Reference [42] suggests SVD and DCT to distinguish picture frauds. The calculation works despite pressure, noise, and obfuscation but fails with tiny picture changes.

8   **Conclusion**

On uninvolved validation approaches, image forgery identification is a growing area of study. In study, we focused on CMFD for digital picture fraud identification. WOS CMFD research publications were examined, and a representative CMFD work methodology was developed from the materials obtained. Managing geometrical transformations like rotation and scaling is limited. Thus, scientists have used component matching/extraction methods to boost block-based class activity. To manage change, they focused on minutes and log-polar change. Surface components have also been used to identify concealed items in photos. PCA, DWT, and S reduce component aspect while speeding up. Thus, LSH, KD-Tree, and Radix matching techniques have also been described. Although progress is ongoing, key point-based strategy appears to work better.

Key point-based techniques suffer from high temporal complexity since they must match many indistinguishable spots in an image. Concentrating on key political campaign highlights and matching processes to reduce complexity while main-taining accuracy is another topic of attention. Using different NN procedures and CMFD, a set number of key point high-lights with a variety of productive descriptor approaches may support mathematical change, locate the surface con-trolled area, and nurture a form district. Recently, professionals introduced the crossover strategy, combining block-based and key point-based processes. They worked on results using key point and pixel highlights.

References

1. Thakur, R.; Rohilla, R. Recent Advances in Digital Image Manipulation Detection Techniques: A brief Review. Forensic Sci. Int, 312, 110311. 2020
2. AbdWarif, N.B.; Wahab, A.W.A.; Idris, M.Y.I.; Ramli, R.; Salleh, R.; Shamshirband, S.; Choo, K.K.R. Copy-move forgery detection: survey, challenges and future directions. J. Netw. Comput. Appl. 75, 259–278.2016
3. Ferreira, W.D.; Ferreira, C.B.; da Cruz Júnior, G.; Soares, F. A review of digital image forensics. Comput. Electr. Eng. 2020, 85, 106685.
4. Dua, S.; Singh, J.; Parthasarathy, H. Detection and localization of forgery using statistics of DCT and Fourier components. Signal Process. Image Commun. 2020, 82, 115778.
5. Gani, G.; Qadir, F. A robust copy-move forgery detection technique based on discrete cosine transform and cellular automata. J. Inf. Secur. Appl. 2020, 54, 102510.
6. Meena, K.B.; Tyagi, V. A copy-move image forgery detection technique based on tetrolet transform. J. Inf. Secur. Appl. 2020, 52, 102481.
7. Sharma, S.; Ghanekar, U. A hybrid technique to discriminate Natural Images, Computer Generated Graphics Images, Spliced, Copy Move tampered images and Authentic images by using features and ELM classifier. Optik 2018, 172, 470–483.

8. Alberry, H.A.; Hegazy, A.A.; Salama, G.I. A fast SIFT based method for copy move forgery detection. Future Comput. Inform. J. 2018, 3, 159–165.

9. Badr, A.; Youssif, A.; Wafi, M. A Robust Copy-Move Forgery Detection In Digital Image Forensics Using SURF. In Proceedings of the 8th International Symposium on Digital Forensics and Security (ISDFS), Beirut, Lebanon, 1–2 June 2020; pp. 1–6.

10. Tinnathi, S.; Sudhavani, G. An Efficient Copy Move Forgery Detection Using Adaptive Watershed Segmentation with AGSO and Hybrid Feature Extraction. J. Vis. Commun. Image Represent. 2020, 74, 102966.

11. Fridrich,J.,Soukal,D.,Lukáš, J.,2003.Detection of Copy-Move Forgery in Digital Images. Int. J. Comput. Sci. Issues 3, 652–663. http://dx.doi.org/10.1109/ PACIIA.2008.240.

12. Muhammad, G., Al-hammadi, M.H., Hussain, M.,Mirza,A.M.,Bebis,G.,2013. Copy move image forgery detection method using steer able pyramid transform and texture descriptor. Euro Con,1586–1592.

13. Lowe DG (1999) Object recognition from local scale-invariant features. In: Proceedings of the 7th IEEE conference on computer vision, Kerkyra, Greece, vol 2, pp 1150–1157.

14. Teerakanok, S., Uehara, T.: Copy-move forgery detection: A state-of theart technical review and analysis. IEEE Access 7, 40 550–40 568 (2019).

15. Aleksandra, P., Glišović, N., Gavrovska, A., & Reljin, I. (2019). Copy-move forgery detection based on multifractals. *Multimedia Tools and Applications*, 1-24.

16. Diwan, A., Mall, V., Roy, A., & Mitra, S. (2019, November). Detection and localization of copy-move tampering using features of locality preserving projection. In 2019 Fifth International Conference on Image Information Processing (ICIIP) (pp. 397-402). IEEE.

17. Hosny, K. M., Hamza, H. M., & Lashin, N. A. (2019). Copy‑for‑duplication forgery detection in colour images using QPCETMs and sub‑image approach. IET Image Processing, 13(9), 1437-1446.

18. Zhong, J.-L., Pun, C.-M.: Two-pass hashing feature representation and searching method for copy-move forgery detection. Inf. Sci. 512, 675–692 (2020)

19. Gani, G., Qadir, F.: A robust copy-move forgery detection technique based on discrete cosine transform and cellular automata. J. Inf. Security Appl 54, 102510 (2020).

