International Journal on Emerging Research Areas (IJERA) *ISSN :2230-9993*

DOI: 10.5281/zenodo.14649508

Enhancing Image Forgery Detection with Multi-Modal Deep Learning and Statistical Methods

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Abstract—**The manipulation of digital images from journalism to social media and in forensics has made detection of image forgery a significant area of research. Techniques for forgery detection are generally classified into three categories: splicing, copy-move, and retouching. The mainstay of the classic methods is handcrafted features which range from resampling artefacts to edge inconsistencies and finally DCT coefficients that point towards anomalies. However, with deep learning, this domainhas totally transformed: it is possible to learn complex patterns straight from pixel data to get even more sophisticated detec- tion. Modern approaches rely on convolutional neural networks (CNNs) and prefabricated architectures such as ResNet50 and VGG16 to embrace both global and local inconsistency in images. Hybrid models combining the capabilities from deep learning and statistical methods have also been found to perform better than others. With all these advances, however, several problems still exist. It is challenging to produce subtle forgeries that survive most post-processing procedures, such as compression and resizing. More generalizable models, along with the designs they are intended to build upon, should be developed for the detection of various kinds of forgeries in diverse image datasets and reflect real challenges in diverse real-world scenarios.**

Index Terms—**Image forgery detection, splicing forgery, copy-move forgery, deep learning, convolutional neural networks (CNNs), ResNet50, VGG16, DCT coefficients, handcrafted features, hybrid models.**

I. Introduction

Digital image manipulation has quickly emerged as one of the most common manipulations simply because various types of image-editing tools and software are available nowadays. Digital image manipulation primarily threatens the authenticity of visual content because it is ostensibly very easy and sophisticated. The most common operations, such as splicing, copy-move, and retouching, are severe re-ingeniering images for distortion purposes or making a false vision. The manipulations could have severe consequences when such are applied in journalism, social media, legal investigations, and security domains. The image forgery detection has become a significant research domain because of this reason. Techniques need to be developed for authenticating digital images that can be used automatically and reliably.

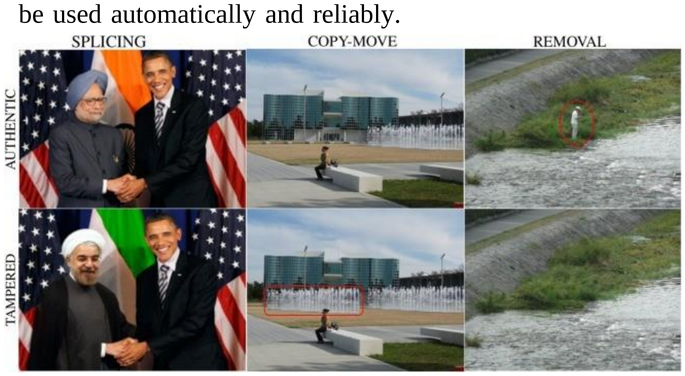

Fig. 1. Various image forgeries

The anomalies have been examined in the conventional approaches used in image forgery detection methods whose presence is deduced from handcrafted features like inconsistency in lighting, resampling artifacts, or statistical irregularities in the frequency domain. Among these, applications using techniques based on SIFT and DCT have been pretty common because of their stated robustness even against splicing and copy-move attacks. These methods are sensitive to post-processing operations, like compression, resizing, and noise addition, and rely heavily on predefined feature sets.

Deep learning has emerged as one of the major developments toward the study of detection of image forgery. These CNNs and architectures, like ResNet50 and VGG16, achieve extraordinary success in learning very complex patterns directly from image data; they do not use handcrafted features. The latter are global and local inconsistency detectors and thus potentially much more effective than handcrafted feature-based detectors of subtle forgeries. Hybrid models based on the combination of deep learning techniques with traditional statistical methods further improve the robustness and accuracy of detection.

Despite these developments, several challenges arise. Old models are typically challenged with the detection of highly complex forgeries or those that have undergone aggressive post-processing operations. Generalization also forms a lead- ing challenge in this area of work since a model trained onone kind of forgery usually fails to perform well on another. The paper introduces a panoramic view and an overall critical review of all the existing techniques in image forgery de-tection stratified between traditional and deep learning-based approaches. It reports notable methodologies, performance comparisons, and current research efforts in developing more robust and generic forgery-detection frameworks.

