A Comprehensive Survey on Methods for Image Integrity

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The outbreak of digital devices on the Internet, the exponential diffusion of data (images, video, audio, and text), along with their manipulation/generation also by Artificial Intelligence (AI) models, e.g., Generative Adversarial Networks (GANs), have created a great deal of concern in the field of forensics. A malicious use can affect relevant application domains, which often include counterfeiting biomedical images, and deceiving biometric authentication systems, as well as their use in scientific publications, in the political world, and even in school activities. It has been demonstrated that manipulated pictures most likely represent indications of malicious behavior, such as photos of minors to promote child prostitution or false political statements. Following this widespread behavior, various forensic techniques have been proposed in the scientific literature over time both to defeat these spoofing attacks as well as to guarantee the integrity of the information. Focusing on Image Forensics, which is currently a very hot topic area in Multimedia Forensics, this paper will discuss the whole scenario in which a target image could be modified. The aim of this comprehensive survey will be 1) to provide an overview of the types of attacks and contrasting techniques and 2) to evaluate to what extent the former can deceive prevention methods and the latter can identify counterfeit images. The results of this study highlight how forgery detection techniques, sometimes limited to a single type of real scenario, are not able to provide exhaustive countermeasures and could/should therefore be combined. Currently, the use of neural networks, such as CNNs, is already heading, synergistically, in this direction.

CCS Concepts: • **General and reference** → **Surveys and overviews**;

Additional Key Words and Phrases: Digital Forensics (DF), Image Forensics, Image Forgery Detection (IFD), Active Methods(AM), Passive Methods(PM), Dependent and Independent Techniques, Pixel Non-Uniformity noise (PNU), Photo Response Non-Uniformity (PRNU)

1 INTRODUCTION

With the increasingly pervasive intentional or unintentional manipulation of data (images, video, audio, and text), the focus on forgery/counterfeit detection is growing exponentially [274]. As highlighted in Fig. 1, Multimedia Forensics is a broad disciplinary area that requires a lot of attention in terms of scientific and forensic activities. It bears the great responsibility of producing and disseminating methods to check internet data, which is often manipulated, altered, and even generated, maliciously, with intentional anti-forensics AF techniques (AFTs)[120]. Restricting the scope to Image Forensics, which is currently a hot topic in Multimedia Forensics, the paper will focus on Image Manipulation, which occurs when operations are performed on an image to modify it. In current literature, Image Forgery considers how the entire image is manipulated with malicious intent while in Image

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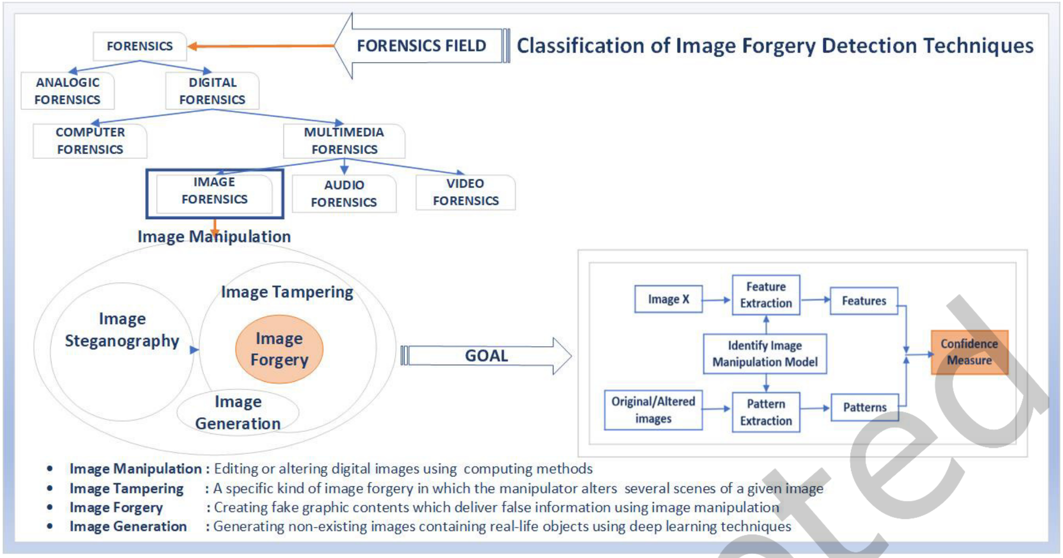


Fig. 1. The Goal of Forgery Detection.

Tampering, only parts of the image are intentionally modified. Image Generation uses computer software or algorithms to produce an image or part of an image simulating real-world scenes. The common denominator of these classes of operations is the malicious intention to violate the integrity of an image to deceive the observer, whereas Steganography has the objective of transporting secret messages from a sender to a recipient. In the latter, the image is modified so that it can store secret information invisible to the human eye, therefore maintaining the original appearance as much as possible. The goal of research in the field of Image Manipulation detection and identification is to examine, analyze, and define an acceptable confidence threshold to ensure data integrity and authenticity. At present, machine learning, and in particular approaches involving deep networks, are playing a supporting role both on the side of the attackers (see GANs[129]), and the defenders (see CNNs [193]), whether they are researchers, Law Enforcement Agencies (LEAs), or in general operators in the forensic sector. Transparent editing operations (manipulation) for tampering, retouching, and enhancement on multimedia objects, which are uploaded or shared through social media or web platforms, alter the original content of the images impeding to still consider them as authentic [247, 309]. However, even without manipulation, two types of artifacts inevitably remain in the image: image acquisition and compression artifacts. The intrinsic properties of these artifacts are essential forensic clues as they differ before and after the manipulation process [179, 198]. All this leads to a lack of a sure and obvious answer on the origin of the image, the user or device capturing it, as well as the truthfulness and originality of the acquired scene. As a consequence, many problems arise in the forensic field, creating a deal of interest in the search for substantial and cutting-edge solutions. The scientific community has unanimously proposed a twofold classification of all the different approaches to assure/verify image integrity. As shown in Fig. 2 "active" technologies usually embed data or signatures into the original image during its digitalization, either in the spatial or frequency domain; "passive" technologies, which are increasingly sophisticated, are based exclusively on digital content and operate without any knowledge of either the original image or pre-defined data or signature, therefore just relying on, e.g., statistical anomalies and/or artifacts. This investigation is a forensic contribution to the general scenario of forgery detection techniques. It will deal with the whole scenario where a target image could be modified. The aim will be 1) to provide an overview of the types of attacks and contrasting techniques and 2) to evaluate to what extent the former can deceive prevention methods and the latter to identify counterfeit images. The widespread diffusion of digital technologies has led, in the forensic field, to a constant increase in cases in which the use of digital evidence has been decisive in identifying the solution. It is easy to understand how their use will soon be pervasive and well-codified within forensic procedures. However, not all the approaches present in the current literature meet the requirements to be exploited in forensic activities [50]. Whenever a method is reproducible and replicable, it can be considered valid in a court and/or in front of a judge, and therefore it is forensic. The evaluation of the Confidence measure to obtain depends only on the common objective of the involved parties. This review has considered this forensic aspect an essential prerogative: all the methods mentioned in the paper have an experimental part, thus appearing as replicable and hence forensically sound. Thanks to the Budapest Convention [269, 322] and according to the reproducibility principle, digital evidence has been made admissible in courts. The Convention and the resulting regulations stipulate that all digital evidence is collected, archived, and presented according to a well-codified and recognized process. Once a scientific method has been identified, it will always be necessary to carry out an experimental evaluation phase before it can become a so-called *Best Practice* and its expected utility can be recognized by also carrying out a technology transfer action to operators in the sector. The European community boasts a network of experts (ENFSI-European Network of Forensics Science Institutes) that promotes knowledge sharing, experience exchange, and the reaching of mutual agreements in the field of forensic sciences through the development and use of good practices and their collection in a devoted manual (ENFSI BPM [1]) also offering a different taxonomy that can inspire further insight into the problems dealt with. Starting from these assumptions as well as current literature, the survey projects itself into an exhaustive search for reliable and forensically sound methodologies to support technological solutions aimed above all at Law Enforcement Agencies (LEAs) and Forensics Personnel. It will represent those treated aspects of the same problem assuming that there are counterfeits but doubting that they are always reproducible in court. This is where *Best Practices* should come into play, by possibly considering a joint use of different techniques having the same forensic purpose.