20. Warif, N. B. A., Wahab, A. W. A., Idris, M. Y. I., Salleh, R., & Othman, F. (2017). SIFT-symmetry: a robust detection method for copy-move forgery with reflection attack. *Journal of Visual Communication and Image Representation*, *46*, 219-232.

21. Muzaffer, G., Karaagacli, E. S., & Ulutas, G. (2017, September). Recent keypoint based copy move forgery detection techniques. In *2017 International Artificial Intelligence and Data Processing Symposium (IDAP)* (pp. 1-7). IEEE.

22. Singh, R., Verma, S., Yadav, S. A., & Singh, S. V. (2022, April). Copy-move Forgery Detection using SIFT and DWT detection Techniques. In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 338-343). IEEE.

23. Sadu, C., & Das, P. K. (2022, November). A Detection Method for Copy-Move Forgery Attacks in Digital Images. In TENCON 2022-2022 IEEE Region 10 Conference (TENCON) (pp. 1-6). IEEE.

24. Shankar, A., Swetha, P. N., &Ramu, B. Image Forgery Detection Method for Copy-Move and Splicing Attacks Using DCT, DWT And Correlation. Journal of Pharmaceutical Negative Results, 3878-3883 (2022).

25. Gani, G., &Qadir, F. A robust copy-move forgery detection technique based on discrete cosine transform and cellular automata. Journal of Information Security and Applications, 54, 102510.(2020).

26. Chennamma, H. R., &Madhushree, B. A comprehensive survey on image authentication for tamper detection with localization. Multimedia Tools and Applications, 82(2), 1873-1904.(2023).

27. Kumar, N., &Meenpal, T. Salient keypoint-based copy–move image forgery detection. Australian Journal of Forensic Sciences, 55(3), 331-354. (2023).
28. Diwan, A., & Roy, A. K. CNN-Keypoint Based Two-Stage Hybrid Approach for Copy-Move Forgery Detection. IEEE Access, 12, 43809-43826. (2024).
29. Wang, X. Y., Wang, X. Q., Niu, P. P., & Yang, H. Y. Accurate and robust image copy-move forgery detection using adaptive keypoints and FQGPCET-GLCM feature. Multimedia Tools and Applications, 83(1), 2203-2235. (2024).
30. Faheem, L., Mukherjee, S., Obaidat, M. S., Pal, A. K., Islam, S. H., &Sadoun, BDL-CMFD: Deep Learning-Based Copy-Move Forgery Detection Using Parallel Feature-Extractor. In 2023 International Conference on Computer, Information and Telecommunication Systems (CITS) (pp. 01-08). IEEE.. (2023, July).
31. Zheng, J., & Zhang, K. Copy-Move forgery detection algorithm based on feature point clustering. In 2022 IEEE 6th Information Technology and Mechatronics Engineering Conference (ITOEC) (Vol. 6, pp. 775-780). IEEE.(2022, March).
32. Akar, F. U. N. D. A. A HYBRID COPY-MOVE FORGERY DETECTION METHOD WITH FAST AND SURF.(2022)
33. Kashyap, A., Joshi, S. D.,. Detection of Copy-Move Forgery Using Wavelet Decomposition, in: International Conference on Signal Processing and Communication (ICSC). pp.1–3. 2013
34. Gan, Y., Zhong, J., &Vong, C. A novel copy-move forgery detection algorithm via feature label matching and hierarchical segmentation filtering. Information Processing & Management, 59(1), 102783. (2022)
35. Devika, A. D., &Rajan, B. K. Copy Move Forgery Detection Methods and Its Advantage of Two Stage Filtering. In 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT) (pp. 111-116). IEEE. (2022)
36. Y. Huang, W. Lu, W. Sun, and D. Long, "Improved DCT-based detection of copy-move forgery in images," Forensic Science International, vol. 206, no. 1–3, pp. 178–184, 2011.
37. B.Mahdian and S. Saic, "Detection of copy-move forgery using a method based on blur moment invariants," Forensic Science International, vol. 171, no. 2-3, pp. 180–189, 2007.
38. J. Zhao and J. Guo, "Passive forensics for copy-move image forgery using a method based on DCT and SVD," Forensic Science International, vol. 233, no. 1–3, pp. 158–166, 2013.
39. G. Lynch, F. Y. Shih, and H.-Y. M. Liao, "An efficient expanding block algorithm for image copy-move forgery detection," Information Sciences, vol. 239, pp. 253–265, 2013.
40. L. Li, S. Li, H. Zhu, S.-C. Chu, J. F. Roddick, and J.-S. Pan, "An efficient scheme for detecting copy-move forged images by local binary patterns," Journal of Information Hiding and Multimedia Signal Processing, vol. 4, no. 1, pp. 46–56, 2013.
41. M. Zandi, A.Mahmoudi-Aznaveh, and A.Mansouri, "Adaptive matching for copy-move Forgery detection," in Proceedings of the IEEE International Workshop on Information Forensics and Security (WIFS '14), pp. 119–124, Atlanta, Ga, USA, December 2014.
42. J.-C. Lee, C.-P. Chang, and W.-K. Chen, "Detection of copy move image forgery using histogram of orientated gradients," Information Sciences, vol. 321, pp. 250–262, 2015.