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Review Article

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Deep Learning Techniques for Image Plagiarism Detection: A Systematic Review

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Abstract: Image plagiarism is unauthorized copying, editing or reusing of digital images without due permission or citing. As social media, online publishing, and Artificial Intelligence (AI)-based tools to edit and remove plagiarism in images have developed at an alarming pace, it has become more difficult to detect image plagiarism. It provokes some serious questions, associated with the copyright violations, intellectual property and the misuse of visual materials ethically. The objective of this review is to explore the increasing challenge of image plagiarism in the time of artificial intelligence and assess deep learning techniques implemented for unauthorized image reuse detection. A systematic, structured Preferred Reporting Items for Systematic reviews and Meta-Analyses aligned methodology was used to collect, screen and analyze the studies published between 2015 and 2025 including traditional models, machine learning models and deep learning models. The feature-based techniques, Convolutional Neural Networks (CNN) architectures, Siamese Networks, Generative Adversarial Networks based detectors, and hybrid multimodal systems are discussed in the review. Key findings highlight the results show that the performance of deep CNN, especially Visual Geometry Group, Residual Network, and Vision Transformers, is largely accurate (94-99%) and also shows good robustness to attack such as cropping, scaling, and color manipulation. However, the analysis shows some significant gaps such as the lack of standardized datasets and the lack of explainability in AI-based decisions. The article concludes that deep CNNs are the most reliable models to be used in image plagiarism detection. Unlike prior surveys limited to architectural overviews, this work uniquely integrates empirical dataset benchmarking across 50+ sources and proposes interpretable multimodal frameworks as the path forward for reliable plagiarism detection. The novelty of this review is to present a complete taxonomy, research gaps, and the necessity of having interpretable and multimodal standardized detection frameworks.

1. Introduction

The accelerated development of the internet and the digitalization of the academic and creative labor turned the visual media to be the indispensable part of the communication, the dissemination of the educational and the research activity. Photographs, drawings, charts and other digital art are some of the images that carry complex contextual information that supplements or even substitutes textual explanation. Nevertheless, the common availability of both digital materials has raised the chances of unethical behaviors like plagiarism where the existing work is reproduced without giving the necessary credits. Plagiarism is a situation where one takes the ideas, research, or any form of creativity of a person without acknowledging the original author [1]. To be more precise, plagiarism can be described as duplication of the thoughts or the work of another person and presenting it as an individual work [2].

There are usually two types of plagiarism, namely text-based plagiarism and image-based plagiarism [3]. Text-based plagiarism is a type of plagiarism in which we re-use the written material of online or published materials without citing them. Image plagiarism on the other hand is the illegal use or alteration of visual objects like figures, charts, diagrams or photographs without giving credit to the original producer [4]. Fishman [5] defines plagiarism as any use of words, idea or work product that can be linked to another identifiable source without crediting the individual. Fabrication, falsification and plagiarism have also been included in the concept to formulate three significant aspects of academic misconduct [6]. In a study by Risquez *et al.* [7], plagiarism is referred to as stealing words or ideas of another person without the due referral, and as such, it deprives the original author of his due credit. Past research also divides plagiarism into various categories such as copy paste plagiarism, paraphrasing, making up of fake references, translation plagiarism, and idea plagiarism [8].

Detection of the plagiarism in the image is more technical compared to the detection of the plagiarism in a text. Images may also undergo numerous transformations like cropping, rotating, scaling, filtering, color modifications and blending of sections of the image. Such changes render the old methods of detection to fail in identifying plagiarized or copied visual material [2, 4]. Image plagiarism can thus be in a variety of forms, such as direct duplication (using an image as it was published), partial duplication (copying a particular region or element of an image), transformed plagiarism (bending geometric or photometric properties), cross-modal plagiarism (converting a visual image into another modality, e.g. text), and compositional plagiarism (assembling elements of many images into a composite image). The process of detecting such manipulations has been generally achieved through feature extraction where discriminative visual features are extracted out of images [9].

Despite the existence of numerous tools that could be used to identify plagiarism in textual materials, there are few reliable tools that could be used to identify plagiarism in images. The most popular plagiarism detection tools that include iThenticate, Grammarly, and Duplichecker are mostly based on the textual comparison of online documents and databases [10, 11]. They have systems that match billions of web pages or academic sources to find textual matches, and in general are not able to match embedded pictures or other visual sources.

The rise in popularity of social media, open-access publishing platforms, and generative artificial intelligence tools has also made the issue of visual plagiarism the more difficult one. Recent generative models like Generative Adversarial Networks (GANs) and diffusion-based models are capable of producing highly realistic synthetic images, and it is becoming harder and harder to distinguish between original and manipulated as well as plagiarized visual images. This results in an increased demand to have automated and intelligent detection mechanisms that can distinguish both literal and manipulated image plagiarism [5, 8].

Machine learning and Artificial Intelligence (AI) can offer solutions to this problem. AI defines systems that have the ability to learn through data and make available learned knowledge to undertake a particular task [12]. In the realm of AI, machine learning algorithms help computers to learn automatically the patterns of training data and make predictions or decisions. Deep Learning (DL), which is a branch of machine learning, has demonstrated great achievement in processing complex data including images. DL models are based on multi-layer neural networks that automatically learn significant features of raw data without necessarily relying on manual feature engineering as a result. Convolutional Neural Networks (CNNs) are one of such models which can be applied especially effectively to image analysis task since they are also based on the concept of convolutional layers, pooling layers, and feature maps used to learn the hierarchical visual representations [13].

More recent experiments indicate that deep learning structures can be utilized to effectively detect manipulated pictures and visual semblance. Niresi and Chi [14] introduced a variation of U-Net to image denoising and droplet reconstruction that was robust and more efficient than a range of other algorithms. Fu *et al.* [15] presented a hybrid-feature deep learning model, which is used together with density-based clustering, to identify and localize copy-move forgeries. Mehrjardi *et al.* [16] designed a hybrid model that combines deep features that are acquired using CNNs and handmade features to enhance the representation of features and the accuracy of feature detection.

Irrespective of these developments, literature on image plagiarism detection is not a unified body of knowledge spread across various areas of research such as multimedia forensics, image similarity analysis, copyright protection, and information retrieval. Most of the available surveys consider image plagiarism to be a minor branch of discussions regarding image manipulation or similarity detection. This leads to the fact that little is done in terms of a detailed analysis of a specific topic such as visual content-based plagiarism detection. Moreover, the effectiveness of various detection methods can be hardly compared due to inconsistencies in datasets, assessment measures, and experimental procedures. Other ethical issues, including bias in the datasets, explainability, and the possibility of using automated systems of plagiarism detection incorrectly are also not studied thoroughly.

To overcome these drawbacks, this review would examine recent development of deep learning-based image plagiarism detection systematically. Specifically, the review aims at answering the following research questions:

- What are the ways in which deep learning methods have enhanced image plagiarism detection as compared to traditional feature-based methods?
- Which image plagiarism detection datasets and deep learning models have the highest consistency in their performance?
- What are the current gaps in AI-based image plagiarism detectors development and actual implementation?