II. IMAGE FORGERY DETECTION TECHNIQUES

Two broad categories may characterize the methods used for image forgery detection: these include traditional techniques and deep learning-based approaches. In each, methodologies vary and have strengths in specific areas according to the kind of forgery detected and the level of sophistication used in the manipulation. The following section explains these techniques in more detail.

A. Traditional Image Forgery Detection Techniques

Traditional methods are mainly based on exploiting hand-crafted features that capture image inconsistencies developed during forgery. Along this line of thinking, these methods can also be classified into several sub-classifications depending on the type of features exploited.

DOI: 10.5281/zenodo.14649508

*1) **Pixel-based analysis**:* Pixel-based anomaly detection analyzes the pixel level of anomaly by studying parts of an image and searching for anomalies or irregular patterns in color, brightness, or noise. [23] This method is very robust in identifying splicing as well as copy-move types of faked images. Example : Statistical methods are widely used with pixel-based techniques to utilize anomalies caused by manipulation in normal distributions of pixels. In ELA, one or more regions of various compression levels were identified, indicating the work of tampering.

2) Statistical analysis: Statistical methods also analyze mean, variance, and frequency distribution of an image to spot abnormal regions in an image [24]. Abnormal regions of an image can be spotted using DCT and DWT. For instance: the DCT coefficients of the actual image-block differ from the DCT coefficients of a spliced block in JPEG images.

*3) **Transform based methods**:* The transform-based methods include several attempts to transform an image into other types of frequency domains, say the Fourier or Wavelet domain and then perform analysis using those representations transformed for tampering detection. [16]These could be presented as effective in detecting local inconsistency caused by forgeries. Example: Contourlet Transform is an extension to wavelet transform and captures the directional information in the image, which makes it fairly useful for detection of forgeries at edges as well as boundaries.

*4) **Resampling Features analysis**:* Other resampling features include interpolation, scaling, rotation, and affine transformations that may become visible traces in an image. Analysis of such traces from the resampling features will help in detection, mostly when parts of an image have been copied and moved. Example: Detection of resampling by interpolation coefficients can reveal copy-move forgeries through consistency of the coefficients throughout the image.

*5) **Lighting and shadow inconsistency analysis**:* This technique detects inconsistencies in lighting and shadow orientation. Most of the image forgeries splicing parts of objects from different sources will always produce lighting and shadow inconsistencies that may not be easy to identify. [17] Illustration: Such techniques are very sensitive to splicing forgeries since they take into account the lighting inconsistencies. This is because even the areas that emphasize the object combination from different images with different illumination are taken into account.

B. Deep Learning-based Techniques

Deep learning has dramatically enhanced the ways of detecting image forgery. Recently, it has been found that deep learning models, in particular CNNs, learn features from data not by predefining them but actually through understanding complex patterns inherent in those data. They are truly outperforming the traditional techniques in many scenarios.

*1) **Convolutional Neural Network Architectures**:* Hierarchical features are learned automatically by CNNs from raw pixel values useful for preserving and capturing bothlocal and global patterns of images. Notably, architecturesbased on deep systems like ResNet50, VGG16, and Inceptionare used in the field. Example: Such a network can be usedto detect minute forgery in images by applying its ability toview fine detail, whether slight inconsistencies in textures oreven the way that pixels are arranged, something that usualdetection methods can't catch.

*2) **Autoencoders and GANs**:* Autoencoders are a class of neural networks for unsupervised learning to learn efficient representations. They have been applied for forgery detection: one learns a compressed representation of natural images and in that case, any mismatch with it may point out forgery. Generative Adversarial Networks are mainly being used for synthetic forgeries, which by themselves are actually usedas training data to train the detection models. Example : Autoencoders are trained in reconstruction of original images, and the reconstruction error is used for forgery localization. GANs is used for creating the following kind of spliced forgeries, and synthetic forgeries are put to use as a better dataset for improving the robustness of the detection model.

*3) **Hybrid Models**:* Hybrid models are the combinations of two approaches: two conventional methods and deep learning. Here, the strength of two approaches is used. For instance, DCT coefficients extracted by handcrafted techniques may be fed into a CNN. This is a multi-modal approach in forgery detection. Example: A hybrid model can make use of CNN to get the high-level features and use Support Vector Machine in the classification to give a high accuracy in the identification of splicing and copy-move forgeries.