Other available surveys in literature often focus on specific kinds of forgery and/or detection strategies (see for example [59] on keypoint-based copy-move forgery detection methods or the recent work in [339] about deep learning approaches). This work aims to provide as wide and encompassing an account as possible of existing strategies, orienting readers in this extremely variated field. Many emerging topics like anti-forensic attacks and deepfake would deserve a deeper and wider critical analysis and discussion of open problems, which is beyond the scope of this survey. However, besides mentioning those topics we suggest references that offer related sufficient and thorough insight. Therefore, although methodologies have evolved up to deep learning and CNNs, this survey demonstrates that the basic work done by traditional techniques, which still support and are the basis for neural networks, is still considerable and indispensable. It also wants to represent a testimony of continuity and tries to establish a common line between traditional and non-traditional approaches. It is worth noting how the statistics show the effective use of these techniques [16] in real operative scenarios. The conceptual map below (Fig.2) proposes an updated scheme of real approaches to identify counterfeits.

The rest of the paper is organized as follows. Section 2 formally introduces Image Forgery Detection, the basic Concepts, the Problem Definition, and the Workflow of blind approaches. Section 3 reviews the methods of Forgery Detection proposed in the current literature, and Section 4 presents an evaluation of benchmark datasets fitting this purpose. Section 5 discusses the Research Challenges and Directions. Section 6 draws some conclusions. Finally, due to the broad scope of the subject, contrasting with the journal's strict space restrictions, further insights, examples, and figures have been included in the Online Appendix available for the online version of the paper.

[1]This Best Practice Manual for Digital Image Authentication was funded by the European Union's Internal Security Fund – Police and it is currently available for download: https://enfsi.eu/wp-content/uploads/2021/10/BPM_Image-Authentication _ENFSI-BPM-DI-003-1.pdf

2 FUNDAMENTALS

Image and Video Forensics (or **Forensics**, for short) refers to a specific area of Digital Forensics **(DF**, for short)[43, 255] that deals with the study and analysis of images (and videos) for their validation and use in Forensics [24]. The field of Image Forgery Detection (**IFD**) has developed 1) to combat the problem of image distortion in various application areas such as forensic and criminal investigation, insurance processing, surveillance systems, intelligence services, medical imaging, journalism [214], and 2) to reply to some important and complex technological questions such as determining if an image is authentic, doctored, or computer generated [99].

2.1 What is Image Forgery?

Counterfeiting can be defined as copying something with the intent to deceive; with it becoming a serious crime when it represents the making of realistic and fraudulent imitations of objects and documents to make them to be considered authentic either for profit or to mislead surveillance systems. There is a slight difference in the law between forgery and counterfeiting, with the former referring to forging documents and images, while the latter to material assets such as money, securities, and consumer products. In this article, the two terms, implying intentional illegality, will be used interchangeably to identify deception. The most frequent tasks in photo manipulation are: deleting/hiding a region in the image, adding a new object to the image, and misrepresenting image information [214].

2.2 Problem Definition

According to current literature [111, 213, 228, 312], Forgery Detection (FD) falls into two categories, namely, active and passive techniques (Fig.2). They can only extract forensic evidence if some information exists in the image [102].

Active Approach (AAFD - Active Approach to Forgery Detection) (3.1.1): as the name suggests, active methods of detection (see Fig.2 left-side) focus on the information that is hidden in an image at the time of its acquisition/digitalization. Given an image, the AAFD algorithms aim to detect the source and therefore forgery using

- **1. Watermarking**
- **2. Digital Signatures**
- **3. Cryptography techniques**

for image authenticity confirmation. They require prior knowledge of the elements associated with the original image, digital watermarking, or digital signatures. When checking the image, if the additional information found is incorrect, the image can be identified as tampered with; otherwise, the image is genuine. These approaches require special hardware or software to insert the authentication code inside the image before the image is distributed [225].

Passive Approach (PAFD - Passive Approach to Forgery Detection) (3.1.2): passive forensic techniques (Fig.2 right-side) do not rely on any additional information in the image and aim to find traces left during the image processing phases (acquisition and storage). They extract features from an image to detect the forgery. These so-called "blind methods" can be classified as: **1. Against Tampering Operations**: *Forgery Type-Dependent* or *Forgery Type-Independent*; **2. Based on Intrinsic Regularities & Inconsistencies** ; **3. Handling Natural & Computer Graphic/AI Images**.

2.3 Some Basic Concepts

This section discusses some concepts that have been mentioned in our previous introduction but will not be included anymore in the following. However, it is worth mentioning their role.

Image Generation (IG) encompasses methods that use machine and deep learning-based techniques to produce artificial images containing real-world objects and scenes from an existing data set: generating a fake image does not necessarily imply a forgery. For this, **IG** is not considered to be a part of Image Forgery. However, the advent of DeepFake (from *Deep Learning* and *Fake*) [4, 267] is quickly changing the way IG is regarded by the forensic community [13, 131, 135, 170, 192, 310, 321]. Basically, it refers to a recent manipulation technique allowing to synthesizing of images or videos from scratch, e.g. using Generative Adversarial Networks (GANs) and overimposing them on existing images or videos [134]. For example, it allows counterfeiting the identity of a person in a video/photo.

Image Warping (IW) is the geometric deformation of a single object in a given image. Warping can be used for correcting image distortion as well as for creative purposes.

Image Resizing is simply changing the size of the images without changing the number of pixels. *When an image is resized, its pixel information changes.* For example, if an image is reduced in size, all the unnecessary pixel information will be deleted from the photo editor. When an image is enlarged, the photo editor must create and add new pixel information, based on its best guesses, to achieve a larger size.

2.4 Generalized Workflow of the *Passive (or Blind*) Forgery Detection Process on the Image

In the passive approaches, before even getting to the identification of the kind of counterfeit, the main objective is to classify whether a given image is original (or authentic) or forged. A generalized scheme includes the steps below and is among the most used in the literature [1, 6, 94, 206, 213, 228, 273].

• Image Pre-processing: before dealing with any image, an initial optional step [94], almost always enforced in best practices, is the image pre-processing . Possible operations performed on the image include image filtering, image retouching, cropping, resizing, low-bypass filtering, the transformation from RGB to grayscale, and the modification of DCT coefficients. The choice of this step and the type of operation also depends on the calculation.

• Feature Extraction: given an input image, feature selection provides both a separation between different image classes and a decrease in computational complexity [153]. Of course, more traditional methods extract hand-crafted features that are engineered according to the chosen method and usually play a specific role in the procedure depending on the kind of forgery and the detection strategy. When Deep Learning-based methods are rather involved in the workflow, the feature extraction step is completely demanded by the network, so that the obtained embeddings are autonomously learned by the architecture and lack a precise explanation.