The main contribution of this review is that it deals specifically with visual content-based plagiarism detection, as opposed to general image processing/similarity analysis. The paper systematizes the available literature with the help of a Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA)-conformable methodology and suggests a systematic taxonomy of methods using which different methods are classified according to the learning paradigm, model architecture, similarity model, and the field of application. Moreover, this review includes the critical comparative analysis of the published empirical studies on the topic published in 2015-2025. Table 1 depicts the difference between image plagiarism, similarity matching and image forensics.

Table 1: Difference between image plagiarism v/s similarity matching v/s image forensics.

Ref.	Aspect	Image Plagiarism	Similarity Matching	Image Forensics
[2, 4]	Definition	Unauthorized use or reproduction of another's image without proper credit or permission.	Computational comparison between two or more images to measure similarity or duplication.	Scientific analysis of an image's metadata, structure, or content to verify authenticity or detect manipulation.
[9, 10]	Purpose	To identify unethical reuse of visual content.	To detect identical or near-identical images for retrieval, deduplication, or plagiarism checks.	To determine whether an image has been tampered with or altered.
[4, 6, 7, 15-19]	Techniques Used	Visual inspection, reverse image search, watermark checking.	Feature extraction (e.g., SIFT, SURF), perceptual hashing, deep learning similarity metrics.	Metadata analysis, error level analysis (ELA), pixel-level inconsistency checks, machine learning-based forgery detection.
[2, 4, 8, 9, 13, 15]	Output	Confirms if an image is reused or stolen.	Provides a similarity score or match percentage.	Provides evidence of editing, compositing, or forgery.
[2, 4, 8, 9, 13-16]	Tools/Software	TinEye, Google Reverse Image Search, PlagiarismCheck.org	ImageHash, OpenCV, Google Vision Application Programming Interface.	Forensically, Amped Authenticate, FotoForensics
[2, 4, 6-9, 13- 15]	Application Area	Academic publishing, digital art, journalism.	Data mining, content moderation, duplicate detection.	Digital forensics, cybersecurity, legal evidence verification.
[12- 16]	Ethical/Legal Aspect	Involves copyright infringement or ethical misconduct.	Neutral used for detection or validation.	Forensic and investigative often used as digital evidence.

Early approaches to plagiarism detection relied heavily on pixel-wise comparison and hashing algorithms such as perceptual hash (pHash) and difference hash (dHash). These methods offered computational efficiency but lacked robustness against geometric or photometric transformations. Feature-based approaches improved resilience by representing images through descriptors like Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF). Nevertheless, these techniques depend on handcrafted feature engineering and often fail when images undergo significant semantic or contextual changes [17-19].

Statistical and dictionary-based approaches, including Bag-of-Visual-Words, attempted to generalize feature representations but were limited by fixed vocabulary size and poor scalability to high-dimensional datasets. Consequently, the detection accuracy and recall rates remained insufficient for large-scale academic or commercial deployment [20]. The design for the image to text conversion with the help of Application Programming Interface and detect the similarity with the help of statistical model [21].

The rest of this paper is structured in the following way. Section 2 reports the PRISMA based research methodology in terms of data sources, screening criteria, and analytical procedures. Section 3 presents the findings, such as the suggested taxonomy, comparisons of datasets, and evaluation of the various detection methods. The findings, research gaps, research ethics and practical implications will be discussed in detail in section 4 of the work, and the conclusions and future research directions will be provided.

2. Materials and Methods

This section presents the systematic procedure followed in order to identify, assess and synthesize contributions related to re-search the topic of image plagiarism detection. The review is based on a structured methodology, based on the PRISMA framework. The objective was to obtain a comprehensive, unbiased and reproducible survey of state-of-the-art techniques, in particular focusing on DL approaches.

The review was intended as a qualitative and comparative synthesis using bibliometric analysis, methodological classification, and critical interpretation such as research gap analysis. The approach has both a systematic and a narrative review component, the systematic review component identifies and categorizes relevant studies based on explicit inclusion and exclusion criteria. The narrative component is interpretation of the identified works by means of conceptual mapping and methodological taxonomy. A flow diagram summarizing the process of PRISMA based workflow for literature review is illustrated in figure 1.

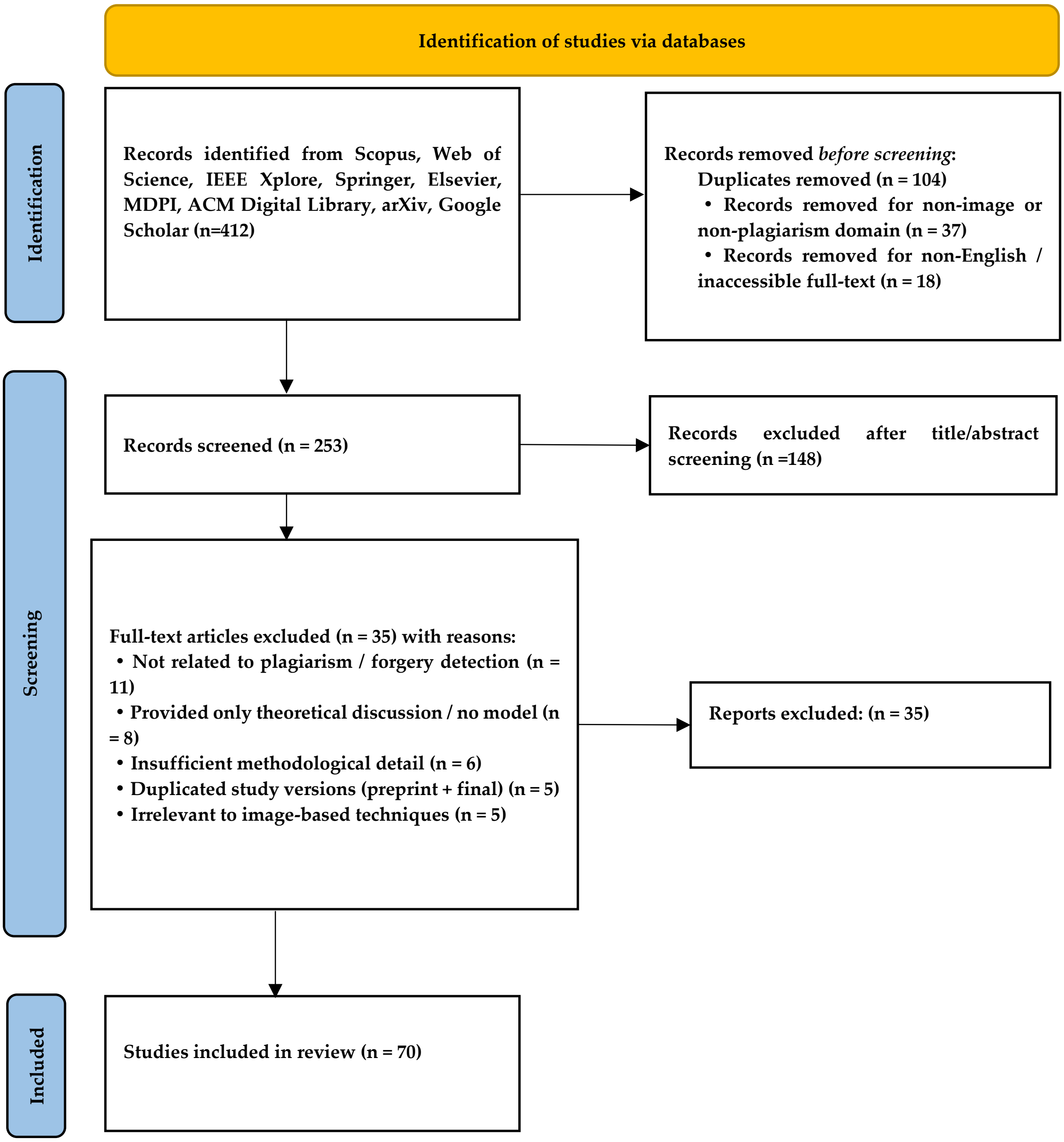

Figure 1: PRISMA-based study selection flow diagram for image plagiarism detection review.

