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Deep Learning Techniques For Image Splicing Detection: A Systematic Review

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Abstract

Currently, images stand for a highly common form of communication, whether through teleconferencing, mobile communication or social media. The identification of counterfeit images is intrinsic because it is crucial that the images used for communication be genuine and original. Images are fabricated referring to the fact that it is challenging to set the difference between a tampered image and the real image. This refers notably to the myriad technological, moral, and judicial implications connected with advanced image editing software. The majority of handcrafted traits are used in traditional approaches for detecting image counterfeiting. The problem with many of the image tampering detection methods now in use resides in the fact that they are confined to identifying particular types of alteration by looking for particular features in the images. Image tampering is currently recognized through deep learning techniques. These methods proved to be promising and worthwhile as they perform better than traditional ones since they can extract complex components from images. As far as this research paper is concerned, we provide a thorough review of deep learning-based methods for detecting splicing images, along with the pertinent results of our survey in the form of findings and analysis.

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1. Introduction

Every day, new digital resources, including images, movies, and video files, are posted to social networks, where images are the most often shared type. The great popularity of modern image-editing software, however, makes it simple to modify photographs without leaving any visible evidence. From this perspective, practical users find it challenging to recognize modified photos [1, 2]. Multimedia forensics, which tries to verify the reliability of digital material, has whetted a spate of scientific interest. Image forging, also known as image manipulation, image tampering, or image forensics, corresponds to a field of study that examines altered images to tackle difficult problems.

Numerous common forms of image forgeries involve composing fake images from real ones. Copy-move images, for instance, are created through copying parts of a real image and then moving or pasting them to other parts of the image [3, 4]. Spliced images represent another type of common image forgery, in which images are created by pasting one or more areas from a real picture into another real picture. Figure 1 depicts the combination of two spliced pictures (right) from two real photos (center) and two copy-move images (left). The blue dashed and red solid arrows portray copy-move and splicing actions, respectively. To shun forgery detection, the tampered place might be resized, flipped, rotated, or otherwise altered from the original region. A single source region can be replicated into multiple modified regions [5, 6].

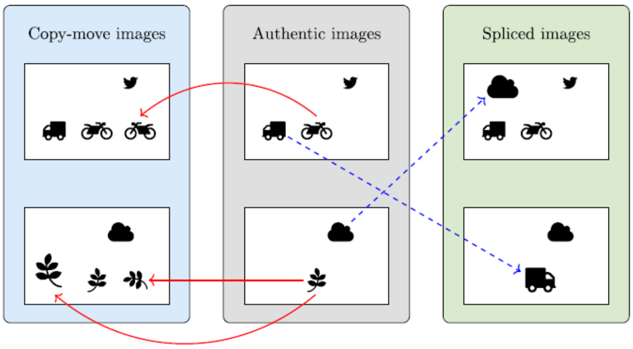

Figure 1. Types of image forgery.

Figure 2 provides examples of spliced photos together with the related real-world photographs. We discover that the genuine picture may be confused with the object removal image derived from the spliced image in two spliced photographs and their corresponding original images. In other words, there are complex relationships among the various forms of image forgeries. The word "detection" has been used in image forgery challenges to refer to two distinct problem categories with varying connotations. Typically, when we talk about Image Splicing Detection (ISD), we are talking about the classification issue between real and spliced images [7].

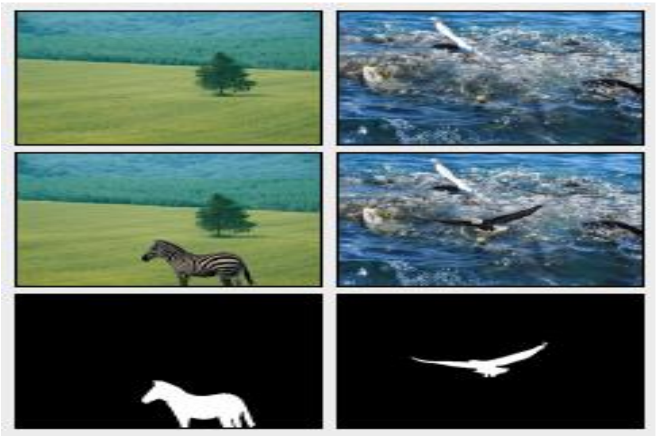

Figure 2. Image splicing forgery.

Image splicing is a key process in terms of creating image forgeries. The identification of image splicing is therefore pivotal to digital image forensics. The tampering traces are hard to spot and follow even if post-processing was not used. One may recognize it with respect to the impacts of splicing on the image's statistics, the image's brightness levels, or the borders of the redundant region. A few methods for detecting image splicing fraud have recently been set forward [8, 9].

This paper is laid out as follows. The details of datasets used in the field of image splicing detection are displayed in Section II. Various Deep Learning (DL) techniques applied to solve the image splicing detection task are addressed in Section III. Section IV discusses the information presented in this paper. Section V introduces the basic challenges. Finally, the conclusion of this work is exhibited in Section VI.

2. Datasets and Benchmarks

In this section, we shall introduce the most well known datasets that have been used in image splicing detection task. A summary of these datasets is highlighted in Table 1. All datasets involve original and forgery color images.