• Feature Matching & Filtering: a classifier, e.g., LDA (Latent Dirichlet Allocation), SVM (Support Vector Machine), or a neural network in general, will be chosen according to the set of features extracted from the previous step. It will determine if the image is original or not [97, 203, 205].

• Image Post-processing operations : tampering operations often involve post-processing operations to smooth the boundaries of tampered regions, to make the final artifact less visually suspectable (active-post-processing) or may be unintentionally introduced to tampered images during data transmission, e.g., JPEG compression, noise adding, and color reduction (passive post-processing) [350]. On the other hand, they can help detect those manipulations, such as location tracking, that might be included in the forged images. To improve the forgery localization several mathematical morphological operations could be performed [123, 228].

3 NOTABLE METHODS OVERVIEW

Digital Image Forgery started to occur a decade after the first image was created in various ways. At present, it exploits various image manipulation software, available for almost all trading platforms. Among the first technical issues to be addressed, the identification of the forgery is especially relevant since the authenticity of the images also follows from it. To achieve this, several FD techniques were used which will be examined in this section (see Fig.2). For the sake of completeness, Table 6 outlines the information. Special attention will be given to forensics-viable methods according to the Budapest Convention.

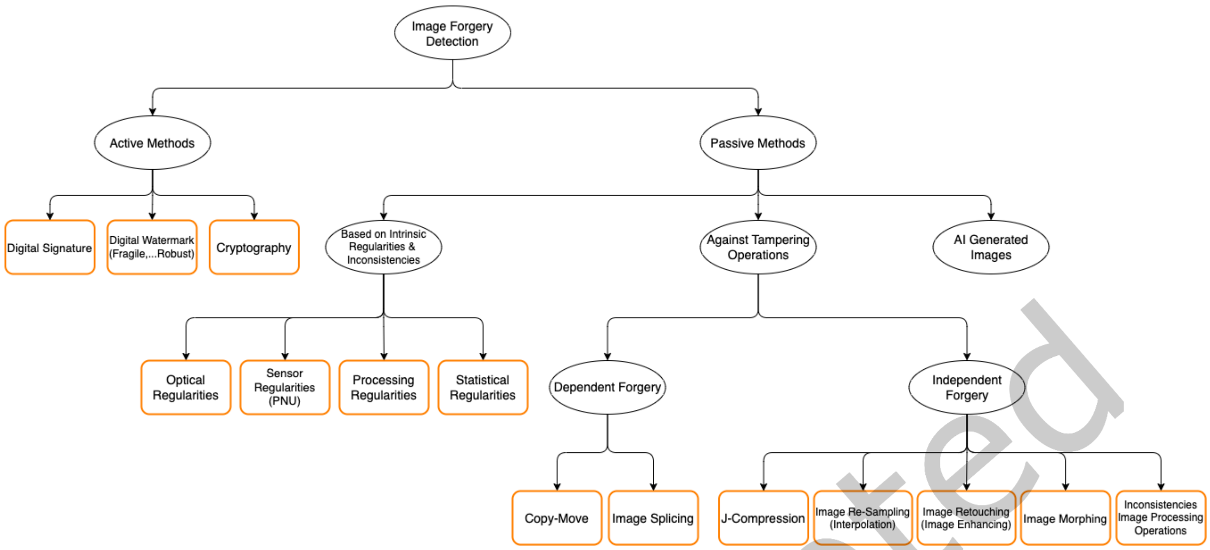


Fig. 2. Conceptual map of Forgery Detection Methods.

3.1 Taxonomy of Digital Forgery Detection Methods

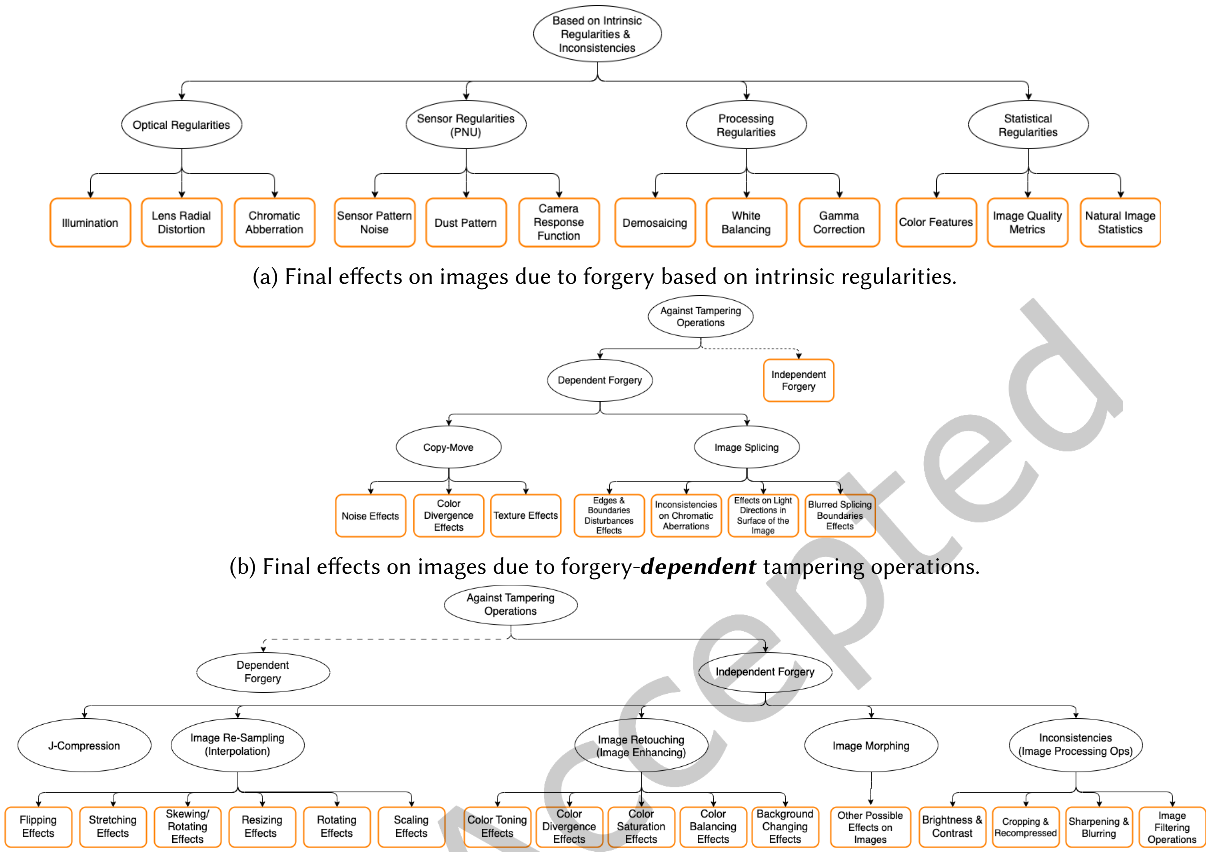
Digital Image Forgery Detection methods aim to detect those manipulations of a digital image that change the semantics of the visual message. As discussed above, the DF techniques are classified into two categories [274]: 3.1.1 **Active** (see Fig.2 (left-side)); 3.1.2 **Passive** (see Fig.2 (right-side)).
This taxonomy depends on the accessibility of the original picture. Each strategy can be further sub-partitioned (Fig.2).