2.1. Data Sources and Search Strategy

To capture a comprehensive set of studies, a multi-database search was conducted between 2015 and 2025. The following repositories were used: IEEE Xplore for deep learning and image forensics research, Elsevier ScienceDirect for applied AI and multimedia forensics., SpringerLink for computer vision and plagiarism detection studies, ACM Digital Library for algorithmic and software tools and Google Scholar for cross-verification and citation tracking.

The primary search terms combined Boolean operators and keywords like "image plagiarism" OR "visual plagiarism" OR "figure reuse" OR "image duplication" AND "deep learning" OR "CNN" OR "GAN" OR "AI-based detection". Additional manual searches were performed in conference proceedings such as Computer Vision and Pattern Recognition (CVPR), International Conference on Computer Vision, International Joint Conference on Artificial Intelligence, and Association for the Advancement of Artificial Intelligence, as well as domain-specific journals like Journal of Visual Communication and Image Representation and Pattern Recognition Letters.

2.2. Inclusion and Exclusion Criteria

A total of 412 papers were initially retrieved from all sources. After multiple screening stages, 70 studies met the inclusion criteria. The eligibility of studies was determined using the following guidelines as mentioned in the table 2.

Table 2: Inclusion and exclusion criteria used for selecting studies in the systematic review.

No.	Criteria Type	Criteria Description
1	Inclusion	Studies explicitly addressing image plagiarism detection or visual content similarity detection. Papers employing machine learning or deep learning models like CNNs, GANs, Autoencoders, Transformers. Research with quantitative evaluation using benchmark image datasets. Peer-reviewed journal or conference publications between 2015 and 2025.
2	Exclusion	Studies focused solely on text plagiarism or generic image enhancement. Articles without sufficient methodological detail or reproducible results. Duplicate records, workshop abstracts, and non-peer-reviewed content.

2.3. Data Extraction, Analysis, and Quality Assessment

The chosen studies were analyzed with a set structured data extraction form which includes author and year, type of model including CNN, Residual Network (ResNet), Visual Geometry Group (VGG), Siamese Networks, image transformation tested, datasets used, performance metrics, tools/frameworks, and major findings. All the extracted information was structured in a taxonomy matrix, from traditional approaches, machine learning, deep learning, and hybrid approaches. The synthesis was based on a three-fold analytical framework of descriptive, comparative and critical analysis, including visualizations, produced with the support of VOSviewer and Tableau. Study quality was assessed with the help of the modified Critical Appraisal Skills Programme checklist for AI research [22] and only papers that achieved a score above 70% were included for the final comparative synthesis.

3. Results

3.1. Taxonomy of Image Plagiarism Detection Techniques

The field of image plagiarism detection has evolved significantly from early handcrafted feature techniques to advanced deep learning architectures. To present a systematic overview, this section introduces a taxonomy that categorizes existing approaches into four major groups traditional (Feature-Engineering-Based) Methods, Machine Learning (ML) Methods, DL Methods, and Hybrid and Multimodal Approaches. Each of the categories is analyzed in terms of underlying principles, representative studies, strengths, limitations and benchmarks for evaluation.

3.1.1. Traditional Methods

a. Pixel-Based and Statistical Approaches

Wu *et al.* [23] worked on the detection of image plagiarism mainly relied on pixel-based matching and the statistical correlation. These techniques compared the gray-scale or color pixel values of two images directly or after some minor transformations. Metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Metric (SSIM) were witnessed for the similarity. While good at detecting exact copies, these methods cannot detect these copies under geometric transformations such as scaling, rotation, and cropping. Furthermore, the variations in lighting or compression often result in high false negatives.

b. Hashing Based Methods

To increase the efficiency, Parmar and Jain [17] used hashing techniques for converting the images into compact and binary signatures. Common variants include: Average Hash (aHash): Computes mean pixel intensity and assigns bits accordingly, dHash: Captures gradient-based intensity differences and pHash: Uses Discrete Cosine Transform coefficients to encode global patterns. Although these methods are computationally light, they are still susceptible to non-linear modifications of the image and content-aware image manipulations.

c. Feature Descriptor Based Techniques

Tang *et al.* [18], and Oyallon and Rabin [19] highlighted traditional feature descriptor algorithms including SIFT, SURF and Histogram of Oriented Gradients (HOG) and they extract local invariant features and match them across images. Elaskily *et al.* [24] developed a deep CNN architecture capable of automatically learning discriminative features for robust forgery detection. Mehrjardi *et al.* [25] proposes a deep learning-based framework specifically designed to detect and localize copy move forgeries by leveraging automatic feature learning and improved patch similarity analysis. These methods introduced partial robustness to rotation and scaling. However, they depend heavily on manual feature engineering and parameter tuning as presented by Vieira *et al.* [26]. Table 3 summarizes the major traditional approaches.

Table 3. Overview of traditional image plagiarism detection methods.

Ref.	Approach	Key Technique	Dataset / Application	Strengths	Limitations
[23]	Pixel-wise Matching	MSE, PSNR, SSIM	Synthetic datasets	Simple implementation	Fails under transformation
[17]	Hashing	pHash, aHash, dHash	Online image reuse	Fast computation	Low robustness to alteration
[18, 19]	Feature Descriptors	SIFT, SURF, HOG	Object-level matching	Transformation invariant	Needs manual tuning

3.1.2. Machine Learning Methods

Machine learning approaches introduced data-driven classification and similarity estimation. These models used handcrafted features as input and applied algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), or Random Forests (RF) for plagiarism classification. As presented in detail review by Frank *et al.* [27], Kavitha *et al.* [28], and Sah and Direkoglu [29], various ML are implemented in scientific computing for data and text mining These systems further incorporate neural network models to enhance performance and improve overall classification accuracy.

Feature based classification in which feature descriptors like color histograms, edges, Gray Level Co-occurrence Matrix texture features are extracted and fed into ML classifiers. However, these models are constrained by the quality of input features if features do not capture semantic content, the model performance deteriorates. Features are extracted from passage phase and word phase but unable to detect the plagiarism on sentential redundancy, word missing, and redundancy [30]. Threshold Feature Selection features are extracted with the help of DenseNet and Long Short-Term Memory (LSTM) classifiers and the features are ranked by the information gain [31].

Some ML models such as KNN, SVM (with distance-based kernels), K-Means clustering incorporate similarity metrics such as Euclidean distance, Cosine similarity, and Mahalanobis distance to assess feature correspondence between image pairs. These methods enhance discrimination but remain susceptible to dataset imbalance and feature noise.