2.1 CASIA Dataset

The Chinese Academy of Sciences' Institute of Automation (CASIA) provides the CASIA v1.0 dataset [10]. There are 800 real photos and 925 spliced pictures in CASIA v1.0. The 1725 JPEG Color pictures in the CASIA v1.0 collection have a 384 × 256 pixel resolution. Among these, 925 are tampered photos and 800 are real images. Eight general categories—animal, architectural, scene, texture, plant, nature, and character—are used to classify authentic photos. Adobe Photoshop is used to perform splicing operations on real photos in order to create the manipulated images. The spliced pictures stand for a useful tool for assessing detection strategies since they encompass a wide range of splicing approaches.

Expanding upon CASIA v1.0, CASIA v2.0 provides a more extensive dataset. It includes 12614 photos, some of which are JPEGs with different Q factors of sizes in pixels ranging from 320 × 240 to 800 × 600, and some of which are uncompressed TIFF and BMP files. This dataset includes 5123 altered photos and 7491 genuine images. Nine broad categories may be used to classify authentic images: animal, architecture, scene, texture, plant, nature, character, and indoor.

2.2 Columbia Image Splicing Detection Evaluation Dataset

Image splicing detection techniques are intended to be evaluated using the Columbia dataset, also called Columbia Uncompressed Image Splicing Dataset CUISD [11]. There are 363 uncompressed photos in the collection. The collection comprises 180 spliced and 183 genuine TIFF-formatted photos. The photos' pixel resolution falls between 757×568 and 1152×768. Four distinct camera models—the "canong3," "nikond70," "canonxt," and "kodakdcs330"—were used to take the pictures. The pictures reveal a variety of settings and things, including tables, books, and piano. 15% of photos are taken outside during overcast weather, which indicates that outside lighting is comparable to inside lighting.

2.3 MISD Dataset

The Multiple Image Splicing Detection (MISD) dataset [12] is designed to address the challenge of detecting splicing in cases where multiple images are combined. While the specific number of images is not stated, the dataset focuses on scenarios where multiple images are manipulated to create a single forged image. MISD comprises 618 genuine and 300 realistic multiple-spliced images with a resolution of 384 × 256, which have undergone scaling and rotation processes. Images from a variety of genres are equally included, such as interior scene, texture, character, nature, plant, animal, architecture, and art. Additionally, this dataset includes ground truth masks that identify the spliced instances for a given collection of multiple spliced photos.

Table 1: Datasets used in image splicing detection tasks

Name of dataset	Number of images	Size of image	Format of images
CASIA v1.0	1725 (800 authentic images and 925 spliced images)	400 × 486	JPEG
CASIA v2.0	12614 (7491 authentic images and 5123 forged images)	320 × 240 to 800 × 600	BMP and TIFF uncompressed images. JPEG
COLUMBIA	363 (183 authentic images and 180 spliced images)	757 × 568 to 1152 × 768	BMP
MISD	918 (618 original and 300 multiple spliced images	384 × 256	JPG

3. Literature Overview of Deep Learning Architectures

A novel counterfeit localization method was devised by Khayeat et al. [13] employing Deep Learning DL of the wavelet-decomposed image's first level DWT LL1 and SegNet. At first, image's dimensions are reduced from 3D to 2D–by converting a color image (RGB) to grayscale. Second, superfluous components are removed from the first level, in particular the DWT LL1 features. The CNNs can understand and learn the intended aim much faster than they could have by simply utilizing the gray picture. Semantic segmentation recognizes fraudulent structures in spliced images, but cannot capture all of them. Therefore, a post-processing method is highly required to settle this issue. A morphological method has been used to generate the mask and produce a better result. The testing findings demonstrate that the proposed method provided a detection accuracy of 89%.

Using ResNet-conv, as a novel DL backbone architecture, Ahmed et al. [14] elaborated a model for spotting image splicing. In order to create ResNet-conv, multiple convolutional layers are integrated into the ResNet feature pyramid network ResNet-FPN. This new backbone is initially used to create the first feature map, which trains ResNet Convolutional Neural Network RCNN to create masks for spliced sections of fabricated images. The main objective of the proposed network is to detect discriminative artifacts from changed areas. Two different ResNet topologies, ResNet-50 and ResNet-101, have been invested. It was realized that the convergence of ResNet-50 occurred more quickly. This refers to the fact that forgery-related characteristics are fundamental properties that may be gleaned from the network's basic levels. The accuracy of the detection did not improve by integrating additional layers; rather, convergence is slowed. Using several augmentation techniques, the model depicted in Figure 3 proved to be resistant to different post-processing techniques. Both He Xavier weight and Xavier normal initialization methods were applied. Results with initialization using the ImageNet dataset were better than those of the other options. The proposed method exhibited an AUC value of 96.7% while training and evaluating with computer-generated false photographs.

