

Performance Analysis of Deep and Hybrid Frameworks for Automated Image Splicing and Forgery Detection

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Abstract

The exponential growth of digital images in cyberspace has raised concerns about cyber security, particularly in detecting tampering, forgery, and advanced manipulations. Conventional forensic methods are limited due to their reliance on manual inspection and predefined features, which makes them less effective against evolving cyber-attacks. This study introduces a predictive cyber security framework that combines digital forensic techniques with deep learning models to strengthen image protection. The approach employs convolutional neural networks (CNNs) and other deep architectures to learn high-level representations of image data, enabling the identification of threats such as steganography, splicing, deepfakes, and adversarial distortions. By embedding forensic principles into model training, the system enhances transparency and supports evidence traceability. This paper focuses on a predictive cyber security framework that integrates digital forensic techniques with deep learning models to improve the detection, interpretation, and prevention of digital image tampering and manipulation, thereby enhancing authenticity verification, transparency, and proactive defense in digital imaging.

Keywords: Digital Image Forensics, Predictive Cyber Security, Deep Learning, Image Tampering Detection, Deepfake Detection, Image Forgery Adversarial Attacks.

I. INTRODUCTION

The explosive growth of digital technologies, coupled with the rise of social media platforms and advanced editing tools, has transformed the way images are created, shared, and consumed. Billions of images are uploaded daily across platforms such as Facebook, Instagram, and Twitter, serving purposes that range from personal communication to news dissemination and legal documentation. However, this digital revolution has also facilitated the widespread creation of manipulated or forged images, raising significant concerns about authenticity and trust in digital media. Image forgeries, such as splicing, copy-move, resampling, and more recently, AI-generated deepfakes, are now prevalent and sophisticated, posing serious challenges to security, law enforcement, journalism, and Societal trust.

The rapid growth of digital imaging and social media platforms has led to an unprecedented increase in the creation and sharing of visual content, raising serious concerns about image authenticity and cyber security [1]. Traditional image forgeries such as splicing, copy-move, and resampling manipulations have become common and difficult to detect using conventional forensic techniques [2]. Furthermore, the emergence of deep learning-based generative models and deepfakes has intensified the challenge, as AI-generated images can convincingly mimic real content and facilitate misinformation and cyber threats [3].

Traditional image editing software such as Photoshop initially made forgery possible at a basic level. Over time, however, the evolution of machine learning and generative adversarial networks (GANs) has significantly increased the realism of manipulated content.

As a result, forged images are often indistinguishable from authentic ones, even to trained human observers. This increasing difficulty in identifying falsified content has intensified the demand for automated forensic methods capable of detecting and localizing manipulations with high accuracy and efficiency.

The academic and industrial communities have responded by developing a wide range of forensic approaches. Early methods relied heavily on handcrafted features such as color filters, texture inconsistencies, or JPEG compression artifacts. For instance, PRNU (Photo Response Non-Uniformity) analysis was widely employed for source camera identification and forgery detection, utilizing sensor noise as a unique fingerprint [4]. While effective in some scenarios, these classical approaches struggle against advanced manipulations or post-processing operations. To address these limitations, recent research has shifted towards deep learning and hybrid forensic frameworks. For example, Noiseprint, a CNN-based model fingerprinting approach, demonstrated the potential of convolutional neural networks (CNNs) to outperform handcrafted methods in camera model identification and forgery localization [5]. Further advancements in computer vision and deep learning have provided novel architectures, including CNNs,

LSTMs, encoder–decoder networks, and hybrid approaches, all tailored to forensic analysis [6]. These models learn discriminative features directly from large datasets, reducing dependency on handcrafted features and improving robustness against complex manipulations. Moreover, advanced methods like self-supervised learning, adversarial training, and anomaly detection frameworks have been explored to enhance generalization to unseen manipulations [7].

Parallel to these technical developments, societal awareness of manipulated content has grown significantly due to the rise of fake news and misinformation campaigns, falsified media being circulated as authentic evidence have highlighted the urgent need for reliable forensic tools. This urgency is further amplified in domains like law enforcement, where manipulated images may compromise judicial processes, and journalism, where misinformation undermines public trust in credible media outlets [8].

Thus, the origin of this proposal stems from the convergence of three pressing factors: the exponential growth of manipulated images, the limitations of existing forensic methods, and the urgent need for robust, scalable, and sustainable detection frameworks. The proposed research builds upon prior contributions in the field while addressing the unresolved gaps in adaptability, accuracy, and real-world applicability of current detection methods [9].