3.1.3. Deep Learning Methods

Deep learning has transformed image plagiarism detection by enabling automatic feature extraction and hierarchical representation learning. CNNs, autoencoders, and transformer-based models dominate this domain. AI systems use deep learning approaches to boost their efficiency without increasing hardware expenses or lowering accuracy by a certain proportion [32]. A well-defined image matching problem is the image retrieval involves ranking the database images in decreasing order of similarity and retrieving comparable images from the database based on a specified query image similarity between the input image and images [33].

a. Convolutional Neural Networks

CNN-based models extract spatial features through convolutional and pooling layers, allowing the detection of modified or semantically similar images. Studies have demonstrated high accuracy which is up to 99% using CNNs such as VGG16, ResNet, and Inception. The author introduced CNNs for large scale image recognition and foundation for CNN based plagiarism detection [34]. VGG networks are widely used for similarity detection in plagiarized images. Bevinamarad *et al.* [35] introduced an advanced hybrid framework that integrates Stationary Wavelet Transform (SWT), a hybrid dilated adaptive VGG16 deep learning model, and an optimization strategy to improve the accuracy of forgery detection and localization.

b. Siamese Networks and Feature Matching

Siamese CNNs learn a similarity function that maps images into a shared embedding space. The distance between embeddings indicates plagiarism likelihood. This architecture enables pairwise comparison and supports few shot learning scenarios [36].

c. Generative Adversarial Networks

GANs are used to detect synthetic or manipulated images by learning the distribution of authentic data. Discriminator networks identify whether an input image is genuine or plagiarized. GAN-based detectors outperform classical CNNs in identifying forged and composite content [5, 8].

d. Transformer-Based Vision Models

Recent advances include Vision Transformers (ViTs), which model long-range dependencies across image patches. Their self-attention mechanisms improve detection of compositional and cross-modal plagiarism. However, transformer models require substantial training data and high computational capacity [33].

Table 4 indicates different deep learning methods in detecting plagiarism in images and other manipulation actions. Parmar and Jain [17] presented VIBRANT-WALK, a new image plagiarism detection algorithm in scholarly papers was presented based on absolute image similarity instead of similarity. It is a contour detector built by creating a Vibrancy Matrix used to compare pixel-based comparisons with a library of known manuscripts. It had a total accuracy of 94.8% in 485 test cases and said no false positives. Thyaghararajan and Kalaiarasi [37] provided a closer overview of computer vision methodology of near-duplicate image detection. The paper has reviewed the state-of-the-art feature extraction and similarity measurement techniques, posed significant technical challenges, and outlined the future research directions to enhance the large-scale duplicate detection performance.

Ch *et al.* [38] combined an error level analysis (ELA) with the CNN models, such as the VGG-16 model, was proposed as a deep learning framework to identify counterfeited images. The ELA-CNN model, which had 5,000 experiments and obtained 99.87% accuracy and 99% hidden forgery rate, was better than the standalone VGG-16 model. Kaur *et al.* [39] created a copy-move forgery detector model based on deep learning that is composed of contrast limited adaptive histogram equalization preprocessing and a CNN forgery classifier. Assessed on benchmark datasets the model was demonstrated to be very robust to scaling, rotation, image compression, and noise as well as to compete in metrics of performance.

Biselli *et al.* [40] presented ChartChecker, a browser extension that can identify deceiving features in the data visualizations like non-linear axis scales. Applying automated data mining chart extraction and participatory design methodology, user perceptions (n=15) indicated that the system was highly rated in terms of usability and transparency to fight visual misinformation. Gharavi *et al.* [41] had been suggested a multilingual text plagiarism detector system with text embedding vectors and adaptive tuning of the threshold. The method demonstrated robust results on both English, Persian as well as Arabic datasets by using online statistical filtering without training datasets, which is comparable or better than other conventional training-based methods.

Pang *et al.* [42] uses recorrupted-to-recorrupted (R2R) data augmentation method to boost unsupervised deep image denoising. The method statistically matches supervised training on noisy pairs of images and showed comparable performance to supervised denoisers and was better than existing unsupervised models. Meng and Zhang [43] proposed that a symmetric dilated convolutional residual system would be used to denoise grey scale images in high noisy conditions. Combining two Rectified Linear Unit functions, the model enhanced objective and subjective image quality, the effect of which is the preservation of edges and textures and higher denoising ability.

Yan *et al.* [44] applied denoising deep learning network to denoise Digital Holographic Speckle Pattern Interferometry interferograms of wrapped phase maps to eliminate speckle noise. The approach was tested on both simulated and experimental datasets and it proved to be effective in increasing the accuracy of defect detection in structural artwork diagnostics. Liu *et al.* [45] investigated joint optimization of image denoising and high-level vision problems using a cascaded deep learning network with joint loss training. Findings indicated that denoising facilitated high-level task performance and semantic guidance facilitated visual quality indicating a mutual dependency between the two processes. Devulapalli *et al.* [46] suggested a hybrid business model that utilizes high-level features provided by a pre-trained GoogLeNet and low-level Gabor texture features. Its built-in ability to represent the features enhanced the robustness of retrieval and reached a 91% precision which is better than various state of art methods. In general, the researches indicate that deep learning models are highly accurate regardless of the type of data and plagiarism-related usage.

Table 4. Deep learning approaches for image plagiarism detection.

Ref.	Architecture	Dataset	Accuracy (%)	Notes
[17]	Attention-based	VIBRANT-WALK	94.8	Detects compositional plagiarism
[37]	DeepFake Detection (EfficientNet)	GAN-generated sets (PG-GAN)	93.6	AI-generated Image Copy
[38]	ELA-CNN v/s VGG-16	Custom dataset, 5000 experiments (counterfeit vs original photos)	99.87	Comparison shows that combining preprocessing (ELA) + CNN significantly improves detection on their dataset.
[39]	Hybrid U-Net (VGG16 feature extraction + modified U-Net for segmentation + classifier head)	CASIA2 (10,000 images with various manipulations)	93	Provides localization (segmentation) + classification for forgery detection; residual connections help refine mask predictions.
[40]	Optical character recognition (OCR) + Plot Parsing	PubMed Central Figures	86.2	Graph/Chart Reuse
[41]	CNN with BiGRU	All programing languages	88	Source Code Plagiarism Detection
[42]	R2R Noise Reduction Method	SIDD Bench mark	70.9	Image Restoration
[43]	Convnet convolutional residual networks	BSD – 68	67.97	Image Restoration
[44]	Denoising Convolutional Neural Network (DNCNN)	Simulated fringe pattern dataset	86.54	Image Restoration
[45]	Fuzzy CNN (F-CNN)	CASIA-IRISV4, IIIT-D Contact ATVS-FIR DB	98	Image enhancement
[46]	Googlenet model	UC Merced from USGS National Map metropolitan territory	90	Feature extraction

3.1.4. Hybrid and Multimodal Methods

Hybrid approaches combine multiple deep learning paradigms or integrate image–text analysis techniques to detect cross-modal plagiarism. Hybrid architectures are more effective by multilevel representation fusion, so they can be used for academic manuscript verification and scientific figures analysis. However, these models are computationally intensive and they need various multimodal datasets [22].