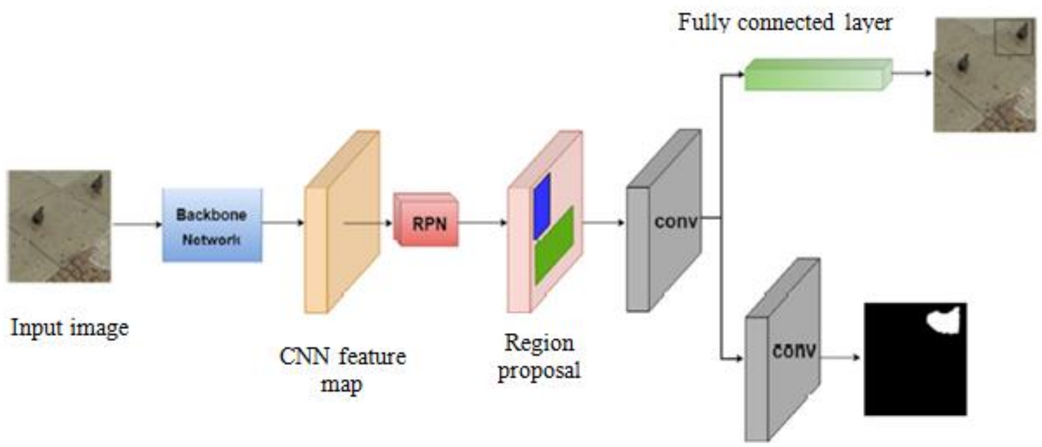

Figure 3. The Mask-RCNN framework

In order to detect image splicing, Wang et al. [15] developed a novel weight combination based on Convolutional Neural Networks (CNNs), as illustrated in Figure 4. The proposed approach deploys a combination of methodologies like YCbCr, edge, and Photo Response Non-Uniformity PRNU characteristics to distinguish splicing manipulation and then combine them in a weighted way. Contrarily to the other methods, these weight values are automatically adjusted while CNN trains to determine the ideal ratio. Relying upon the obtained results, the suggested technique performs better than other CNN-based methods despite the use of a considerably shorter neural network. The accuracy of the introduced method was 99.45% for the CASIA v 1.0 dataset and 99.32% for CASIA v2.0, outperforming cutting-edge forgery detection methods.

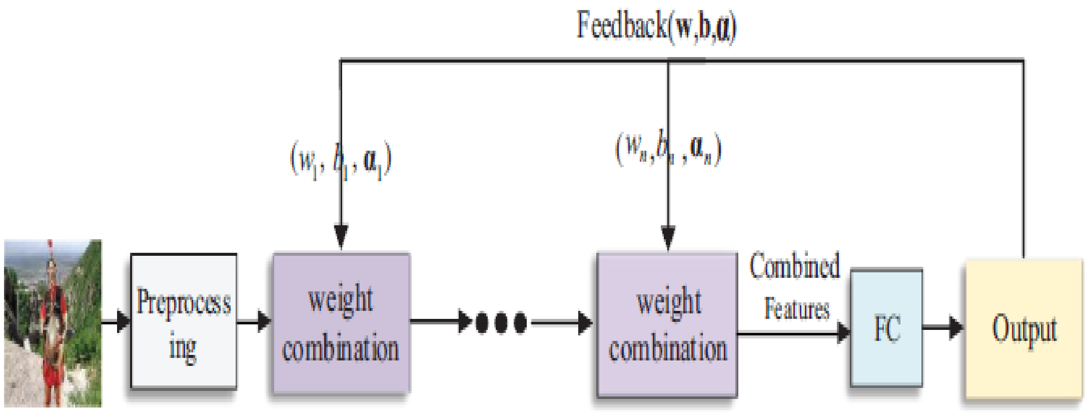

Figure 4. The architecture of the weight combination CNN model

A Ringed Residual U-Net (RRUNet), created and introduced by Bi et al. [16], may identify forgeries without the need of pre- or post-processing. The proposed RRUNet boosts CNN's learning methodology through the feedback and propagation of the residual, which is modeled after consolidation with recall processes in human brain. Additionally, we simultaneously establish the dependability of the ringed residual structure in RRU-Net by theoretical analysis and practical comparison. Experimental findings reveal that the recommended detection approach may yield a good result on CASIA and Columbia datasets when compared to sophisticated splicing forgery detection tools.

Abd El-Latif et al. [17] developed wavelet transform and deep learning in terms of a method for identifying the spliced image, as foregrounded in Figure 5. The DL approach resting on dynamically obtaining image characteristics from spliced photos uses CNNs features. Subsequently, the DWT was performed for extracting relevant features from the image. SVM classifier was next used to solve classification problem. Several experiments were undertaken in this work. In this regard, a discrete cosine transform was employed rather than the DWT, and then principal component analysis was performed. The proposed method was evaluated on CASIA v1.0 and CASIA v2.0 databases deploying a variety of public image splicing datasets. To achieve good accuracy, feature vector, which is quite modest in dimension, was invested. The results demonstrate the goodness of fit of the recommended approach, which yields superior spliced image detection. The proposed technique achieves outstanding accuracy amounting to 97.27% by CASIA v2.0 dataset.

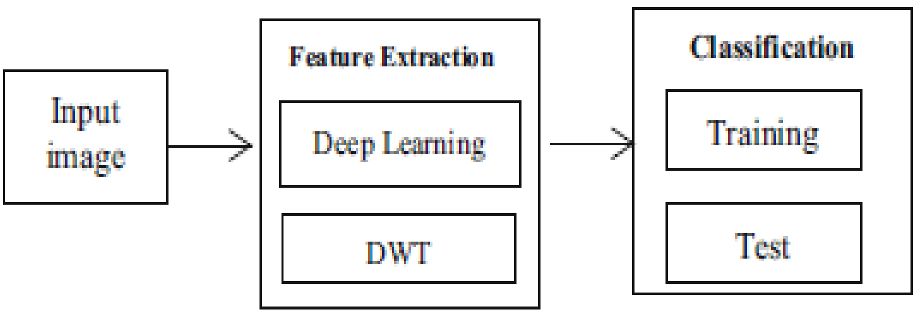

Figure 5. Model architecture in [17]

DL based method was developed by Meena et al. [18] to detect image splicing in the images. As noticed in Figure 6, the input image was initially pre-processed using ResNet-50 as a feature extractor in order to reduce the image content. To assess whether the recovered features are authentic or spliced, the SVM classifier was last utilized. The CUISDE dataset trials reveal that the proposed solution performs better than other existing approaches. An average of 97.24% is achieved in classification accuracy using the suggested strategy.