*4) **Attention Mechanisms**:* Attention mechanisms are introduced into CNN architectures to selectively pay attention to some areas in the image where forgery is potentially happening. This selective focusing enhances the detection of fine-grained manipulation especially for cases with small or subtle forgeries. Example: A model that uses an attentionmechanism can find forgery within a small object that maybe evaded by standard CNN in a large scene.

*5) **Transfer Learning and Pre-trained Models**:* Use of pre-trained models, like ResNet, VGG, or Inception, trained on big image datasets (e.g., ImageNet), fine-tune them for forgery detection. This reduces training time and exploits the feature extraction ability of such models.

III. IMAGE FORGERY METHODS

Generally, there are several techniques for changing reality or telling fictitious stories. Other approaches to forgery include splicing-adding together different images, as parts of the resulting scene were in separate originals-and copy- move forgery-moving some items, including objects or parts of objects, in a digital image to hide or bring attentionto information. Image retouching only changes brightness, contrast, color balance, but resampling changes brightness much more drastically using pure geometric transforms such as scaling or rotation, that tends to leave some tiny interpolation artifacts, inpainting or region removal is like an eraser of unwanted objects as if the content that fills the place smooths over perfectly in the surroundings. [3] Further sophisticated algorithms can trace textures and structures. Furthermore, digital techniques refine such manipulations by adjusting lights, shadows, and shades of colors; this is much more realistic and difficult to trace. Techniques like GANs, developed using

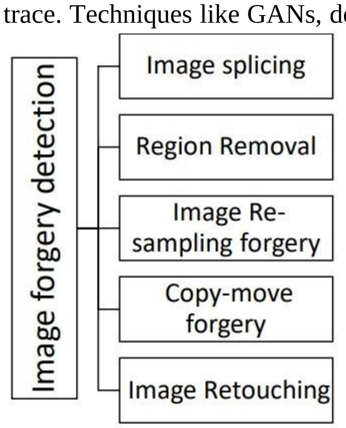

Fig. 2. Various forgery detection methods

machine learning, have raised the stakes because of the very high resolution and even up to undistinguishable differences in producing fake images and videos from the real ones. Such a subtle manipulation requires equally advanced detection techniques since traditional techniques cannot trace such slight anomalies. This has made it a never-ending "cat-and-mouse" game between forgers and forensic experts. [6] Researchers are trying to innovate by combining deep learning techniques with traditional forensic analysis that can enhance detection accuracy and flexibility. With the advancement of technology, authenticity and integrity of digital visual content have to be maintained; thus, the increased complexity and realism of image forgeries require a more powerful and scalable solution.

A. Image Splicing

Digital splicing is a manipulation technique whereby part of one image is copied and seamlessly superimposed over another. Its goal is to blend these two images so perfectly that the spliced region would not be distinguishable from its surroundings. [10] Often enough, spliced images combine contents from several sources, fabricating visual images that even keen-eyed observers may find misleading. This technique is very popular where the intention is to representan event or scene that has never taken place. For instance,a picture is made of bringing people together to depict astory that is not true. This method may indeed produce pretty convincing results, but it still carries subtle distortions that,at times, can indicate its manipulative nature.

Major issues in detecting spliced images include distortions that emanate from lighting and shadow variances. Because the region is being spliced from a different source, the lighting will reflect on it with the original light settings of its host image. [11] In consistency, mismatched shadows, uneven brightness, and color tones are inconsistencies in conflict with the host when such spliced regions are used over them. For instance, an object that appears photorealistic and was taken by a camera in an extreme outdoor lighting condition would be completely ridiculous if it were put indoor where the lighting is soft. These advanced forgers manipulate most of these properties of the lighting using the sophisticated editing tools available and such that these flaws are at times blind to the human eye. However, sometimes analysis of light directions, the orientation of shadows, or even tonal balance reveals anomalies.

Other key indicators of image splicing involve artifacts that occur across the edges where the splice overlaps withthe rest of the picture. Such artifacts may include unnatural changes or abrupt changes in color along the boundaries or texture disparities. [12] The artifacts are strong indicators of tampering in an image, especially when it comes to edge detection techniques or other gradient-based methods. However, a good forger will blend the edges through advancedblending techniques so that it is completely seamless and thus quite imperceptible to the naked eye-the artifacts of the boundary are no longer present.

Other than artifact removal through smoothing and blurring techniques, other manipulations can create a realistic appearance. They help to smooth out the sharp edges so that the spliced region melts into an overall texture. The processis efficient, but it often leaves traces around: over-smoothened areas stand out from the natural roughness of the other regions. Sometimes, forgers inject subtle noise or distortionsto simulate the imperfections existing in the original images. This adds another layer of complexity, making it increasingly difficult to identify spliced content using traditional forensic methods [5].