The current taxonomy demonstrates the development of image plagiarism detection from handcrafted pixel-based methods to AI-driven methods that are able to perform semantic understanding and multi-modal reasoning. Traditional techniques provide interpretability and efficiency but lack robustness, ML models provide generalization, DL methods provide accuracy and transformation resilience and hybrid systems promise the understanding of plagiarism comprehensively, across modalities [24].

Table 5 is an overview of hybrid and multimodal approaches to detect image plagiarism that combine several data sources with various modeling approaches. Amirzhanov *et al.* [47] offered a systematic review of all the types of plagiarism (verbatim, paraphrasing, translation, idea-based) and detection algorithms. In comparison with the traditional string-matching approach to plagiarism detection, it is worth noting such difficulties as cross-language and AI-generated plagiarism. Bharati *et al.* [48] suggested deep learning method of image provenance analysis to estimate the sequence of edits applied to related images. The method compared with the available handcrafted and deep learning descriptors performs better with transformation-aware descriptors and rank-based quadruplet loss.

Moreira *et al.* [49] gave a detailed review of image provenance analysis, paying attention to modeling pairwise relationships between manipulated images. Surveyed the state-of-the-art methods of reconstructing a history of edits in order to aid in forensic investigation of authenticity. Lin *et al.* [50] presented uncertainty-guided refinement network (URN) to detect image splicing in scientific papers. The model had better splicing detection results due to the newly built SciSp data (1,290 images). Ruikar and Patil [51] suggested a copy-move forgery detection approach of image segmentation and SIFT feature extraction. The method finds repeated areas by comparing the scale-invariant key-points in the image. Elaskily *et al.* [52] given an overall review of the traditional and deep learning-based copy-move forgery detection (CMFD) algorithms. In comparison to feature extraction methods, evaluation measures and benchmark datasets, it analyzes the strong and weak points of different methods. On the whole, these techniques indicate that more effective robustness is attained by integrating visual, textual, temporal and metadata cues, but at the cost of greater complexity of computation.

Table 5: Hybrid and multimodal image plagiarism detection techniques.

Ref.	Model	Components	Dataset	Key Strength	Limitation
[47]	CNN + LSTM	Visual-temporal fusion	PAN14	Robust to sequential patterns	Slow convergence
[48]	Transformation-Aware Embedding Network	Combines CNN-based visual feature extraction with transformation modeling (geometric, photometric) for forgery and provenance detection	Synthetic transformation datasets; public image sets for provenance	Learns embeddings invariant to common transformations; strong for image provenance tracing	Focused only on visual domain; lacks metadata/text integration
[49]	Provenance Graph Framework	Visual patch matching + graph-based relational modeling of image derivations	Public provenance datasets (NIST, Reddit Photoshop Battles)	Captures relationships among multiple derivative images (edit lineage detection)	Computationally expensive; depends on high-quality pairwise matching
[50]	Uncertainty-Guided Refinement Network (URN)	CNN for pixel-level forgery detection + uncertainty estimation modules (UGGC, UEMA)	BioSp, BioFors, RSIID (scientific image splicing datasets)	Enhances localization accuracy via uncertainty-guided refinement; robust to biomedical image artifacts	Moderate F1 (~47%) on pixel-level detection; ignores non-visual modalities
[51]	OCR NLP CNN Hybrid Pipeline	Combines OCR for text extraction + NLP semantic comparison + CNN for visual similarity	Image-text datasets (figures, screenshots of text)	Effective for detecting text-in-image plagiarism (e.g., screenshots, charts)	OCR errors reduce accuracy; dependent on text legibility
[52]	Multimodal Image Forgery Detection System	Integrates CNN-based visual classifier + metadata analysis + text caption alignment	Collected online image-caption pairs	Cross-verifies plagiarism through both visual and textual cues; multimodal reasoning improves detection	Complex to train; metadata often missing or inconsistent

3.2. Datasets & Tools

3.2.1. Benchmark Datasets

One of the most important factors that affect the performance of an algorithm is the quality and diversity of the data. While there are abundant resources available for text plagiarism research such as Plagiarism Analysis, Authorship Identification, and Near-Duplicate Detection (PAN) and Turnitin, image plagiarism detection research does not have standardized benchmarks for the entire spectrum of domains.

VIBRANT - WALK Dataset is a modern, large-scale dataset that integrates synthetic manipulations created using GANs and diffusion models [17]. Containing 120,000 images, it enables the evaluation of deep architectures such as Vision Transformers and hybrid CNN-BERT systems. PAN Image Plagiarism Datasets: The Plagiarism Analysis, Authorship Identification, and PAN shared tasks provided early benchmarks for plagiarism research. PAN13 and PAN14 datasets contain thousands of manipulated images and corresponding originals with metadata describing applied transformations [53]. These datasets support baseline ML and shallow CNN evaluation but are relatively small by modern standards.

Microsoft Common Objects in Context (MS COCO) is a large-scale dataset that provides more than 330,000 images of the real world annotated with object labels, bounding boxes, and segmentation masks for 80 object categories [54]. Even though it is not intended for plagiarism detection, it is often reused for the analysis of semantic image similarity and partial image reuse. The dataset is rich in contextual annotations that can be used for deep learning models of region-based and attention-driven similarity learning. It does not have plagiarism labels and needs transformation strategies.

CIFAR-10/100 are low data image datasets that contain 32×32 color images. CIFAR-10 has 60,000 images in 10 classes, while CIFAR-100 has 100 more refined classes [55]. These datasets are commonly employed in plagiarism and similarity research to test robustness in low-resolution and class-level variations, but they do not have plagiarism labels.

MICC-F220 data has been popular amongst the image forensics community to test and compare copy-move forgery detection and localization algorithms especially key-point-based ones such as SIFT features [56]. The presence of the original and tampered images (in case of ground truth in certain subsets) enables the researcher to test the accuracy of detection and, in the case of ground truth, the localization performance on a pixel basis.

CASIA v2.0 is a popular dataset that is utilized in the detection of tampering of images [57]. It consists of 12,614 images, 7,491 of them being genuine and 5,123 of them having been tampered with, mostly on manipulations of image splicing. The dataset contains resolution, format Boost Juice (JPEG, BMP, TIFF), and post-process manipulations, including resizing, rotation, blurring, recompression, and so on. CASIA v2.0 is highly utilized in testing machine learning and deep learning-based image forgery detectors because of its size and variety.

Columbia Image Splicing Detection Evaluation Dataset is a forensic benchmark that is widely used [58]. It has 1,845 blocks of images (128×128 pixels) approximately an equal number authentic (933) and spliced (912) samples taken off real photos. All blocks are divided by their texture and type of boundary, which allows different evaluation situations. The data set facilitated the comparative stability of the detection of image splicing methods in passive forensic studies.

Image Manipulation Dataset 2020 (IMD2020) is a large-scale benchmark that is aimed at the image tampering detection and localization [59]. It has a massive number of manipulated images with pixel-level ground truth masks. The dataset consists of a variety of editing operations, as well as the effects of the post-processing in a realistic manner, which allows evaluating both classical and deep learning-based forensic models. IMD2020 overcomes the drawbacks of previous smaller datasets, which were focused on comparing only a few aspects of performance on various methods of detection.