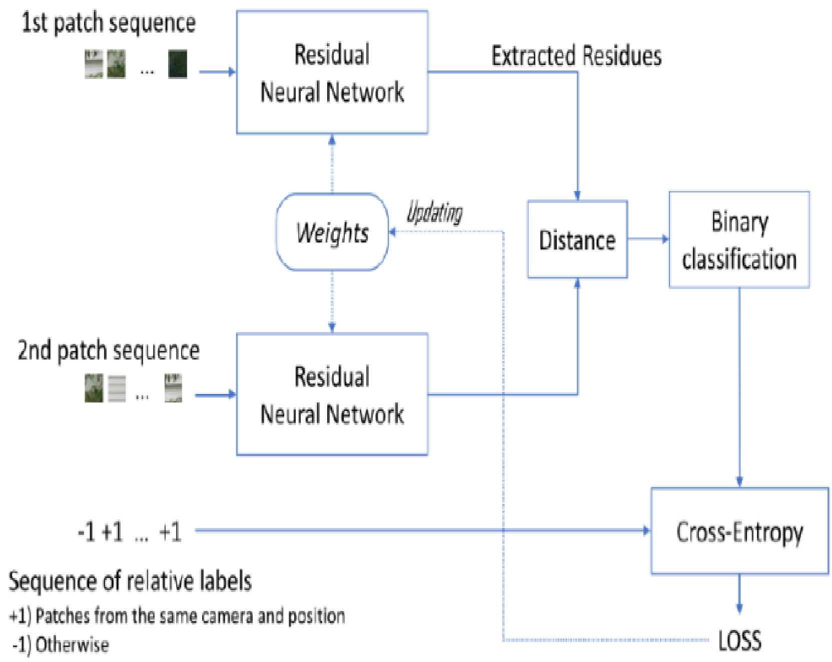

Figure 6. The architecture of the Noiseprint model [18]

Mask R-CNN with MobileNet v1 was introduced by Kadam et al. [8] as a straightforward model for image splicing detection fraud. It equally provides a fictitious percentage score for a number of composited images. The recommended model was trained and assessed using the MISD dataset. ResNet 51, ResNet 101, and ResNet 151 versions were compared to the suggested model. The recommended model yielded an average accuracy of 82%. An innovative CNN-based method for identifying image-splicing frauds presented in Figure 7 was applied by Xiao et al. [19]. The coarse-to-refined convolutional neural network (C2RNet) was used in the proposed technique to anticipate the findings, and a post-processing strategy was set forward to identify the final found tampered regions. The proposed C2RNet works by cascading a CNN to extract the differences in the picture characteristics between authentic and tampered regions from image. Typically, questionable course forging areas may be predicted by a *Cascades*-CNN (C-CNN). The recommended detection method was evaluated and compared to other cutting-edge detection techniques on two open datasets. The results of the experiment demonstrate that the suggested approach works better than the other conventional detecting methods.

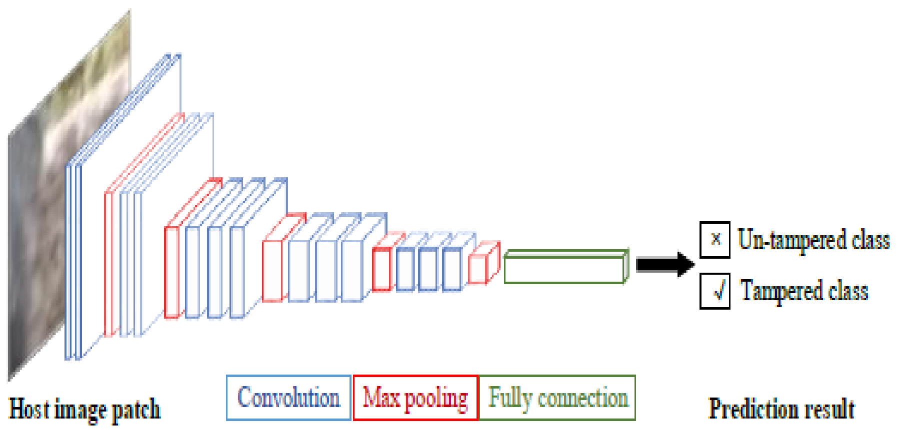

Figure 7. Architecture of coarse CNN (C-CNN) [19]

Rao et al. [1] to develop a deep learning-based system that automatically learns hierarchical representations from the input color pictures used convolutional neural networks (CNNs). Image splicing as well as copy-move detection are only a couple of the applications that the suggested CNN is designed to Rephrase. The weights at the network's first layer are determined by a simple high-pass filter set that is employed as a regularize in the production of residual maps in a spatial rich model (SRM). Three publicly benchmark datasets for forgery detection—CASIA v1.0, CASIA v2, and Columbia gray DVMM—are used in all testing's. The experimental findings amounted to 98.04%, 97.83%, and 96.38% in terms of accuracy, respectively.