3.1.1 ***Active Methods****.*

Active methods are robust mechanisms for safeguarding the integrity of digital images and exploiting certain information entered into them during the process of image acquisition and digitalization [58]. Alterations in an image are detected by analyzing such embedded (known) data. The main applications of these image authentication methods include intellectual and owner identification. They are classified according to whether they ensure strict integrity, content authentication, and the storage strategy of authentication data (i.e., watermark or external signature). These approaches include Watermarking, Digital Signatures, and conventional Cryptography [139].

• **Digital Watermarking techniques:** A large amount of literature currently deals with the topic [76, 110, 152, 188, 225]. Intuitively, Image Watermarking alters an image by inserting a mark that guarantees its authenticity. Watermarking methods are classified into three categories: *1) fragile watermarks 2) semi-fragile watermarks 3) robust watermarks.*

Fragile watermarking methods only allow a strict integrity check, while *semi-fragile* watermarking methods, based on external signatures, ensure content authentication. The former watermarking methods are highly sensitive to any type of tampering even in the modification of a single bit. The results obtained with these techniques show that they are both robust and secure and are therefore the best solution for copyright protection. The latter semi-fragile watermarking methods can be used for forensic purposes. Through these techniques, the authenticator can distinguish the original images from those whose content is intentionally modified while preserving the content of an image. The results offered by them show that despite their computational complexity, these techniques are secure and robust for all types of counterfeiting attacks. Finally, there are the kinds of *robust*



(a) Final effects on images due to forgery based on intrinsic regularities.

(b) Final effects on images due to forgery-***dependent*** tampering operations.

(c) Final effects on images due to forgery- ***independent*** tampering operations.

Fig. 3. Passive approach: each (sub-figure) represents effects on images due to different types of Forgery.

watermarking algorithms that can survive the content by preserving changes such as compression, noise addition, and filtering, as well as geometric changes such as resize, translation, rotation, cropping, and many more. They are used for ownership authentication [64]. These approaches have a high computational complexity and also offer less embedding capability. Fragile watermarking methods remain the simplest to implement ([271]). In digital watermarking, a specific message (digest) is inserted when an image is captured from a digital device. The watermarking is either "visible" or "invisible ([223]) and is, generally, independent of the image data ([323]). The basic underlying idea is that any attempt to alter the content of an image will also alter the watermark itself. In the following stages, a summary is then extracted from it to verify its legitimacy to compare it with the original digest. The result will indicate whether the image has been modified after acquisition. Therefore, the watermarking techniques consist of two phases: in the first, the image is generated and the watermark is also inserted. In the second stage, once the destination is reached, the watermark is extracted from the image and compared with the initial watermark. These techniques can be broadly classified into two categories depending on the kind of image transformation: 1) the *Spatial Domain* (LSB (Least Significant Bit) [284], SS (Spread Spectrum) [46], RIF (Random Insertion in File) [36]); 2) the *Frequency Domain* (DWT (Discrete Wavelet Transform) [304], DCT (Discrete Cosine

Transform) [95], DFT (Discrete Fourier Transform) [306], SVD (Singular Values Decomposition) [217]). It has been pointed out that the frequency domain methods are more robust than the spatial domain techniques [79].

Advantages: These methods provide authenticated multimedia content and focus on four essential features: robustness, security, capacity, and invisibility. ***Disadvantages:*** 1) Few (and generally expensive) devices have the function to incorporate a watermark in the image acquisition process. 2) These techniques, which require specialized software to incorporate the abstract into the image, are unable to distinguish the legitimate manipulations performed for the enhancement of the image quality (enhancement of contrast, sharpening, etc.) from the illegitimate ones (see [271]).

• **Cryptographic techniques** : Encryption techniques involve two steps: in the encryption stage, the plaintext is converted into ciphertext using a cipher. Conversely, in the decryption stage, the same cipher is used to convert ciphertext to plaintext. Approaches, e.g., classic cryptographically secure hash functions such as MD-4, MD-5 (message digest), CRC-32 (32-bit cyclic redundancy check), and SHA-1 (secure hash algorithms), are just some of the many methods existing in the literature that adopt a common general procedure. Due to the large research field, interested readers are advised to see [127, 194, 323, 328, 329, 336].

•**Digital Signatures techniques**: The validation of the authenticity of digital messages is normally based on a digital signature. Thanks to the valid signature, the recipient can assume that the message belongs to the known sender. The digital signature guarantees that the content is authentic, reliable, and from an authentic source. Applications of these techniques have been found to improve data integrity and image authentication in many industries, and some techniques are combined with watermarking, steganography, and cryptographic techniques [15, 181, 259, 301].

In Conclusion, in active methods, a trustworthy camera calculates a digital watermark or signature from the image at capture time, and any subsequent changes to the image can be detected by checking the value of the digital watermark or digital signature value at the time of its use. The disadvantages of active methods include that digital cameras must be equipped with a watermarking chip or a digital signature chip which, using a private key wired into the camera itself, authenticates each captured image before storing it on the memory card. This implies the definition of a common standard protocol: a requirement that would limit the application of such solutions only to very limited scenarios [254].

3.1.2 ***Passive Methods***. As discussed above, active methods use specially designed digital signatures and watermarking tools in cameras. Passive methods, sometimes known as blind methods, overcome this limitation by exclusively analyzing the binary information of an image[101], relying directly on image statistics, without requiring any prior information on image acquisition. Passive methods fall into three categories: *a) based on Tampering Operations, b) based on Intrinsic Regularities and Inconsistencies* and, *c) coping with Natural & Computer Graphic Images*. The most characteristic is certainly the first and second ones. The first is divided into forgery-dependent and forgery-independent methods [35, 42, 242, 264, 312]: **forgery type-dependent techniques** *depend on the different types of forgery performed on the image* and include methods to detect the most popular kinds of attack copy-move and image slicing; **forgery type -independent techniques** *are independent of the type of attack.*

a. Based on tampering operations

Forgery Type-Dependent Techniques

• **Copy-Move Forgery.** Copy-Move attack refers to forgeries that use a single image to copy a region from it and paste it into the same image to hide or duplicate specific objects. The copied part may or may not be modified. Since it belongs to the same image, its essential properties such as noise, color, and texture do not change, so the final forged image has homogeneous characteristics. This makes it difficult to even locate the forgery. Further operations such as rescaling, filtering, and noise scattering can be applied to hide any traces of the forgery.

Copy-Move Forgery Detection techniques is the process of identifying the occurrence of a copy-move in an image and can be classified into three categories, namely: 1) Brute Force detection 2) Block-based detection and 3) Keypoint-based detection. Due to the computational time complexity of the first category, literature mainly refers to approaches based on blocks and key points.

- 1. Brute Force detection is based on an exhaustive search and autocorrelation technique, which checks for any position change. The exhaustive search examines the corresponding image segment through circular shifts, producing a large number of comparisons. The computational times are relatively high.

- 2. Block-based detection divides the forged image into overlapping or non-overlapping blocks to analyze the block features in the frequency domain.