A comparative summary of the most commonly used benchmark datasets in image plagiarism research is presented in table 6, highlighting differences in dataset manipulation types, domain coverage, and public availability.

Table 6: Comparative summary of key datasets in image plagiarism research.

Ref.	Dataset	Manipulation Types	Domain Coverage	Public Availability
[17]	VIBRANT - WALK	69 Research Papers	Natural Scenes	Public availability depends on research access
[53]	PAN13 and PAN14	Copy–move	General web images including objects, scenes, and graphics	Public
[54]	MS COCO	No inherent manipulation	Real-world scenes	Public
[55]	CIFAR-100	No built-in manipulation	Animals, Vehicles, And Everyday Objects	Public
[56]	MICC-F220	Copy-move	Natural scenes	Public
[57]	CASIA v2.0	Splicing, copy-move	General images	Public
[58]	Columbia Dataset	Splicing	Indoor/outdoor scenes	Public
[59]	IMD2020	Copy-move	Diverse objects	Public

3.2.2. Tools/Frameworks

The development of image plagiarism detection systems has been closely tied to the availability of benchmark datasets and software frameworks that facilitate reproducible experimentation [17-19]. This section presents an overview of existing tools and highlighting their strengths, limitations, and role in shaping the field.

For the past decade, a number of tools commercial and academic have been developed to automate the detection of image similarity. These tools differ in the algorithmic sophistication, scalability, and domain of application. Table 7 shows the key tools and frameworks that have been created in image plagiarism detection in fields of forensic, academic, and large-scale retrieval.

Acuna *et al.* [60] created a large-scale figure reuse detector based on automated systems that are resistant to rotation, scaling, cropping, and variations of contrast. The 760,000 articles were examined with an estimated 0.6% being fraud and 9% of biological reuses being suspicious. The article by Saliba and Rotzinger [61] surveyed the issues of AI-based plagiarism detection in text and images and revealed the shortcomings of existing detection software. Stated that the image manipulation detection should be included into the standard plagiarism systems to assure the preservation of academic integrity. Li *et al.* [62] suggested the VirtualActionNet which was a 3D human action recognition in two streams (appearance and motion) with joint loss training based on point cloud network. Posted high results on three publicly available datasets.

Rodriguez-Ortega *et al.* [63] proposed two deep learning methods (custom CNN and transfer learning with VGG-16) in copy-move detection. Transfer learning was able to attain accuracy which was about 10 percent high but took almost twice the inference time. El-Rashidy *et al.* [64] created a deep learning-based plagiarism detection system on newly constructed similarity-feature database. Zhang [65] conducted a literature review of deep supervised hashing-based image retrieval and Shadow Recurrent Hashing. The CNN based stimulated raman histology model performed well on the CIFAR-10 data. Jakhar and Borah [66] suggested a hybrid near-duplicate detection system that can combine perceptual hashing, Siamese networks, and Vision Transformers. Obtained benchmark datasets of achieved area under the receiver operating characteristic curve of 0.99 and 0.92, which is better than traditional methods.

Rao *et al.* [67] presented the model of CNN-based forgery detection using multi-semantic CRF attention on localization of the boundary artifacts. It exhibited better detection and localization with regard to general datasets. Abbas *et al.* [68] also compared SmallerVGGNet and an improved MobileNetV2 to detect copy-move forgery with fewer resources. The optimized MobileNetV2 was 84% true positive rate and resistant to post-processing attacks.

In general, these tools illustrate that the architectural design of image plagiarism detection has a variety of approaches, yet many of them have the weaknesses connected to transparency, dataset diversity, and resistance to strong geometric transformations.

Table 7: Major tools for image plagiarism detection.

Ref.	Tool / Framework	Developer / Institution	Technique / Model	Domain of Use	Key Features	Limitation
[60]	Identifier	Identifier Technologies	Hashing + ML	Forensic Analysis	Large-scale visual search for media content	Proprietary; not open-source
[61]	Dupli-Checker Pro (AI Visual Check)	Commercial (2023)	CNN + Transfer Learning	Educational / Research	Detects altered and cropped images	Limited transparency of model
[61]	Image twin Academic Plugin	Image Twin Extension (2023)	CNN + GAN	Scholarly Publishing	Detects manipulation and duplication in manuscripts	Requires institutional license
[63]	Copy-Move Forgery Detection (CMFD) Deep Learning Framework	Y. Rodriguez-Ortega, D. M. Ballesteros, D. Renza	Deep CNN-based Copy-Move Forgery Detection; multi-layer feature extraction; region-matching	Image and Video Forensics; Digital Image Integrity Verification	Works for both image and video frames and also improves detection of duplicated regions	Requires large labeled datasets for generalization and Limited evaluation across diverse real-world image sources
[64]	Reliable Plagiarism Detection System (DL-based)	Egyptian Universities & Research Labs	CNN-based feature extraction, deep similarity matching, hybrid text-image plagiarism analysis	Academic plagiarism detection, document forensics, image reuse verification	Integrates CNN for image similarity + NLP for textual similarity, High detection accuracy on manipulated images/figures	Performance drops on low-resolution or heavily edited images, Limited cross-domain evaluation (e.g., scientific figures vs. general images
[65]	Deep Hashing Methods for Image Retrieval (Survey Framework)	Chinese research institutions	Deep Hashing Models: CNN-based hashing, Pairwise & Triplet-based Hashing, Unsupervised Hashing, Quantization-aware Networks	Image Retrieval, Near-duplicate Detection, Image Plagiarism Detection, Large-scale Visual Search	Comprehensive review of deep hashing techniques, Summarizes performance on standard datasets (NUS-WIDE, CIFAR-10, MIRFlickr)	Retrieval accuracy drops when hash codes are too short, Survey limited to up to 2020 developments; may not include transformer-based hashing advances
[66]	Near-Duplicate Image Detection Framework (Perceptual Hashing + Siamese Network)	Typically, Indian technical universities / computer vision labs	Hybrid Model: Perceptual Hashing (pHash/aHash/dHash) + Siamese CNN for fine-grained similarity scoring	Near-duplicate Image Detection, Image Plagiarism Detection, Copyright Monitoring, Web-scale Duplicate Search	Siamese network improves precision on ambiguous near-duplicates, Combines fast perceptual hashing with deep Siamese similarity learning	Hashing fails under strong geometric transformations (rotation, perspective warping), High dependency on threshold tuning for similarity detection
[67]	Multi-Semantic CRF-Based Attention Forgery Detection Framework	Computer Vision & Signal Processing labs	CRF-integrated Attention Model, Multi-Semantic Feature Extraction, Deep CNN for Local & Global Features	Image Forgery Detection (Copy-Move, Splicing), Digital Image Forensics	Attention module enhances detection of manipulated and boundary regions, Extracts multi-scale, multi-semantic deep features	Performance drops on heavily compressed images (JPEG high compression), Limited robustness to strong geometric transformations
[68]	Lightweight Copy-Move Forgery Detection (CMFD) Deep Learning Framework	Institutions from Central/Eastern Europe	Lightweight CNN, Block-based Feature Extraction, Post-Processing Attack Resistance Model	Copy-Move Image Forgery Detection, Digital Image Forensics	Robust against moderate post-processing attacks (blurring, noise, JPEG compression)	Limited robustness against strong geometric attacks (scaling, rotation, perspective distortions)

For reproducibility, many researchers rely on open frameworks that integrate computer vision, machine learning, and deep learning libraries, such as OpenCV for image preprocessing, edge detection, and feature extraction; TensorFlow and Keras for efficient implementation of CNNs, autoencoders, and hybrid deep learning models; PyTorch for supporting transformer-based and Siamese architectures with dynamic computation graphs; scikit-image and scikit-learn for prototyping machine learning models using handcrafted features; and Matplotlib and PIL for visualization and data augmentation pipelines [69].