A brand-new method for locating image tampering dubbed dual-channel U-shaped network DCU-Net was devised by Ding et al. [20]. Its foundation is the dual-channel U-Net. The three essential elements of the DCU-Net-based detection architecture correspond to the encoder, feature fusion, and decoder. The original altered image and the modified residual image serve as the model's inputs. Dilation convolution is used to recover the altered features with varying granularities after the deep features from the dual-channel encoding network are fused. The secondary fusion is then completed. The input of the fused feature map into the decoder is then utilized to decode the expected picture layer by layer. The testing results demonstrate that DCU-Net outperforms the most recent method and is capable of precisely pinpointing tampered regions on the CASIA v2.0 and Columbia datasets. On the CASIA dataset, the DCU-Net model's F-measure, precision, recall, and accuracy are 86.67%, 87.72%, 88.93%, and 97.93%, respectively, while on the dataset for Colombia, they account for 94.98%, 98.71%, 91.76%, and 97.27%, respectively.

Li et al. [21] proposed deep learning model for image splicing localization, it can be seen in Figure 8. The use of multi-scaled learning allows the model to take notice of an image's global characteristics. Furthermore, it also features self-attention methods, which give the model a more radical focus towards tampered areas instead of what content information the image holds, thus improving its detection capabilities. To put it simply, this model knows where to look and is fantastic at finding tampered regions. For testing purposes, the Columbia Uncompressed and CASIA v1.0 datasets were used after training on CASIA v2.0 dataset. Experimental findings showed that thanks to multi-scale directed learning technique and self-attention processes, this model has a higher accuracy rate in identifying tampered region than other state-of-the-art models.

Muniappan et al. [22] introduced convolutional Neural Network (CNN) model. It learns to extract features from convolutional, pooling, and Rectified Linear unit layer and classifies the picture as authentic or fake using fully connected layers. Three datasets, namely MICC-F2000 (2000 pictures), CASIA v1 (1721 images), and CASIA v2 (12615 images), are examined and contrasted using currently available deep learning-based techniques.

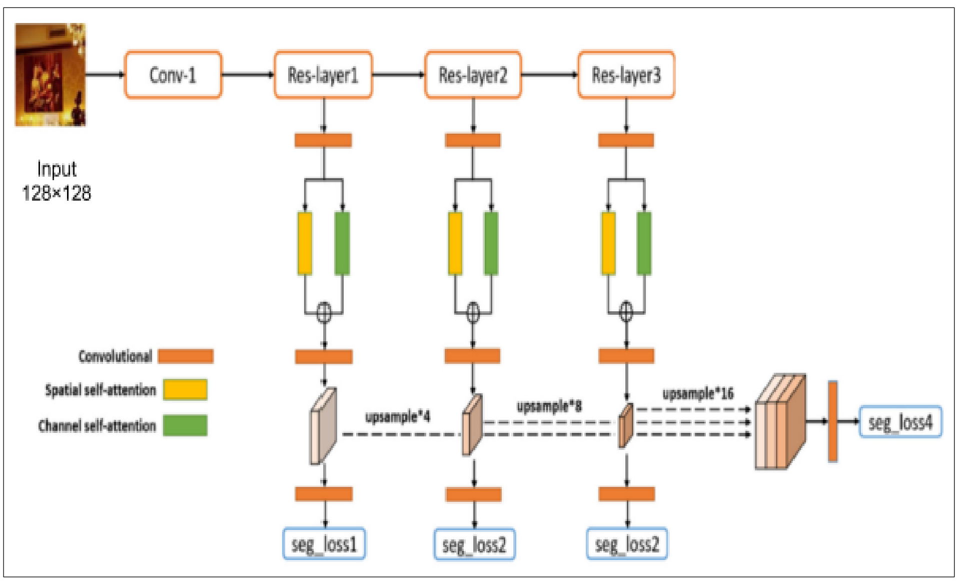

Figure 8. The self-attention mechanism model

The outcomes demonstrate that the CNN model performed best, with an accuracy of 79% for CASIA v1 and 89% for CASIA v2. A lightweight image splicing and tampering localization technique based on MobileNetV2 and Shi et al. [23] elaborated Spatial Rich Model SRM. The present study utilizes a lightweight convolutional neural network to reduce the number of down-samplings of the current MobileNetV2, thereby lowering the model's complexity and speeding up the detection process. The model also makes use of a dual-stream network, which extracts noise inconsistencies between tampered and un-tampered portions of the image using the SRM stream and sharp contrast differences using the RGB stream. The F1-Score results of the proposed methods achieved 58% and 75% for the Columbia and CASIA v1.0 datasets, respectively.

Another study in [24] tackled image splicing detection. The researchers developed a novel deep learning model, specifically designed for low-end computers with limited resources. Their approach involves incorporating residual network (ResNet) modules into a modified VGG-16 architecture. Compared to ResNet-50, the proposed model achieved superior performance on tasks requiring low memory and smaller batch sizes. This was evident in the experimental results, where the proposed model outperformed ResNet-50 in terms of accuracy and loss across training, validation, and test sets. Notably, the proposed model achieved a test accuracy of 92.5%, significantly exceeding the 85.6% accuracy obtained by ResNet-50 on CASIA v 2.0. Table 2 provides a summary of the deep learning techniques used to identify image splicing published in the last five years.