In the ***Phase of Block Feature Extraction*** (see Fig. 6) several approaches have been applied:
i) Since the Local Binary Patterns (LBP) operator is a texture descriptor for rotation-invariant grayscale images, it is widely used as a grayscale operator. LBP codes can be extracted from blocks beyond block texture verification. The approach in [105] proposed a generic passive image forgery scheme that combines a spatial rich model (SRM) with a textural feature based on the LBP operator. The combination of LBP with co-occurrence matrices makes the model capable of detecting almost all types of forgeries with improved detection accuracy.
ii) The use of the frequency domain, through a signal transform, can carry on the signatures for the image blocks, thus allowing for the identification of duplicate regions. In [215] *Mahmood et al.* used the stationary wavelet transform (SWT) and DCT to detect and localize the copy-move operation in digital images. The SWT allows it to work in both spatial and spectral domains, and the feature vectors are reduced by applying DCT. Dimension reduction processes are widely used to enhance the performance of the frameworks. Table 1 references the most used algorithms.

- 3. Keypoint-based detection. Feature-based or Keypoint-based approaches extract key points from forged images. They use a two-step process of locating and describing the local interest points. Robust local descriptors are constructed which must be invariant to affine alterations. They are not only robust to noise and geometric transformations but also use scale and rotation invariant feature detectors and descriptors. Table 1 lists the main algorithms used in the Feature Extraction phase (see Fig. 5). These methods rely on the identification and selection of high-entropy image regions (i.e. the "key points"): one feature vector per keypoint is then extracted. As a result, fewer feature vectors are estimated, resulting in reduced computational complexity of feature matching and post-processing. Post-processing thresholds are also lower than those of block-based methods. The downside is that the copied regions are not always covered by a satisfactory number of corresponding key points. If the copied regions show little structure, the region may be completely missing. Recently, [331] proposed a key point-based copy-move forgery detection and location technique based on a hierarchical point matching that reduces the number of points to improve the matching process. Feature-based approaches are relatively better than block-based and brute force methods in terms of computational efficiency, complexity, and robustness against many transformations such as scaling, rotation, cropping, etc. [167].

In the ***Phase of Matching and Filtering***, both in Block-based and Keypoint-based detection approaches, in identifying matching amongst the feature descriptors and to reduce the probability of false matches, most authors propose the use of main similarity measures and algorithms such as the Euclidean Distance, Correlation Coefficient, Sorting (lexicographic sorting, KD-tree, radix sort), Hash (counting bloom filters, locality-sensitive hashing), DCT and Sequential Clustering, Best Bin First, 2NNg, 2NN, Clustering (HAC, WPGMC) and others.

In Conclusion, both classes of methods have strengths and limitations. To address the limitation of these methods in flat regions, some approaches (see in [111]) also implemented mixed processes to tackle copy-move tampering detection problems, combining techniques based on features with block-based techniques. The approach in [140] combines the key point-based SIFT method with the block-based method using the dyadic wavelet transform (DyWT). Also in [295] a combination of the two different approaches is proposed by

Table 1. a. Based on tampering operations - 1st Part - Main methods.

A - BASED ON TAMPERING OPERATIONS - 1st PART			
FORGERY TYPE-DEPENDENT TECHNIQUES			
Copy-Move Forgery Detection techniques : Main methods			
Block-based detection			
Algorithms	Ref.	Algorithms	Ref.
Discrete Wavelet Transform (DWT)	[123, 169, 187, 330, 342]	Texture and Intensity	[146, 222, 300, 314]
Singular Value Decomposition (SVD)	[93, 167, 187]	Discrete Cosine Transform (DCT)	[114, 190]
Fourier Transform (Fourier-Mellin Transform)	[33]	Log-Polar Coordinates or transform	[47, 227]
Log-Polar Fast Fourier Transform (LPFFT)	[325]	Radix Sort	[195]
Dyadic Wavelet Transform (DyWT)	[224, 261]	Wiener Filter Wavelet	[70]
Multi-resolution wavelet decomposition	[22]	Principle Component Analysis (PCA)	[256]
Moments Invariant	[209]	Dimension Reduction	[180]
SVD (Singular Value Decomposition)	[187, 317]	KPCA	[21, 86]
Radon Transformation and Phase Correlation	[241]	Local Binary Patterns (LBP)	[317]
Fast Walsh Hadamard Transform (FWHT)	[289]	Zernike Moments	[216, 245, 272]
Keypoint-based detection			
Algorithms	Ref.	Algorithms	Ref.
SIFT (Scale Invariant Feature Transform)	[11, 150, 166, 191]	Principle Component Analysis (PCA)	[286]
ORB (OrientedFAST and rotated BRIEF)	[295]	Harris Corner Detector	[154]
BRISK (Binary Robust Invariant Scalable KPs)	[182]		
Splicing Forgery Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Bispectral Analysis	[98]	Bicoherence magnitude and phase feature	[235]
Inverse camera response functions (CRF)	[115, 240]	Expectation/maximization (EM) algorithm	[74, 230]
Based on the use of the VGG-16 CNN	[178]	Wavelet decomposition-D phase congruency	[97, 115]
Multi-size block discrete cosine transform	[285]	Moment features and Image Quality metrics	[282]
CRF signature	[234, 282]	DCT coefficients and SVM	[202]
Based on DCT and image quality features	[347]	Gray level co-occurrence matrix (GLCM)	[315]
Based on computing the inverse CRF functions	[200]	Hilbert-Huang transform (HHT)	[65, 115, 252]
Planar homography constraint	[345]	Based on Chroma spaces	[349]
Artificial NN, indip. CA, and auto-regres. coeff.	[130, 142]	Based on Sobel edge detc.,deriv. op., Hough transf.	[160]
Based on the image of a person's eyes	[164]	Based on geometry invariants	[147, 148]
Based on statistics of 2-D phase congruency	[97]	Based on natural image model	[285]
Based on a NN architecture called CAU-Net	[250]	Based on a fully convolutional network (FCN)	[275]
Based on a ringed residual U-Net (RRU-Net)	[37]	Based on SVM	[91]
Based on computing the inverse CRF functions	[200]	Locally Planar Irradiance Points and CFR	[149]

extracting the key SIFT points in an image and then combining LPP (Locality Preserving Projection) to obtain low-dimensional feature descriptors.

• **Image Splicing.** Splicing is the process of cutting out a section of an image and pasting it onto the same image or another image. To create a fake image, splicing entails merging a minimum of two images. When images with contrasting bases have been well blended the edges between the spliced regions can be visually imperceptible. Unlike copy-move forgery, in splicing used objects are harvested from more than one image. The splicing, however, disturbs the higher-order Fourier statistics. These insights can then be used as an element to distinguish fakes [115, 237, 238, 348].

Image Splicing Detection is fundamental in Image Forgery Detection[42]. Table 1 lists the main related algorithms.

It appears from the literature that many of the methods mentioned work well when the analyzed image is compressed by a high-quality factor. Otherwise, compression artifacts make it very difficult to spot the fake.

Forgery Type-Independent Techniques

Table 2. a. Based on tampering operations - 2nd Part - Main methods.