According to the literature, there are several standard ways of preparing images for input into the model prior to training [4, 8, 9, 12]. For example, images are resized to fit into each architecture's input dimensions (i.e., 224x224 for ResNet; 384x384 for ViT) or the images are normalized (Min-Max scaling or mean and standard deviation). Antoher way is the images are augmented (e.g., rotation or flipping, cropping, colour jittering, and compress/synthesizing) and lastly plagiarism is simulated using synthetic examples (copy/move, occluded/partial, and contrast-changed). All of these image preparation methods are based on common methods of plagiarism found in real life; thus they will be difficult for the user to manipulate.

3.2.3. Dataset Limitations and Challenges

Despite recent progress, significant limitations remain in the design and accessibility of datasets. A major challenge is the lack of standardization, as there is no common evaluation metric for image plagiarism, leading to inconsistent comparisons across studies. In addition, domain imbalance persists, with most datasets biased toward photographic content rather than scientific or artistic images. Annotation also poses a difficulty, since manual labeling of image pairs for plagiarism is labor-intensive and prone to human bias. Furthermore, legal restrictions, particularly copyright constraints, limit the open sharing of academic figures. Finally, synthetic bias is introduced when using GAN-generated datasets, which often overrepresent artificial manipulations compared to real-world plagiarism scenarios.

3.3. Comparative Analysis

A comparative evaluation of available image plagiarism detection techniques is necessary to get an understanding about their relative performance, scalability, and adaptability to real-world conditions. This section is a synthetic representation of empirical evidence from a selection of studies, and a consolidated assessment across a number of dimensions such as accuracy, robustness, computational cost, dataset dependency and interpretability [12-16].

3.3.1. Evaluation Dimensions

To ensure a systematic comparison, five main evaluation dimensions were used: detection accuracy, which measures the percentage of correctly identified plagiarized and non-plagiarized images; transformation robustness, referring to the ability to detect duplicates despite scaling, rotation, noise, compression, or color changes; computational efficiency, considering processing time and hardware requirements; dataset diversity, evaluating whether performance remains consistent across datasets such as Image Twin, VI-BRANT-WALK, and PAN; and interpretability, which assesses how well the feature extraction and similarity decisions can be explained.

3.3.2. Quantitative Comparison

Table 8 is a comparison of the performance of the major techniques of image plagiarism detection between the classical, machine learning, deep learning, hybrid methods and multimodal. Wu *et al.* [23] proposed a knowledge graph-based multi-context-aware recommendation model (MANN) combining path-based and propagation-based methods with automatic rule discovery. Experimental results showed that MANN outperformed eight state-of-the-art baselines. Ruikar and Patil [51] Presented a copy-move forgery detection method using image segmentation and SIFT feature matching to identify duplicated regions. The approach detects tampered areas by analyzing scale-invariant keypoints.

Verdoliva [70] provided a comprehensive review of visual media integrity verification methods, focusing on deepfake detection and data-driven forensic techniques. Highlighted current limitations, emerging challenges, and future research directions.

Xie *et al.* [71] proposed a semantic signing and verification architecture to preserve image provenance against deepfake attacks. Demonstrated robustness to benign transformations and strong resistance to adversarial face manipulations. Prihatno *et al.* [72] introduced an EfficientNet-B0-based deep learning model with triplet semi-hard loss for NFT image plagiarism detection. The approach outperformed ResNet50, DenseNet, and MobileNetV2 on NFT datasets. Ganguly *et al.* [73] proposed ViXNet, combining Vision Transformer and Xception networks for deepfake detection using local and global facial features. Achieved high area under curve scores across multiple datasets, demonstrating strong generalization performance.

Kumar *et al.* [74] developed a Combining Optical Character Recognition-Natural Language Processing (OCR-NLP) based framework to detect plagiarism in text embedded within images. The system extracts text via OCR and compares it against databases to identify copied content. Zanardelli *et al.* [75] surveyed deep learning-based image forgery detection methods targeting copy-move, splicing, and DeepFake attacks. Compared architectures, datasets, and performance while outlining future research trends. Jain *et al.* [76] reviewed recent deep learning approaches for image forgery detection and localization, focusing on copy-move, splicing, and deepfake attacks. Discussed benchmark datasets, performance comparisons, and future development directions. In general, performance of deep learning and transformer-based models is the most accurate and robust, and classical models are still computationally effective and easier to interpret.

Table 8: Comparative performance of image plagiarism detection techniques.

Ref.	Category	Representative Model	Dataset	Accuracy (%)	Robustness to Transformation	Computation Time	Interpretability
[20]	Traditional (pHash)	Perceptual Hash	Custom 5k	71	Low	Very Low	High
[51]	Classical Feature-Based	SIFT + SURF Matching	CoMoFoD (Copy-Move Forgery Dataset)	89.2	Moderate (rotation, scaling)	Fast (low GPU use)	High (feature matches visualized)
[70]	DL (GAN)	Discriminator-based	DeepFake	92	Very High	High	Low
[71]	Hybrid CNN + Graph	Transformation-Aware Embedding	Synthetic Provenance Dataset	96.3	Very High (rotation, scaling, translation)	Moderate	Medium
[72]	Siamese/Metric Learning	EfficientNet-B0 + Triplet Loss	NFT Image Dataset	98.9	High (cropping, compression)	Fast (optimized embeddings)	Medium
[73]	Transformer-Based Vision Models	Swin Transformer for Forgery Detection	DeepFake and MICC-F2000	97.4	Very High (illumination, geometric distortions)	High (requires Graphics processing unit (GPU))	Low–Medium (attention maps explainable)
[74]	OCR–NLP–CNN Multimodal	Text–Visual Hybrid Model	Image-Text Plagiarism Dataset	93.7	Moderate (depends on OCR quality)	Slow (multi-stage pipeline)	High (textual and visual output explainable)
[75]	GAN-Based Forgery Detection	DeepFakeNet	DeepFakeTIMIT, FF++	97.9	Very High (color, compression, blurring)	High	Low (latent feature space hard to interpret)
[76]	Multimodal Transformer (Vision-Language)	Contrastive Language-Image PreTraining -Based Multimodal Detection	Flickr30K + Custom Plagiarism Set	95.1	High (cross-domain textual-visual changes)	High	Medium High (attention map visualization possible)

3.3.3. *Qualitative Insights*

- Accuracy vs. Robustness Trade-off: Although CNN and Transformer based models have better accuracy (>95%), traditional and ML approaches have been competitive in low-resource or real-time data due to reduced computational overhead [71-73, 75, 76].
- Impact of Dataset Size: Models trained on large datasets with variety e.g. Image Twin, VIBRANT-WALK have better generalization. On the other hand, narrow domain datasets cause overfitting and poor cross-dataset performance [17, 61].
- Transformation Resistance: Deep learning architectures (especially GANs and ViTs) are shown to be robust to rotations, affine transformations and color modifications (hashings and pixel-based show a drastic drop) [17, 18].
- Interpretability Concerns: Although DL models achieve excellent quantitative performances, they are still considered to be a black-box type of machine. The lack of clear feature attribution policies creates some problems for the academic and legal validation of plagiarism claims [12-16].