Table 2: Comparison between different splicing detection techniques

Authors	Approach	Datasets	Results
Bi et al. [16]	RRUNet	-CASIA v1 -Columbia	F1-score (0.841) F1-score (0.915)
Khayeat et al. [13]	Deep learning + DWT LL1	-CASIA v1 and v2	Accuracy (0.89)
Ahmed et al. [14]	ResNet-conv	ImageNet	Accuracy (0.967)
Rao et al. [1]	Automated learning of hierarchical representations from the input color images using a CNN	-CASIA v1 -CASIA v2 -Columbia gray	Accuracy (0.980) Accuracy (0.978) Accuracy (0.963)
Xiao et al. [19]	Coarse-to-refined CNN	-CASIA v1 -Columbia	F 1 score (0.675) F 1 score (0.695)
Kadam et al. [8]	lightweight model using Mask R-CNN with MobileNet V1	-MISD	Accuracy (0.82)
Wang et al. [15]	CNNs	-CASIA v1 and v2	Accuracy (0.994) Accuracy (0.993)
Abd El-Latif et al. [17]	CNNs	-CASIA v1 and v2	Accuracy (0.954) Accuracy (0.972)
Meena et al. [18]	ResNet-50	-CUISDE	Accuracy (0.972)
Ding et al. [20]	New image tamper location technique called DCU-Net based on Dual-Channel U-Net	-CASIA v2 -Colombia	Accuracy (0.979) Accuracy (0.972)
Li et al. [21]	Self-attention mechanism	-CASIA v1 -Colombia	F1 score (0.64) F1 score (0.53)
Muniappan et al. [22]	CNNs	-MICC-F2000 - CASIA v1 - CASIA v2	Accuracy (0.76) Accuracy (0.79) Accuracy (0.89)
Shi et al. [23]	MobileNetV2	-CASIA v1 - Columbia	Accuracy (0.58) Accuracy (0.79)
Nguyen et al. [24]	Used ResNet modules into a modified VGG-16 architecture	-CASIA v2	Accuracy (0.925)

4. Discussions

The discussion of the methodologies invested for image splicing detection allows a deeper insight into a diverse array of approaches, each leveraging different techniques and architectures to tackle the challenge. Khayeat et al. reported a novel method employing Deep Learning (DL) of wavelet-decomposed images, focusing particularly on the DWT LL1 feature to enhance computational efficiency. Through reducing image dimensions that consist of converting a color image (RGB) to grayscale and employing semantic segmentation, they achieved a detection accuracy of 89%, displaying the effectiveness of their approach. Similarly, Ahmed et al. introduced a DL model using ResNet-conv, which demonstrates promising results in image splicing detection. Their utilization of ResNet-50 and ResNet-101 architectures highlights the significance of model selection in achieving optimal performance. Meanwhile, Wang et al. adopted a CNN-based method for weight combination, achieving higher accuracy rates compared to existing techniques. This emphasizes the importance of feature selection and combination methodologies in fostering detection capabilities. Bi et al. proposed the RRUNet, which innovatively integrated residual feedback mechanisms, illustrating the potential for advancements in CNN learning methodologies. Abd El-Latif et al. integrated a combined approach utilizing wavelet transform and DL, which offers an effective solution for spliced image detection, particularly relevant for its high accuracy rates. Furthermore, Meena et al. incorporated a DL-based method utilizing ResNet-50 and SVM classification, demonstrating robust performance on the CUISDE dataset. Kadam et al. built up a straightforward model, Mask R-CNN with MobileNet V1, for image splicing detection, highlighting the importance of model simplicity and efficiency. Xiao et al. constructed the C2RNet, demonstrating the effectiveness of cascading CNNs for coarse-to-refined detection, emphasizing the potential for sequential learning methodologies in addressing complex image manipulation tasks. Xiao et al. introduced a novel CNN-based method, the Coarse-to-Refined Convolutional Neural Network (C2RNet), serving to identify image splicing frauds. Utilizing cascaded CNNs, the proposed C2RNet extracts differences in picture characteristics between tampered and undamaged regions, enabling the identification of tampered areas. Comparative evaluation against existing methods on open datasets revealed the higher performance of the suggested approach. Additionally, Rao et al. developed a deep learning-based system employing convolutional neural networks (CNNs) for image splicing and copy-move detection, achieving high accuracy on publicly available benchmark datasets. Ding et al. foregrounded the DCU-Net, a dual-channel U-Net-based method for locating image tampering. By leveraging high-pass filters and dual-channel encoding, DCU-Net proved to outperform previous methods in pinpointing tampered regions on the CASIA v2.0 and Columbia datasets. Li et al. introduced a deep learning model for image splicing localization, leveraging multi-scaled learning and self-attention mechanisms to extract global features and focus on tampered regions, respectively. Trained on CASIA v2.0 and tested on CASIA v1.0 as well as Columbia Uncompressed datasets, their model outperformed state-of-the-art methods, revealing superior effectiveness in accurately locating tampered areas. Furthermore, Muniappan et al. created a CNN model for feature extraction and classification of authentic and fake images, achieving notable accuracy rates on various datasets. Shi et al. introduced a lightweight image splicing and tampering localization method based on MobileNetV2 and SRM to promote detection speed when maintaining competitive performance on Columbia and CASIA v1.0 datasets. These methods, which exhibit impressive results, demonstrate the intricacy and variety of the picture splicing detection job and further guide future research directions in this area. Lastly, using ResNet modules in a modified VGG-16 architecture, Nguyen et al. created a unique deep learning model for picture splicing detection. Their method beat ResNet-50 by performing better in terms of accuracy and loss on low-resource computer systems. On the CASIA v 2.0 dataset, they particularly achieved a test accuracy of 92.5% as opposed to ResNet-50's 85.6%. On the other hand, we provide an overview on some well-known datasets that are widely used in image splicing detection task, including CASIA Dataset, which contains CASIA v1.0 and CASIA v2.0, Columbia Image Splicing Detection Evaluation Database, MISD dataset. Researchers develop their algorithms using these databases to create strong methodologies to detect manipulated images efficiently.