A - BASED ON TAMPERING OPERATIONS - 2nd PART			
FORGERY TYPE-INDEPENDENT TECHNIQUES			
J-Compression Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Maximum likelihood estimation to identify what quantization table was used	[96, 253]	Double compression by examining the histograms of the DCT coefficients	[257]
Operations based on DCT coefficient structure	[231]	Histograms of coefficient subbands analysis	[303]
Benford's law statistical model for probability distributions of the block-DCT first digits	[116]	Exploration of conditions under which primary quantization coefficients are identified	[290]
Tampered areas detection in double JPEG2000 compression tampered images	[343]	Mismatch information of BAG as a clue of copy-paste forgery	[189]
Shifted DJPEG with a convolutive model	[262]	Markov process/transition probability matrix	[61]
Probabilities of the first digits of quantized DCT coefficients from alternate current modes	[184]	Classification from the first order statistics of DCT modes of low-frequency DCT coefficient	[252]
Double/multiple quantization effects and CNN-First Quantization Estimation solutions	[25–27, 141, 179, 199]	Detection of either block-aligned or misaligned recompression	[68]
PCA on separate different SFQ noises	[291]	Detection of the presence of NA-JPEG images	[38–40]
Detection via B-G analysis of Jpeg artifacts	[41]	First quantization matrix estimation	[119]
Analysis of the blocking periodicity	[67]	Analysis of the properties of the image blocks	[187]
Maximum likelihood estimation of JPEG quantization steps was developed	[96]	Detection of composites created by JPEG images of different qualities	[100]
Detection of DJPEG images with periodic artifacts of re-quantization and discontinuities	[107]	Analysis of weakness/strength points of the current solutions on DCT and JPEG properties	[28]
Exploration of the image-specific artifacts	[212]	Estimation of the kind of source encoder	[196]
Based on blocking artifacts	[335]	Based on Multi-domain CNN	[12]
Re-Sampling Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Prefiltering/derivation vs. resampling traces	[82]	Detection of adaptive scaling of images	[112]
Relations: rotation angle/frequencies at peaks	[277]	Property of 2°der. of interpolated periodicity of images	[118, 229]
Decomposition and random matrix principles	[311]	EM algorithm to estimate probability maps	[258]
Multidirectional high-pass filters on an image	[248]	Re-sampling detection in JPEG images	[176]
Cyclostationary process	[211]	Zero-crossings of the second difference signal	[260]
ML to distinguish between seam-carved (or seam-inserted) and normal images	[277]	Dual-filtering-based CNN to extract features directly from the images	[251]
Cumulative periodograms	[174, 319]	Radon transformation	[211]
Retouching Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Identify/rebuild gamma correction operations	[51]	Identify the use of histogram equalization	[292, 293]
Two contrast enhancement-based algorithms via histogram peak/gap artifacts analysis	[53]	PRNU-based forgery detection algorithm based on the whole image	[69]
To measure the distortion between two images, the first original and the second processed	[18]	Statistical anomalies through the Laplace modeling of the derivative histogram	[34]
Algorithm vs cut-and-paste image forgery	[197]	Image sharpening detection methods	[351]
Detection of USM sharpening op. in images	[52]	A JPEG-robust forensic method based on CNN	[283]

• **J-Compression.** Editing an image involves loading it, modifying it, and then saving it again. Knowing the history of these compression operations, as well as whether a bitmap image has been previously compressed, is a clue in FD.

Image J-Compression Detection techniques. Table 2 lists the main used methods.

These methods work well for detecting saved images: the problem is when they are rotated, resized, and/or enhanced.

• **Image Re-Sampling.** When spatial transformations such as resizing, rotation, and stretching are applied to a digital image (to a specific object in the image or to all the image content), the type of forgery is known as re-sampling. The resizing of an image changes the dimensions of an object but does not improve the quality of that object. Re-sampling can be performed in different ways: Up/Down-sampling, Mirroring, Skewing, and Seam Carving.

Table 3. a. Based on tampering operations - 3rd Part - Main methods.

A - BASED ON TAMPERING OPERATIONS - 3rd PART			
FORGERY TYPE-INDEPENDENT TECHNIQUES			
Morphing Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
De-morphing method without needing a reference image or prior information about the morphing process	[19]	Wavelet domain analysis to gain insight into the spatial-frequency content of a morphed face	[3]
De-morphing generative adversarial network (FD-GAN) to restore the accomplice's facial image	[249]	FM Detection strategy with 3 modules (ICAO-aligned pre-processing, feature extraction, and classification module)	[233]
NN exploiting layer-wise relevance propagation (LRP) to analyze the differences in the decision-making process of the differently trained neural networks	[281]	StirTrace framework towards benchmarking face morphing forgeries extending it by additional scaling functions for the face biometrics scenario	[144]
MAP methodology vs. the Morphing potential attack	[109]	Framework for the Continual Learning Strategies	[45]
Demorphing approach to protecting ABControl systems	[108]	Micro-texture variations extraction using BSIF with SVM	[265]
Morphing attack detection approach based on convolutional neural networks	[280]	Use of transferable features from pre-trained Deep CNN to detect both digital and print-scanned morphed face images	[266]
Discriminative 2D Discrete Wavelet Transform (2D-DWT)	[2]	The Fourier spectrum of sensor pattern noise (FS-SPN)	[344]
Morph detection algorithm based on an analysis of PRNU	[85]	Distribution of Benford features extracted in Jpeg images	[218]
TDA (Topological Data Analysis) approach to detect various known morphing attacks	[156]	Morphing detection by using state-of-the-art facial recognition algorithms based on hand-crafted features and D-CNN	[313]
Detection for FM forgeries on image degradation	[232]	Facial landmarks shifting patterns reference/probe image	[83]
Deep MS Context Aggregation Net for denoised images	[307, 308]	Automated morph detection on pat.-recog. algorithms	[279]
Inconsistencies (Image Processing Operations) Detection techniques: Main methods			
Algorithms	Ref.	Algorithms	Ref.
Classifiers of distortion between original/processed images	[18, 30, 32]	Based on blind deconvolution	[297]
Based on image segmentation techniques	[17]	Based on non-intrusive component forensics	[175, 298]

Image Re-Sampling Detection: To create a fake image, some selected regions need to undergo geometric transformations such as rotate, scale, stretch, skew, flip, and so on. For example: if the face of a person is larger in an image, it should be scaled to the extent that the sizes of the faces are similar in the composite image. This requires re-sampling the image to compose a new sample and adding periodic correlations between pixels in the neighborhood. These transformations leave traces that are not typically present in the original images, and forgery techniques seek to identify such traces that constitute re-sampling cues. The interpolation phase also (e.g., nearest neighbor, bilinear, bicubic) plays an important role in the re-sampling process and introduces non-negligible statistical changes due to the specific periodic correlations in the image. These correlations can be used to recognize falsehoods caused by re-sampling [210, 259]. Table 2 summarizes several elements proposed and combined over time.

• **Image Retouching.** The image retouching forgery aims to enhance an object or image to exhibit or hide a specific feature such as coloring, lighting, or background changing. It is commonly used for aesthetic and

Table 4. b. Based on Intrinsic Regularities & Inconsistencies - Main methods.

B - BASED ON INTRINSIC REGULARITIES & INCONSISTENCIES			
Optical Regularities Detection Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
How the direction of a point light source is estimated	[161–165]	Automatic estimation of chromatic and aberration	[126, 162, 337]
Based on the geometric and photometric constraints	[103, 168]	Based on the focus on lens radial distortion	[71]
To calculate the surface normal matrix of the image	[207]	Based on camera lens-distortion correction	[128]
Processing Regularities Detection Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Detection framework of demosaicing regularity	[54, 299]	A 3-layer feedforward backpropagation NN(BPN)	[151]
Sensors Regularities Detection Detection techniques : Main methods			
Algorithms	Ref.	Algorithms	Ref.
Based on imperfections of CCD pixels	[122]	Based on the detection of sensor dust characteristics	[89]
Based on sensor noise	[63, 172, 185]	Based on camera response normality and consistency	[200]
The color filter array (CFA) is examined	[31, 258]	Based on significant noise residual regions	[201]
Based on the PRNU & PNU	[8, 49, 55, 204]	Based on Colour-Decoupled PRNU (CD-PRNU)	[186]
Statistical Regularities Detection techniques : Main Methods			
Algorithms	Ref.	Algorithms	Ref.
Based on binary similarity and image quality measures, higher-order wavelet statistics with SVM Class	[57]	By analyzing image variations using Statistical Process Control	[23]
SVD-based image manipulation detection	[137]	To categorize a camera model	[104, 173]

Table 5. c. Natural & Computer Graphic Images (CGI).