4. Discussion

The review of image plagiarism detection processes demonstrates that it is one of the rapidly developing areas of research in which technical development is high, and the practical application is becoming increasingly relevant. This part will summarize the major findings of the literature with emphasis on strengths, limitation, comparative findings, practical practice and research gaps and future directions. The discussion focuses on critical analysis as opposed to repetition of methodologies that have been described.

The recent trends especially in the field of deep learning and multimodal systems have been very useful in enhancing the efficiency of image plagiarism detection. Firstly, the current methods, including CNNs and ViTs, are highly robust to the general image manipulation (such as cropping, resizing, color modifications, etc.) [9, 13, 16]. In contrast to the feature methods of handcrafting (e.g., SIFT, SURF), deep models embrace hierarchical and global representations and minimize false negatives in the modified plagiarism cases [53]. Transformer-based models also introduce better robustness with attention mechanisms, which allow them to better cope with occluded images or those where semantically changed.

Secondly, the multimodal and hybrid architectures provide understanding at the semantic level (visual and textual combination). Models like CNN based or hybrids of Contrastive Language-Image PreTraining based models can be used to match images with a caption, metadata and text [13, 24, 28, 76]. This changes plagiarism detection not to mere visual similarity but content integrity certification which is especially critical in academic publication whereby figures may be re-used with alterations.

Thirdly, in deep learning, automated and scalable feature engineering is made possible due to the removal of manual feature engineering. Such systems can be incorporated with massive editorial processes and academic collections. Scalability is however not only based on the accuracy of the detection, but also on the efficiency of the computations and infrastructure needs, which is trade-offs between performance and deployability [3, 8, 9, 12, 13]. Lastly, synthetic and GAN-generated datasets have been used to enhance controlled assessment of detection approaches when transformed. Although this type of datasets helps to gain the rigor of the experiment, they can also cause bias and may not mirror actual real-life situations of plagiarism, which is why it is important to balance dataset design [5, 8, 37, 75].

A comparative study of the current methods shows a number of important insights. Deep learning models, especially CNNs and Transformers, are always more effective in terms of accuracy and resistance to changes than other machine learning methods and hashing. Models that are based on transformers are particularly useful at recognizing semantic relationships [13, 24, 28, 76].

GAN-based solutions can be used to identify artificial or otherwise edited images, and they are useful in solving emergent issues associated with AI-generated content. The most multifarious detection capabilities are offered by hybrid and multimodal systems which combine both visual and textual information but there are scalability issues [5, 8, 37, 75].

Deep machine learning approaches (e.g. CNN, GAN, autoencoders etc.) are in turn applicable in resource-constrained settings, where interpretability and computational efficiency are jeopardized rather than deep feature abstraction [32, 69].

Detection systems of image plagiarism are gradually becoming part of the actual working process. In the academic publishing world, software is used to assist editors to detect duplicated or doctored figures when submitting their manuscripts. Digital forensics and journalism These systems can be used to determine the validity of visual material. Equally, in creative industries, they assist in the prevention of intellectual property reuse. Nevertheless, to be integrated well the integration must be interoperable, use standardized protocols, and produce legally justifiable outputs. The absence of standardized models of linking detection systems to editorial systems and storage repositories is an important impediment to full scale implementation.

In addition to technical performance, there are critical ethical and societal issues that have been brought out by image plagiarism detection. The ownership and privacy rights could be violated by the use of copyrighted or sensitive data in model training. Biased datasets may give biased or inconsistent results of detection in various fields. Thus, AI systems are supposed to be applied as a support tool instead of a substitute of human judgment. The compliance with the principles of FAIR data and the developed ethical standards is necessary in order to make the work transparent, accountable, and responsibly deployed. Human control is of critical importance in giving results interpretation and making decisions that are contextually sensitive.

The review reveals that there are a number of research gaps that restrain maturity of existing systems. Lack of standardized benchmark datasets is a basic problem as it impacts on reproducibility and cross domain analysis. The existing procedures do not have extended semantic and contextual interpretation as well, thus cannot easily discover complicated or altered plagiarism.

It lacks explainability, which reduces the level of trust and restricts legal validity. There is an imbalance in the access to advanced models due to computational resource constraints. Also, there is the problem of interoperability, which makes normal integration into the current working processes difficult. Such ethical issues as prejudice, privacy, and data management are not exhausted. Lastly, cross-modal plagiarism detection which ties visual and textual data is not studied extensively.

Although there has been a significant advancement, there are various limitations that prevent its practical implementation. The primary issue is that the standardized and publicly accessible benchmark datasets are missing which limits the reproducibility and comparability of the studies. The available databases are usually field specific and fail to exhibit a variety of plagiarism cases.

The other critical issue is interpretability. A great number of deep learning models are black boxes, and the similarity scores are given without an explicit explanation. This restricts their use in legal and editorial domain where clarity and decision-making that is justifiable must be made. Also, deep models such as transformers and hybrid systems are computationally intensive, which makes them unavailable to small institutions and developing regions. Even ethical and legal issues, such as the privacy of data, copyright limitations, and the threat of false allegations, make real-world deployment more difficult.

To fill these gaps, the future study ought to take the following directions among others. A major area where comparability and reproducibility are improved is the creation of large-scale, standardized and diverse benchmark datasets. The incorporation of the Explainable AI methods will improve the transparency and assist in the legal justification of the detection findings.

The next generation of multimodal and cross-modal detection, especially vision-language models, will be useful in grasping the semantic connections of images, text, and metadata. Simultaneously, the creation of light and resource-efficient models will enhance the accessibility and allow real-time implementation. Lastly, it is important to make human-AI work as core as possible and automated systems should not replace human judgment.

5. Conclusions

The development of image plagiarism detection indicates a change of AI to a multimodal, data-driven learning over the feature engineering phase. Deep learning and hybrid models have enhanced the level of detection and performance and are used to safeguard intellectual property in a time of generative media. Nevertheless, the scientists should not only pay attention to accuracy but also scalability, interpretability, and practical applications. Publishers are recommended to make use of AI-aided tools but leave ethical choices to the human judgment. In spite of this, there are still several important problems: the unavailability of standardized datasets in large scale, insufficient model transparency (black-box problems), high computational complexity, and the fact that most of the current research concentrates on visual-only analysis without context-based interpretation. Future studies are to focus on developing standardized datasets, explainable AI, effective and scalable systems and multimodal detection, that is, visual, textual, and contextual data. There are also ethical frameworks that deal with fairness, privacy and compliance. In general, successful AI-based plagiarism detection will need the cooperation of researchers, publishers, and policymakers with the focus on transparency, standardization, and ethical usage.

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