5. Challenges and Suggestions for Future Works

After summarizing this literature study effort, the following considerations need to be made in order to design an appropriate artificial intelligence system-based picture splicing detection model. Notably, since contemporary image alteration techniques are so sophisticated and complicated, using machine learning and deep learning techniques for picture splicing detection presents a number of challenges. Several of these difficulties include computational complexity and resource requirements, which are important considerations when implementing deep learning techniques for image splicing detection. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), often require significant computational power and memory to train and deploy. The complexity of these models can lead to longer training times, higher energy consumption, and the need for specialized hardware. Moreover, large-scale datasets for training deep learning models demand substantial storage and efficient data handling capabilities.

Overfitting and generalization are also key challenges in applying deep learning techniques to image splicing detection. Overfitting occurs when a model becomes overly tailored to the training data, capturing its noise and outliers, which can lead to poor performance on new splicing techniques. Generalization, on the other hand, refers to the model's ability to perform well on such new data. In the context of image splicing detection, overfitting can reduce the model's ability to detect diverse splicing methods not encountered during training, while poor generalization can result in inaccurate detections on new splicing techniques. Addressing these issues requires careful model design, regularization techniques, and diverse training data to ensure robust and reliable performance in real-world applications.

Handling diverse splicing techniques presents significant challenges in deep learning techniques for image splicing detection. As previously seen, image splicing techniques can vary from basic cut-and-paste operations to advanced blending and morphing methods. Additionally, images used in splicing can vary widely in quality, resolution, and compression levels, affecting the visibility of splicing artifacts. Deep learning models need to be robust and adaptive to accurately detect splicing across these diverse techniques and quality levels. Ensuring that a model can generalize well and learn to identify subtle and complex splicing artifacts, regardless of the image quality or splicing method used, remains a complex task. This necessitates comprehensive training datasets that encompass a wide variety of splicing techniques and image qualities, along with advanced model architectures and training strategies to handle this variability effectively.

Future work in deep learning techniques for image splicing detection can focus on several fronts to address these challenges. In particular, tackling computational complexity and resource requirements can involve optimizing model architectures for efficiency, leveraging techniques like model pruning, quantization, and edge computing to create lighter and faster models. Advanced hardware solutions tailored for deep learning tasks could also be explored to enhance computational efficiency. For overfitting and generalization issues, the development of robust regularization techniques and adaptive learning algorithms could help create models that generalize well across diverse splicing techniques and quality levels. The generation of synthetic or augmented datasets that capture the variability and complexity of real-world splicing scenarios, aiding in better generalization and mitigating overfitting, can complement this. Addressing the challenges posed by diverse splicing techniques and quality levels requires comprehensive datasets that cover a wide range of splicing methods and image qualities. Future work could focus on creating standardized benchmarks and evaluation metrics, as well as exploring multi-modal and domain-specific approaches to enhance model robustness and adaptability. Collaborative efforts involving interdisciplinary research and the integration of domain knowledge from forensic experts can accelerate progress in these areas, leading to more efficient, robust, and reliable deep learning solutions for image splicing detection.

6. Conclusion

This work provides an overview on the most prominent techniques for image splicing detection. We focused on reported approaches using DL architectures in the task of image splicing detection with the most commonly used datasets in this field. This survey exhibits cutting-edge techniques. The approaches were examined with respect to the various DL architecture categories. At this stage of analysis, we would assert that this research paper contributes valuable insights and worthwhile. Indeed, it serves as an enlightening guideline for future work to further amplify the scope of this study. In this regard, the current research can be extended in several ways. This notably involves considering various DL-based approaches and their architectures changes. As a final note, it is noteworthy that even if DL-based methods have yielded promising results when compared to older methods utilizing handmade characteristics; utilizing new methods like deep learning’s attention mechanism, reinforcement learning algorithms and data augmentation might boost classification performance.

References

[1] Y. Rao and J. Ni, "A Deep Learning Approach To Detection of Splicing and Copy-Move Forgeries in Images," in *2016 IEEE International Workshop on Information Forensics and Security (WIFS)*, pp. 1-6, 2016.

[2] C.-S. Park, C. Kim, J. Lee, and G.-R. Kwon, "Rotation and Scale Invariant Upsampled Log-Polar Fourier Descriptor for Copy-Move Forgery Detection," *Multimedia Tools and Applications*, vol. 75, no. 23, pp. 16577–16595, Dec. 2016.

[3] G. K. Birajdar and V. H. Mankar, "Digital Image Forgery Detection Using Passive Techniques: A Survey," *Digital Investigation*, vol. 10, no. 3, pp. 226–245, 2013. doi: 10.1016/j.diin.2013.04.007.

[4] A. H. Saber, M. A. Khan, and B. G. Mejbel, "A Survey on Image Forgery Detection Using Different Forensic Approaches," *Advances in Science, Technology and Engineering Systems*, vol. 5, no. 3, pp. 361–370, 2020. doi: 10.25046/AJ050347.