The implications of image splicing are quite extensive since it undermines the authenticity of digital content, and verifying the integrity of the visual media becomes difficult. For spliced images detection, one may use a combinationof manual inspection and automated tools. Inconsistencies in lighting, boundary artifacts, and anomalies in textures become critical in revealing the spliced forgeries. Deep learning has improved dramatically over the last few years to enable splicing detection. High accuracy of forgery detection is achieved through large datasets, training machine learning models on even the subtlest patterns and irregularities at pixel level [7].

In a nutshell, despite being one of the most potent techniques for producing artificial images, image splicing is far from being signless. The increasing complexity in forgery, therefore, calls for innovative detection techniques to ensure digital content, which plays such a pivotal role in this world's communication and dissemination of information, is indeed original.

A. Copy-move forgery

Copy-move forgery is an image manipulation technique where a portion of the image is copied and pasted elsewhere in the same image, mainly for purposes like duplication of objects or hiding unwanted parts of the image. [15] It is the most commonly used forgery technique for masking specific details such as duplicating objects in an image or hiding flaws. The copied area is usually modified in a variety of ways, including scaling, rotation, or blurring, to make it look like it belongs to the surrounding region. However, the detection of these modifications is a challenging task because of a number of factors inherent in the process of manipulation. One of the main reasons is that normally, the copied and paste regions share a common interest or property with one another due to which conventional feature extraction methods that solely depend upon feature or pattern detection within an image fail to differentiate between the original image and the pasted one.

Furthermore, once a pasted region is inserted, this usually transforms in such a manner that its shape or orientation is distorted with scaling, rotation, and affine transformations, aligning it with its new position. [9] This just created more problems because pixel-matching algorithms, which rely upon a direct comparison of pixels, were no longer applicable when a given copied segment had undergone such transformations. Furthermore, noise and blurring applied to the duplicated part can mask some the characteristic signs of a forgery. The noising drowns the edges of the duplicated region, whereas the blurring effect makes even the transitions between the copied parts and the original parts smoother, thereby even more difficult to detect through the traditional means. [14] These challenges require more powerful techniques of forensic, such as ML or DL-based techniques, that can efficiently identify copy-move forgeries.

B. Image Retouching

Image retouching refers to the alteration of visual properties, such as color balance, brightness contrast, sharpness, etc, with the purpose of enhancing the look and beauty of an image by manipulation. It is totally different from splicing and copy-move forgery as retouching does not include the additionof complete content to the picture or its portion but only gives an aesthetically appealing effect by modifying the alreadypresent contents in terms of appearance. [22] Retouching is widely used in both professional photography and casual image editing for purposes like improving visual appeal, correcting lighting or color imbalances, or highlighting certain features of the image. For example, adjusting brightness or contrast can make an image appear more vibrant or clearer, while changing sharpness might enhance fine details, making the subject of the image stand out more.

It is really challenging to detect retouching in images because the changes are so minute. In general, the changes done in the process of retouching are so minute andunobtrusive that they are barely noticed, especially if such changes do not drastically distort the structure of the image. Both human observers and automatic detection methods have a hard time detecting such alterations unless they are extreme. Further complicating detection, retouching can be either global applied to the entire image or local applied to specific regions. [**?**] A local enhancement might adjustbrightness or contrast in only one part of an image, such asa person's face, leaving the background untouched. Selective editing makes it challenging to distinguish between natural variation and intentional manipulation.

The natural property variations like contrast and brightness could impact what is seen in the image instead of what is actually there. They might mask or hide changed parts of the image so much that one can barely distinguish what exactly has been changed. [20] Change may be so slight that it introduces no obvious artifacts, so there won't be any tracethat something is wrong. This essentially means that detection of retouching requires more advanced techniques than simple pixel analysis and often involves comparison with the original image or statistical models of the property of the image.

C. Image Re-sampling forgery

Re-sampling forgeries. These are manipulation operations performed with an image in which a geometric transformation takes place over some parts of the image: scaling, rotation, or an affine transformation. Such transformations change the proportions, orientation, or position of objects in an image and are the most commonly used operations when itis required that a visual presentation of an image must be changed [18].Re-sampling forgeries are used to hide or alter objects, add new features, or change the view of an imageand are applied

DOI: 10.5281/zenodo.14649508

primarily to alter the content of the image for deceptive purposes.