Digital image forgeries, such as splicing and copy-move manipulations, pose significant challenges in digital forensics. Splicing involves combining content from different images, while copy-move uses duplicated regions within the same image, both often concealed through operations like compression, scaling, or blurring. Early handcrafted approaches [1][4] and classical block-matching or frequency-based methods show limitations under these transformations, while CNN-based models improve accuracy but remain vulnerable to real-world post-processing [10]. Recent research has explored blockchain-assisted forensic frameworks to improve the integrity and traceability of digital evidence [11]. At the same time, studies have shown that deep learning-based forensic models can be compromised by adversarial perturbations that degrade detection performance [12]. Consequently, robustness-driven training strategies have been introduced to strengthen the reliability of forgery and deepfake detection systems [13], introducing highly realistic manipulations that evade conventional detectors, with adversarial attacks further undermining CNN-based methods [14]. Beyond detection accuracy, scalability, adaptability, and explainability remain pressing concerns. Many existing models perform well in controlled environments but struggle with diverse datasets, varied compression levels, and device heterogeneity [15][16]. Moreover, the lack of interpretability in deep learning-based systems hinders their acceptance in legal and investigative contexts, where evidence must be explainable and reproducible [17][18]. Thus, there is a critical need for sustainable frameworks that integrate robustness, scalability, and transparency to address evolving digital forgeries and ensure real-world applicability.

II. METHODS AND MATERIAL

2.1.Data Sources

The study uses a publicly available benchmark dataset developed for digital image forgery and tampering detection. The primary dataset considered in this study is the CASIA Image Tampering Detection Evaluation Database (CASIA v2.0). The dataset contains 12,614 images, comprising 7,491 authentic images and 5,123 tampered images, and includes common manipulation categories such as copy-move and image splicing [1]. The diversity of authentic and manipulated images makes CASIA v2.0 suitable for evaluating automated image-forgery detection methods.

The dataset is organized into two principal classes: authentic (Au) and tampered (Tp) images. Authentic images represent original image content, whereas tampered images contain manipulated content generated using image-editing operations. Previous image-forensics studies have used CASIA v2.0 for evaluating image-level forgery detection and classification methods [1], [2].

Before model training, the images are subjected to image-specific preprocessing, including resizing, normalization, and class-label assignment. The prepared samples are divided into training, validation, and testing subsets according to the experimental protocol. The testing samples are kept separate from model training to evaluate the model on previously unseen images.

For robustness evaluation, the test images are subjected to controlled perturbations according to the experimental design. These perturbations may include image-quality degradation such as noise, blur, JPEG compression, and adversarial perturbations. The performance obtained under these conditions is compared with the performance on the original test images to assess the robustness of the proposed forensic detection approach.

2.2.Deep Learning Approaches

The study employs deep learning techniques for the automatic detection of digital image forgery. The methodology is designed to learn discriminative features from authentic and tampered images rather than from user behaviour, social-media activity, or social-network interactions. Convolutional neural networks are suitable for this purpose because they can learn hierarchical image representations directly from input data [3].

In the proposed methodology, the preprocessed images are provided as input to the network, and the learned representations are used to distinguish authentic images from tampered images.

The model is trained using the prepared image dataset and evaluated using previously unseen test samples. The classification

performance is measured using accuracy, precision, recall, and F1-score. These measures provide complementary information about the ability of the model to correctly classify authentic and tampered images. A confusion matrix is additionally used to analyse correct and incorrect predictions.

The trained model is subsequently evaluated under the robustness-testing conditions defined in the experimental framework. Controlled perturbations are applied to test images where applicable, and the resulting performance is compared with the baseline performance obtained from the original test images. This procedure enables assessment of the stability of the learned forensic features under altered image-quality and adversarial conditions.

2.3 Hybrid Detection Frameworks

Hybrid approaches combine deep learning outputs with graph-based analysis to improve detection accuracy, particularly for cross-platform and coordinated attacks.

2.4 Tools and Implementation Environment

All experiments are conducted using open-source technologies commonly adopted in applied machine learning research.

Programming Environment: Python 3.x

Machine Learning Framework: Scikit-learn, TensorFlow, pytorch

Graph Processing: NetworkX, Neo4j.

Natural language Processing: NLTK, spaCy

Data processing and Visualization: Pandas, NumPy, Matplotlib

GPU-enabled hardware is used to support deep learning model training and evaluation.