[5] N. T. Pham and C.-S. Park, "Toward Deep-Learning-Based Methods in Image Forgery Detection: A Survey," *IEEE Access*, vol. 11, pp. 11224-11237, 2023.

[6] C. N. Bharti and P. Tandel, "A Survey of Image Forgery Detection Techniques," in *Proc. 2016 IEEE Int. Conf. Wireless Commun. Signal Process. Networking (WISPNet)*, pp. 877–881, 2016. doi: 10.1109/WISPNet.2016.7566257.

[7] M. D. Ansari, S. P. Ghrera, and V. Tyagi, "Pixel-Based Image Forgery Detection: A Review," *IETE Journal of Education*, vol. 55, no. 1, pp. 40–46, 2014. doi: 10.1080/09747338.2014.921415.

[8] K. D. Kadam, S. Ahirrao, K. Kotecha, and S. Sahu, "Detection and Localization of Multiple Image Splicing Using MobileNet V1," *IEEE Access*, vol. 9, pp. 162499–162519, 2021. doi: 10.1109/ACCESS.2021.3130342.

[9] S. Nath and R. Naskar, "Automated Image Splicing Detection Using Deep CNN-Learned Features and ANN-Based Classifier," *Signal, Image and Video Processing*, vol. 15, no. 7, pp. 1601–1608, 2021. doi: 10.1007/S11760-021-01895-5.

[10] J. Dong, W. Wang, and T. Tan, "CASIA Image Tampering Detection Evaluation Database," in *Proceedings of the 2013 IEEE China Summit and International Conference on Signal and Information Processing*, pp. 422–426, Beijing, China, July 2013.

[11] Y.-F. Hsu and S.-F. Chang, "Detecting Image Splicing Using Geometry Invariants and Camera Characteristics Consistency," in *Proceedings of the International Conference on Multimedia and Expo (ICME)*, Toronto, Canada, July 2006.

[12] K. D. Kadam, S. Ahirrao, and K. Kotecha, "Multiple Image Splicing Dataset (MISD): A Dataset for Multiple Splicing," *Data*, vol. 6, no. 10, p. 102, 2021.

[13] A. R. H. Khayeat, A. A. Al-Moadhen, and M. R. H. Khayyat, "Splicing Detection in Color Image Based on Deep Learning of Wavelet Decomposed Image," *AIP Conference Proceedings*, vol. 2290, no. December, 2020. doi: 10.1063/5.0027442.

[14] B. Ahmed, T. A. Gulliver, and S. Alzahir, "Image Splicing Detection Using Mask-RCNN," *Springer*, 2020.

[15] J. Wang, Q. Ni, G. Liu, X. Luo, and S. K. Jha, "Image Splicing Detection Based on Convolutional Neural Network with Weight Combination Strategy," *Journal of Information Security and Applications*, vol. 54, p. 102523, 2020. doi: 10.1016/J.JISA.2020.102523.

[16] X. Bi, Y. Wei, B. Xiao, and W. Li, "RRU-Net: The Ringed Residual U-Net for Image Splicing Forgery Detection," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, vol. 2019-June, pp. 30–39, 2019. doi: 10.1109/CVPRW.2019.00010.

[17] E. I. Abd El-Latif, A. Taha, and H. H. Zayed, "A Passive Approach for Detecting Image Splicing Based on Deep Learning and Wavelet Transform," *Arabian Journal for Science and Engineering*, vol. 45, no. 4, pp. 3379–3386, 2020. doi: 10.1007/S13369-020-04401-0.

[18] K. B. Meena and V. Tyagi, "A Deep Learning Based Method for Image Splicing Detection," *Journal of Physics: Conference Series*, vol. 1714, no. 1, 2021. doi: 10.1088/1742-6596/1714/1/012038.

[19] B. Xiao, Y. Wei, X. Bi, W. Li, and J. Ma, "Image Splicing Forgery Detection Combining Coarse to Refined Convolutional Neural Network and Adaptive Clustering," *Information Sciences*, vol. 511, pp. 172–191, 2020. doi: 10.1016/J.INS.2019.09.038.

[20] H. Ding, L. Chen, Q. Tao, Z. Fu, L. Dong, and X. Cui, "DCU-Net: A Dual-Channel U-Shaped Network for Image Splicing Forgery Detection," *Neural Computing and Applications*, vol. 4, 2021. doi: 10.1007/S00521-021-06329-4.

[21] Z. Li, Q. You, and J. Sun, "A Novel Deep Learning Architecture with Multi-Scale Guided Learning for Image Splicing Localization," *Electronics*, vol. 11, no. 10, p. 1607, 2022.

[22] T. Muniappan, N. B. Abd Warif, A. Ismail, and N. A. Mat Abir, "An Evaluation of Convolutional Neural Network (CNN) Model for Copy-Move and Splicing Forgery Detection," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 11, no. 2, pp. 730-740, 2023.

[23] X. Shi, P. Li, H. Wu, Q. Chen, and H. Zhu, "A Lightweight Image Splicing Tampering Localization Method Based on MobileNetV2 and SRM," *IET Image Processing*, 2023.

[24] H. L. Nguyen and K. T. Huynh, "A Deep Learning Model for Splicing Image Detection," *Rev Journal on Electronics and Communications*, vol. 13, no. 3-4, 2024.