C - NATURAL & COMPUTER GRAPHIC IMAGES (CGI) : MAIN METHODS			
Algorithms	Ref.	Algorithms	Ref.
Edge properties features	[183]	Residual pattern noise	[171]
Statistical moments of 1-D and 2-D characteristic functions	[296]	Color, edge, and texture properties	[80]
An aggregate of existing features	[276]	Features to identify computer-generated images	[87, 88]
Zero connectivity and fuzzy membership	[324]	Progressive randomization	[221]
Models on 1)first-order and higher-order wavelet statistics 2)characteristic function of the image and wavelet subbands	[66, 208]	The combination of three different algorithms based on the geometry, the wavelet, and the cartoon features	[236, 239]

commercial purposes, to enhance or reduce image features, and to create a compelling composite of two images which may require transformations such as rotating, stretching, or scaling, one of the images.

Image Retouching Detection: Many methods have been proposed for the detection of retouched forgeries, which is difficult if the image is significantly changed from the original image. Also, human intervention is often required to interpret the result. Table 2 lists the main related proposals.

• **Image Morphing.** A gradual transformation from one graphical object or image (source) to another graphical object or image (target) is called Image Morphing [155]. Differently from Warping, Image Morphing interpolates two or more graphical objects. It is a combination of image warping and blending techniques to interpolate objects to create a novel one. The basic idea of morphing is to distort the first image into another image by some predefined set of rules. The two basic principles of image morphing are image warping and cross-fading which must be coupled. Obviously, during this transformation, the central image, i.e., the generated one, is the key point of the technology because it decides whether the sequence will look good or not. It is intuitive to think that as the source image evolves, it begins to degrade and the target image evolves with new characteristics. The first images in the sequence will look more like the source. The central image will have the characteristics of both the source and the final images and will be distorted [60].

Image Morphing Attack Detection (MAD): Table 3 lists the basis of the latest generation algorithms and Automated MAD approaches recently proposed [219, 307].

• **Inconsistencies (Image Processing Operations).** An altered image has undergone basic image processing operations (Brightness&Contrast, Cropping&Recompressed, Sharpening&Blurring, and Filtering Operations). Tampering produces inconsistencies in the regular models and the traces of these operations can be useful in identifying forgery.

Image Processing Operations Detection. Table 3 lists the most recently proposed techniques.

b. Based on Intrinsic Regularities & **Inconsistencies.** Image regularities are of different nature, e.g., *Optical, Processing-related, Sensor-related, and Statistical.*

• **Optical Regularities.** Imperfections due to illumination, radial distortion of the lens, and chromatic aberration.

Optical Regularities Detection. Table 4 lists the most recently proposed techniques.

• **Processing Regularities.** Demosaicing, White Balancing, and Gamma Correction.

Processing Regularities Detection. Table 4 lists the most recently proposed techniques.

• **Sensor Regularities (Pixel Non-Uniformity - PNU for short)** . The Source Camera Identification (SCI, for short) techniques identify the intrinsic evidence left in images by the corresponding digital cameras responsible for their acquisitions. It is worth mentioning Sensor Pattern noise (the photo response non-uniformity (PRNU), Dust pattern, Feature Extraction, and Camera Response Function (CRF).

Sensor Regularities Detection. Table 4 lists the most recently proposed techniques.

• **Statistical Regularities.** Color Features, Image Quality Metrics, Natural Image Statistics.

Statistical Regularities Detection. Table 4 lists the most recently proposed techniques.

Methods based on image features do not work well when the image from a camera having a similar CCD [312].

c. Natural & Computer Graphic Images (CGI). Graphic software can generate photorealistic images. A challenging problem is to distinguish between computer-generated photorealistic and real (photographic) images.

Natural & Computer Graphic Image Detection. Table 5 lists the main bases for the proposed algorithms.

3.2 Summary Table: a summary outline

Table 6 reports some essential helpful information for the identification of the main classes of methods in this context.

4 DATASETS AND EVALUATIONS

4.1 Benchmark Image Datasets.

This subsection presents some public benchmark datasets (see Table 7) for the training and evaluation of the PAFD approaches. Each dataset was created for specific forgery attack detection methods. A combination of existing ones can be used for a wide range of applications. However, this requires some preliminary work to create a unified structure with consistent annotations. It is worth underlining that it would be extremely interesting to compare the real performance of methods and their effectiveness in the wild. However, a serious and thorough performance comparison would entail a shared benchmark and widely acknowledged protocols that are presently missing. These requirements represent an engaging challenge for the future, especially assembling a single dataset for all the detection methods.

5 DISCUSSION: LIMITATIONS, CHALLENGES AND OPPORTUNITIES

At present, generative AI techniques [270] and diffusion models [75] are a continuous source of new challenges. These techniques are spreading so quickly and in such a pervasive way that they would deserve much more space than a section herein. We hope that the suggested references can effectively complement the present survey. Diffusion models can be used also for audio synthesis [341]. As can be deduced from Fig. 2, Multimedia Forensics, in addition to Image Forensics, also includes Audio and Video. In particular, following the increasing popularity of DeepFakes, interest in Video Forensics is growing more and more. Currently, Deepfake detection is classified into machine learning-based classical methods, and more recent ones based on deep learning-based (the most widely used), statistical, and blockchain-based techniques [267]. Literature testifies that most deepfake detection research uses DL algorithms looking for inconsistencies in deepfake videos. However, since these are generated through adversarial training (often GANs), their ability to evade AI-based detection systems will improve as they become familiar with new detection methods. The challenge of recognizing them is increasingly difficult. The wide range of forensic video products available nowadays for forensic investigators [157] provides an overview that is not able to tackle all challenges. For a complete discussion of this area of research we suggest referring to exhaustive related works [9, 92, 113, 124, 133, 136, 143, 294, 332, 333].

The main challenge in detecting tampering is represented by the structural changes that occur in digital images. Due to their massive and widespread use in every field of application and considering the speed by which neural networks tackle/propose challenges, research is increasingly projected towards a combined use of traditional techniques with machine learning solutions. In addition to the traditional detection techniques

Table 6. A summary outline of the public forgery type detection methodologies considered in this review.

Rif.	Name	Category	Operation[2]	Class.	Rif.	Name	Category	Operation[2]	Class.
3.1.1	Digital Signature	Active	–	–	3.1.2	Copy-Move	Passive	ATO	Dependent forgery
3.1.1	Digital Watermarking	Active	–	–	3.1.2	Image Splicing	Passive	ATO	Dependent forgery
3.1.1	Cryptography	Active	–	–	3.1.2	J-Compression	Passive	ATO	Independent forgery
3.1.2	Optical Regularities	Passive	BOIR	–	3.1.2	Image Re-Sampling	Passive	ATO	Independent forgery
3.1.2	Source Camera Identification	Passive	BOIR	–	3.1.2	Image Morphing	Passive	ATO	Independent forgery
3.1.2	Processing Regularities	Passive	BOIR	–	3.1.2	Inconsistencies	Passive	ATO	Independent forgery
3.1.2	Statistical Regularities	Passive	BOIR	–	3.1.2	Image Retouching	Passive	ATO	Independent forgery
–	–	–	–	–	3.1.2	Others	Passive	N&CGI	–

[2] ***BOIR:*** Based on intrinsic regularities & inconsistencies. ***ATO:*** Against Tampered Operations. ***N&CGI:***Natural & Computer Graphic Images.