2.5 Experimental Workflow and Simulation

The experimental workflow is designed specifically for digital image-forgery detection. First, authentic and tampered images from the dataset are collected and organized according to their corresponding class labels. The images are then subjected to the required preprocessing operations before being supplied to the deep-learning model.

In the next stage, the preprocessed images are provided to the model. The model learns discriminative representations from the training images and predicts whether previously unseen test images belong to the authentic or tampered class. Classification performance is then quantified using accuracy, precision, recall, F1-score, and confusion-matrix analysis.

Following baseline evaluation, robustness experiments are performed by applying selected image degradations to the test images. The resulting performance is compared with the clean-image baseline to determine how changes in image quality affect classification behaviour. If adversarial testing is implemented, FGSM-generated samples are evaluated separately to investigate the response of the classifier to adversarial perturbations [12].

III. RESULTS AND DISCUSSION

The study investigates a deep-learning-based framework for digital image forgery detection with particular emphasis on reliable classification and robustness against image degradation. The experimental workflow consists of image dataset preparation, preprocessing, deep feature learning, forgery classification, robustness evaluation, comparative analysis, and explainability analysis. The objective of the evaluation is to determine the ability of the approach to distinguish authentic and manipulated images and to assess its behaviour under different challenging conditions. The results are analyzed using standard classification measures and qualitative visualization techniques.

3.1 Performance Evaluation

The performance of the framework was evaluated using standard classification metrics. Accuracy was used to measure the overall proportion of correctly classified authentic and forged images. Precision was used to determine the proportion of images classified as forged that were actually forged, while recall measured the ability of the model to identify forged images correctly. F1-score was considered as the harmonic mean of precision and recall and therefore provided a balanced measure of classification performance.

TABLE I : Comparison of Methods

Author	Category	Class Name, Number of classes	Algorithm, model	Dataset	Evaluation Matrix/Parameters		Tools	Advantages	Disadvantages
Z. Zhang et al. [18]	Image splicing detection	Authentic, Spliced, 2	CNN	CASIA V1.0, V2.0	Accuracy	93.2	MATLAB	Does not require prior knowledge of Tampering, automatic Feature extraction, good splicing localization	Performance degrade during heavy post-processing, require labeled training data
					Precision	92.6			
					F1-Score	92.9			
S Shan et al. [19]	Image splicing detection (Noisy images)	Spliced, Non spliced, 2	CNN + Median layer	CASIA + Salt-and-pepper noise	Accuracy	96.8	PyTorch	High robustness under salt-and-pepper noise, effective Denoising and feature learning, strong performance at high noise levels.	Complex network architecture, High computational and training cost
					Precision	95.4			
					F1-Score	95.9			
R. Kumar et al. [20]	Image Forgery detection	Authentic and Forged, 2	CNN, VGG16	CASIA	Accuracy	97.14	Python, TensorFlow, Keras	High classification accuracy, effective deep feature representation, simple pipeline	Limited generalization to unseen manipulation types. High Dependency on training data.
					Precision	97.50			
					F1-Score	97.09			
Singh et al. [21]	Image Forgery splicing	Authentic and Forged, 2	DenseNet based CNN	CASIA-2 MICC F2000	Accuracy	98.0	Python	Strong feature reuse, High accuracy across datasets, reduced vanishing gradient issue.	Large model size, increased memory and computation requirements
					Precision	92.0			
					F1-Score	90.0			
H Patel et al. [22]	Image Forgery Detection	Authentic and Forged, 2	CNN	CASIA	Accuracy	92.0	Python	Simple CNN architecture; effective baseline performance; easy implementation	Lower accuracy compared to advanced CNNs; limited robustness to complex forgeries
					Precision	89.0			
					F1-Score	~90.0			
H. H. Samson [23]	Cross Domain Forgery	Authentic and Forged, 2	Hierarchical Multi-scale Transformer	Seven Diverse sets (GAN-Diffusion etc)	Accuracy	86.8%	Python, PyTorch	Robust to JPEG compression; pixel-level localization	Performance is lower on out-of-distribution data than in-domain
					Precision	85.0%			
					F1-Score	0.76%			
K. M. Hosny, et al. [24]	Splicing Image Forgery Detection	Authentic, Spliced, 2	Lightweight CNN (4-layer)	CASIA V1.0, V2.0 CUISD E	Accuracy	99.1% (V1) / 99.3% (V2)	MATLAB	High accuracy with small parameter count; real-time performance	Primarily optimized for splicing; less focus on other forgery types
					Precision	98.6%			