Some of the characteristics of re-sampling forgeries include interpolation artifacts. Any geometric transformation like rotation or scaling usually involves resampling of pixels. This process, at times, may generate artefacts that occur as visual aberrations, such as blurring, jagged edges, or pixelation.
[1] These artefacts occur because of the fact that the transformation procedure requires calculating the new pixel value based on its neighboring pixel values, and sometimes interpolation may introduce small errors, especially if scaling or rotating is done by a non-integer value. These artifacts are often easily discovered in the frequency domain, where they may appear as visible patterns or spikes in frequencynot present in the original image. [21] The frequency domain of an image can be searched for anomalies and areas thathave been subjected to re-sampling using special forensic techniques.

Loss of Original Image Properties Another issue of re-sampling forgeries is the loss of the original characteristics of the image. Geometric transformations like scaling or rotation change spatial locations of pixels around an image, hence it changes the structure of the image. These changes make impossible to recover the original content of an image for comparison. Since geometric transformations distort the inherent properties of image-analyzing pixels' locations and neighbor relations, the results of the traditional pixel-based analysis are not reliable. [19] However, the loss of those original properties complicates matters because the changes often are quite subtle and do not introduce easily noticed artifacts like other types of forgeries.

Overall, detecting re-sampling forgeries involves sophisticated forensic techniques that would look at the unique patterns and artifacts of the geometric transformations. [2]These are usually focused on interpolation artifacts in the frequency domain, image statistical properties, or through the use of machine learning algorithms in order to recognize and distinguish between manipulated and authentic content.

D. Region Removal

Region removal or inpainting is a technique in which the unwanted objects or regions are removed from an image, then filling the removed area with content that blends with the surrounding background. Advanced inpainting algorithms rely on patch-based methods or deep learning models to create realistic content so that the gap left behind appears filled in a way that is natural and undetectable. The problem with region removal is that the inpainted region is very difficult to distinguish from the original image. [13] Modern inpainting techniques are designed to make content look very realistic, so it would almost look like the inpainted area mimics the textures, colors, and structures of the surrounding areas. Thus, the manipulated part of the image often becomes indistinguishable from the rest of the scene. This seamless integration makes very difficult for the traditional image forensic techniques to detect such types of alterations. Moreover, inpainting algorithms have a hard task like texture synthesis and structure inference, that is, where the model makes textures or structures that perfectly match the rest of the image, even including transitioning from areas with high details to those with less structure. [8]This makes detection even more complicated since even the most advanced forensic tools have difficulty in identifying such subtle alterations.

IV. CONCLUSION

In a nutshell, various forms of image forgery- splicing,copy-move forgery, retouching, re-sampling, and removal of region (inpainting)- bring specific problems in the detectionof an individual form due to particular content modificationin their type. In general, without advanced approaches, inconsistencies of lighting from splicing and copy-move forgeries or patterns of duplicated boundaries are not detected.
[4] Altering intrinsics such as color or sharpness-consider,those to be impossible to detect given how these changes are invisible by even looking- is a nonobvious retouching. Even though geometric transformations in interpolation do leave interpolation artifacts that become visible in the frequency domain, they often require considerable extra processing for accurate identification of forgery. One of the hardest forms to detect is region removal or inpainting, which has photorealistic blending and seamless integration of content because it can mimic textures and structures in natural detail. These are very complex manipulations that have grown with the development of editing tools and techniques based onmachine learning for creating forgeries.

This is resulting in increasing needs for robust, scalable, and intelligent mechanisms of detection. Therefore, strong techniques that identify such forgeries and ones based on deep learning including usage of CNNs, transformers, as well as ensemble methods, have thus seen to be better. Still, these ones are very much effective, provided appropriate large-sized datasets, and computer memory, frequently hindering the generalization. Consequently, future directions in research will seek to address gaps between classic feature-based techniques and latest approaches deep learning.

Through the best features of both paradigms, researchers are attempting to develop generalized frameworks that could detect a variety of forgery types under varying conditions.It will also attempt to strengthen algorithmic robustness for variations in the quality and resolution of images and the intensity of the manipulation as well as adversarial attacks towards detection systems. Interpretability and transparency have become very important in deep learning models, as trust in automated detection systems builds up from them. That leads to the ultimate goal of keeping digital visual content intact and authentic in this ever-manipulated and digitizedworld.

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