Table 7. List of the Public Forgery Digital Image Datasets.[2]

Ref.	Dataset Name	Year	Forgery Type	Ref.	Dataset Name	Year	Forgery Type
[278]	UCID	2003	For Source Camera Identification purposes	[56]	UniSA TIDE	2014	Tampered color images with different resolutions, splicing operations, blur filtering
[237]	COLUMBIA GRAY	2004	SCI: Splicing, BMP format gray images	[288]	CMH	2015	Copy-move, rotation, resizing, rotation, and resizing
[147]	COLUMBIA COLOUR	2006	Splicing, TIFF format color images	[14]	CVIP	2015	Translation, copy-move, rotation, scaling
[158]	INRIA_Copy Days	2008	Cropping, scaling, jpeg compression, combined strong attacks	[84]	RAISE	2015	SCI: High luminance images, uncompressed images, and camera native images
[90]	SIDD	2008	For Source Camera Identification purposes	[327]	SCUT-FBP	2015	For automatic facial beauty perception
[90]	CASIA v1.0	2009	SCI: Jpeg formatting and splicing (at preprocessing)	[318]	Wattanachote	2015	Seam-carved/seam-inserted images at various quality factors
[90]	CASIA v2.0	2009	SCI: Copy-move and splice images	[338]	Wild WEB	2015	SCI: Cut&paste,copy-move, erase forging
[11, 125]	DRESDEN	2010	SCI: Multiple cameras, multiple file formats, and different visual qualities	[320]	COVERAGE	2016	Copy-move along with interpretations
[20]	BOSS_Bases v0.93	2011	Greyscale, no PGM, multiple camera models, and appropriate raw EIF	[132]	NC	2016	Splice and localization detection, provenance modification
[11]	MICC-2000	2011	SCI: Coloring, copy-move, and jpeg formatting	[177]	RTD v.2.0	2017	Modifications, PRNU signatures, TIFF/PNG formatting, Ground Truth Maps of 3-level
[11]	MICC-F220	2011	SCI: Coloring,copy-move, jpeg-format, images with no mask, lacks post-processing	[287]	VISION	2017	For Source Camera Identification purposes
[41]	Bianchi	2012	Jpeg and TIFF formatting	[5]	DHFI	2018	For Source Camera Identification purposes
[72]	CMEN	2012	Copy-move images, resized images	[121]	KAGGLE	2018	For Source Camera Identification purposes
[72]	IMD	2012	Copy-move images	[132]	MFC	2018	Splicing investigates processing events, source modification camera verification, GAN modifications
[72]	MANIP	2012	Copy-move images	[302]	DSID_DAXING	2019	For Source Camera Identification purposes
[305]	CoMoFoD	2013	Coloring PNG/jpeg formatting,copy-move	[117]	SOCRATES	2019	For Source Camera Identification purposes
[106]	IEEE IFS-TC	2013	Copy-move images and Splicing	[138]	FODB-FORCHHEIM	2020	For Source Camera Identification purposes
[10]	MICC-F600	2013	SCI: Coloring PNG and jpeg formatting, copy-move	[243]	IMD	2020	Multiple-forged advanced GAN, inpainting-forged-images,images-from-2322-device
[77]	CMFDdb grip	2014	Rotation, scaling, jpeg compression	[48]	UNISA2020	2021	For SCI(on PNU): images from multiple conventional digital cameras of the same type

[1] The columns provide the following information for each dataset (from left to right): reference section, name, year, and forgery type.

mentioned above, convolutional neural networks (CNNs, for short) can represent an ambitious and effective solution to detect counterfeits. Touted as one of the most popular deep learning methods, CNN-based approaches are recently gaining success in Digital Image Forensics [12, 29, 62, 73, 78, 145, 220, 268, 316, 346]. In Active Forgery Detection, Kandi et al. in [340] proposed a watermarking technique based on an auto-encoder CNN network for robust non-blind watermarking, that achieves better performance than that of domain transform techniques. On the other hand, in Passive Forgery Detection, a CNN has been used to identify the camera that captured the particular image. Yao et al. in [334] proposed a multi-classifier based on CNNs that subjected images to post-processing attacks such as JPEG compression and adding noise. Several CNN-based approaches deal with copy-move operation [44, 78, 159, 226, 326]. Ouyang et al. in [244] used an adjusted network obtained from an existing trained ImageNet model and obtained a satisfactory performance compared to automatically generated spoofed images, while it does not apply to real spoofed images. Quan et al. in [263] proposed a CNN generic framework to classify images as computer-generated or natural with robust results against resampling (resizing) and JPEG compression. In [7] a useful list of CNN-based techniques with related comparisons is mentioned.

Actually, in the context of image tampering, new proposed solutions based on **Image Anomaly Detection** (IAD) and **Deep Anomaly Detection** are emerging. Anomaly Detection, or Novelty Detection, is referred to as the process of discovering data instances that deviate significantly from the majority of data instances. Due to the complexity of the problem and difficulty of learning, an advanced approach such as Deep Anomaly Detection is currently also required [246]. The work in [81] surveyed the concerns and efforts made so far to optimize and improve Anomaly/Tampering Detection methods. It includes a comprehensive table that summarizes image tampering detection and image anomaly detection datasets fit for purpose. The direction of all these aforementioned efforts introduces the need for a rigorous consideration of new and increasingly complex challenges related to tampered image detection. The most promising trend in terms of research, challenges, and opportunities is the use of machine learning techniques.

6 CONCLUSIONS

The huge diffusion of data (images, video, audio, and text), often uploaded/shared via social media or web platforms, and the possibility of their manipulation/generation also through Artificial Intelligence (AI) models, poses serious problems. Some examples are counterfeiting biomedical images, deceiving biometric authentication systems, cheating in scientific publications, in the political world, and in school activities.

In particular, the Deepfake technique, e.g. photo-realistic video or image content creation via DL methods, with the associated social and legal problems, poses serious threats to the privacy, reputation, and security of the victims. Despite many recent proposals for Deepfake detection, the rapid progress in multimedia technology and the proliferation of application tools continuously pose new challenges calling for a reliable and definitive solution [135]. A side effect is a decreased focus on more traditional forgery techniques, that, however, still represent not completely solved problems.

Whatever the nature of the manipulation, once a digital image represents a crime, it is necessary to detect the forgery. This document has presented a comprehensive overview of current and past research specially developed to list Image Forgery Detection algorithms in the Digital Forensics scenario. The paper overviews the most important methodologies used so far, restricting the scope to cases where the solution is forensic. Taking into account the various other public investigations for the detection of forgery images available in the current literature, it aims to provide a comprehensive longitudinal overview of the entire image-related forensic scenario. As mentioned in the introduction, retracing the fundamental work carried out so far, this investigation aims to represent a testimony of continuity between traditional and non-traditional approaches. We hope this survey will help forensic groups to tackle the detection of existing attacks, and get basic information about the rising ones while providing a compass for a deeper insight. In the future, we plan to move the focus toward deep manipulation detection in the context of deep fake applications.

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