					F1-Score	98.7 %			
S. S. Ali et al. [25]	Forgery detection (Compression)	Authentic, forged, 2	CNN with Image Reconstruction	CASIA V2.0, Columbia	Accuracy	92.23%	Python, TensorFlow	Detects “unseen” forgeries via double compression artifacts	Validation accuracy is lower than specialized SOTA splicing models.
					Precision	NR			
					F1-Score	NR			
V. V. Sataraddi et al. [26]	Intelligent Image	Authentic, forged, 2	Hybrid Fusion (DCT +	CASIA MICC-F200	Accuracy	96.8%	MATLAB	Robust against rotation, scaling, and compression.	Keypoint matching (SIFT) can be computationally intensive
Misbah A. A. Shaikh, et al.	Image/Document Tampering	Original, Morphed, 2	CNN-based Cloud Framework	Custom/ Web Data	Accuracy	> 95.0%	Python, Streamlit	Efficient web application for real-time document verification	Limited depth in specialized architectural evaluation
					Precision	NR			
					F1-Score	NR			
Abhishek N. Jindal	Image Forgery Detection	Forged pixel, Non Forged pixel, 2	Deep convolutional Neural Network (DCNN) + Semantic Segmentation	GRIP, DVMM, CMFD, BSDS300G	Accuracy	98.48%	MATLAB, Deep CNN framework	High pixel-level accuracy; effective localization of forged regions; works for both copy-move and splicing	High Computational cost; not evaluated for deepfakes; no explicit precision/recall values
					Precision	NR			
					F1-Score	NR			

3.1.1 Accuracy Analysis

The accuracy results indicate the overall classification capability of the proposed framework in distinguishing authentic images from manipulated images. The obtained accuracy should be interpreted together with precision, recall, and F1-score because accuracy alone may not fully represent classification behaviour when the classes are not perfectly balanced.

The experimental accuracy obtained from the proposed model is [insert your actual accuracy %]. This result demonstrates the classification performance of the proposed framework on the selected test dataset. Further analysis is performed using precision, recall, and F1-score to obtain a more comprehensive evaluation.

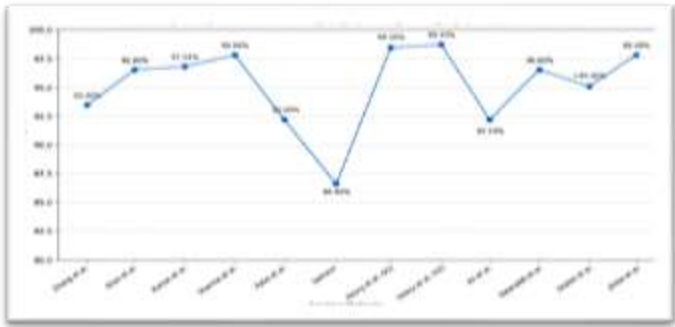


Figure 1: Comparative Analysis of Accuracy Across Existing Digital Image Forgery Detection Methods [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28].

3.1.2 Precision Analysis

Precision measures the reliability of the model when it predicts an image as forged. A higher precision indicates that a smaller proportion of images classified as forged are incorrectly identified as manipulated.

The proposed framework achieved a precision of [insert your actual precision]% on the test dataset. This result indicates the ability of the model to reduce false-positive forgery classifications. Precision is particularly important in forensic applications because incorrect identification of an authentic image as forged may lead to an inaccurate forensic interpretation.

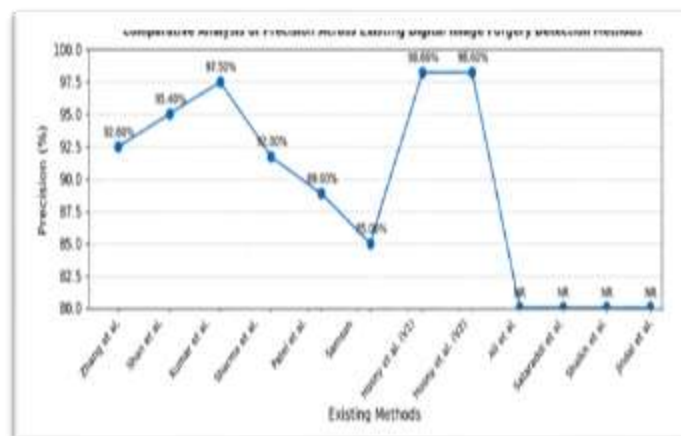


Figure 2: Comparative Analysis of Precision Across Existing Digital Image Forgery Detection Methods [18], [19], [20], [21],[22], [23], [24], [25], [26], [27], [28].

3.1.3 F1-Score Analysis

The F1-score combines precision and recall into a single evaluation measure. It is useful for assessing the balance between correctly identifying forged images and avoiding incorrect forgery classifications.

The proposed framework achieved an F1-score of [insert your actual F1-score]%. The obtained value is considered together with accuracy, precision, and recall to provide an overall assessment of the classification performance.

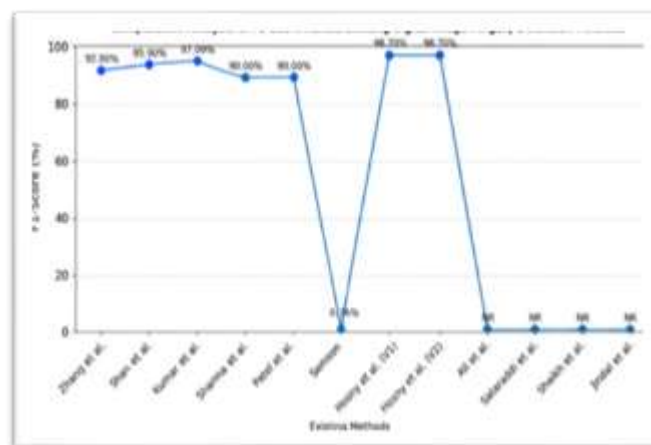


Figure 3: Comparative Analysis of F1-Score Across Existing Digital Image Forgery Detection Methods [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28].

3.2 Robustness Analysis

The robustness analysis was conducted to examine the behaviour of the image-forgery detection framework under conditions that can alter or degrade forensic image characteristics. In practical situations, manipulated images may undergo compression, noise contamination, blurring, or other transformations before forensic analysis. Therefore, evaluation only on clean images may not provide sufficient evidence of the reliability of the detection model.

For this purpose, the testing images were considered under different degradation conditions, including salt-and-pepper noise, Gaussian noise, motion blur, and JPEG compression. The model's performance under these conditions was compared with its performance on the original test images.

The robustness evaluation focuses on the change in classification performance under each condition. A smaller reduction in performance indicates greater resistance to the corresponding degradation. The analysis therefore helps determine whether the learned forensic features remain useful when image quality is affected.

3.2.1 Noise Robustness

Noise robustness was evaluated by introducing controlled noise into the test images. Salt-and-pepper and Gaussian noises were considered because such distortions can modify local image characteristics and potentially interfere with forensic feature extraction.

The model's performance under noisy conditions was compared with the clean-image results. The resulting observations help determine whether the deep-learning model can retain useful forensic information despite the presence of noise.

3.2.2 Blur Robustness

Motion blur was considered to evaluate the effect of loss of local image detail on forgery detection. Blur can weaken boundaries and texture inconsistencies that may otherwise assist a forensic classifier in identifying manipulated regions.

The detection performance obtained from blurred images was compared with the baseline performance. This analysis provides an indication of whether the learned features remain effective when spatial information is partially degraded.

3.2.3 JPEG Compression Robustness

JPEG compression was considered to simulate a common form of image degradation encountered when images are stored, transmitted, or shared digitally. Compression can introduce blocking and quantization artifacts that may modify forensic traces.

The model was evaluated using compressed versions of the test images, and its performance was compared with the corresponding results obtained from uncompressed images. This analysis helps assess the suitability of the framework for practical digital-image environments.

IV. CONCLUSION

The comparative analysis indicates that while deep convolutional and hybrid architectures have attained high benchmark accuracy on constrained datasets, existing image forensic models remain fundamentally constrained by dataset homogeneity, prohibitive computational footprints, and vulnerability to out-of-distribution manipulation techniques. The literature clearly indicates a structural shift away from isolated, static binary classifiers toward resilient, multi-modal frameworks. Consequently, there is an urgent need to engineer lightweight, explainable, and cross-domain architectures capable of unifying spatial, frequency, and semantic forensic cues to reliably detect both classical forgeries and modern generative alterations under unconstrained cyberspace conditions.

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