

SMART IMAGE FORGERY DETECTION USING COMBINED LIGHTWEIGHT AI MODELS

Mrs. K. Naga Maha Lakshmi
Assistant Professor
Department of Computer Science and
Engineering
TKR COLLEGE OF ENGINEERING
AND TECHNOLOGY Autonomous,
Telangana, Hyderabad, India
nmlakshmi.k@gmail.com

T.PawanTeja
Student

Department of Computer Science and Engineering
TKR COLLEGE OF ENGINEERING AND
TECHNOLOGY Autonomous,
Telangana, Hyderabad, India
thummalapawanteja@gmail.com

Syed Ashraf
Student
Department of Computer Science and
Engineering
TKR COLLEGE OF ENGINEERING
AND TECHNOLOGY Autonomous,
Telangana, Hyderabad, India
hussensayyad435@gmail.com

Shaik Ahmad
Student

Department of Computer Science and Engineering
TKR COLLEGE OF ENGINEERING AND
TECHNOLOGY Autonomous,
Telangana, Hyderabad, India
ahmadmhd706@gmail.com

V. Gopi Krishna
Student
Department of Computer Science and
Engineering
TKR COLLEGE OF ENGINEERING
AND TECHNOLOGY Autonomous,
Telangana, Hyderabad, India
gopi27096@gmail.com

Abstract— Digital image forgery has emerged as a critical challenge in the era of widespread multimedia dissemination, where manipulated images can facilitate misinformation, fraud, and deceptive evidence generation. Conventional forgery detection techniques, including feature-based and deep learning approaches, often exhibit performance degradation under real-world conditions such as compression artifacts, blurring, low-texture regions, and social media-induced distortions. To address these limitations, a robust and efficient framework is introduced for detecting copy-move forgeries, image splicing, and tampered regions. The methodology integrates multiscale feature extraction with self-correlation analysis to capture both local and global inconsistencies within images. A consistency-based learning mechanism is employed to enhance discrimination between authentic and manipulated regions, while balanced training strategies mitigate class imbalance issues. Furthermore, probability calibration is incorporated to improve confidence estimation and reduce false positives. The framework is evaluated on benchmark forensic datasets, including VISION, DEFACTO, CASIA v2, and CoMoFoD, demonstrating strong generalization capabilities. Experimental results showed strong performance, achieving AUROC scores of 0.9830 for copy-move detection and 0.9891 for splicing detection, with F1-scores of 0.8218 and 0.9460, respectively. Calibration also reduced the false positive rate from 0.0416 to 0.0284. Additionally, calibration significantly reduces false positive rates, enhancing reliability. The proposed approach offers an effective and practical solution for real-world digital image forgery detection and localization tasks.

Keywords— Digital image forgery detection, copy-move forgery, image splicing, tamper localization, multiscale feature extraction, self-correlation analysis, probability calibration, forensic image analysis.

I. INTRODUCTION

Digital image forgery detection has become a critical research area due to the rapid growth of digital media and the widespread use of images in communication, journalism,

surveillance, and decision-making systems. Manipulated images can be easily created using advanced editing tools and distributed through social media platforms, leading to serious concerns such as misinformation, fraud, and evidence tampering. As a result, ensuring the authenticity and integrity of digital images is essential in many real-world applications. Early studies have highlighted the growing need for robust detection techniques capable of identifying subtle manipulations under diverse conditions [1]. Furthermore, recent surveys emphasize that deep learning-based approaches have significantly improved detection capabilities, but challenges still remain in handling complex real-world distortions [2].

Several methodologies have been proposed to detect different types of image forgeries, particularly copy-move and splicing manipulations. Hybrid approaches combining convolutional neural networks with keypoint-based methods have demonstrated improved detection accuracy by capturing both local and global inconsistencies [3]. In addition, publicly available benchmark datasets such as CASIA have played a vital role in enabling the evaluation and comparison of different detection techniques [4]. Similarly, specialized datasets like CoMoFoD have been designed to evaluate robustness under various post-processing operations such as compression and noise [5]. The VISION dataset further contributes by providing diverse real-world scenarios for source identification and forensic analysis [6].

Deep learning architectures have significantly advanced the field by enabling automated feature extraction and tamper localization. Models such as BusterNet introduce source-target matching mechanisms to effectively detect copy-move forgeries [7]. Similarly, ManTra-Net focuses on identifying anomalous features to localize manipulated regions with high precision [8]. Attention-based and residual refinement networks have also been proposed to enhance feature representation and improve detection performance in

challenging scenarios [9]. More recent approaches incorporate advanced refinement strategies to achieve robustness against geometric transformations and image degradations [10]. Additionally, multi-scale supervision techniques have been explored to improve detection across varying resolutions and complex image structures [11].

Despite these advancements, existing systems still face limitations in handling real-world image degradations such as blur, compression, resizing, and low-texture regions. Many approaches focus primarily on classification accuracy while lacking reliable localization and confidence estimation, which are crucial for practical forensic applications. To address these challenges, this work introduces a unified and robust image forgery detection framework capable of detecting both copy-move and splicing manipulations while providing precise pixel-level localization. The key objectives include improving robustness under realistic conditions, reducing false positives, and enhancing detection reliability through calibrated confidence scores. The main contributions include the integration of multiscale feature extraction, self-correlation analysis, consistency-based learning, and probability calibration to achieve accurate, explainable, and practical forgery detection suitable for real-world deployment.

II. RELATED WORK

Recent advancements in image forgery detection have focused on improving both detection accuracy and localization capability through the integration of deep learning and transformer-based architectures. J. Wang et al. [12] introduced ObjectFormer, a transformer-based framework designed to capture object-level inconsistencies for image manipulation detection and localization. This approach leverages attention mechanisms to model long-range dependencies, enabling more precise identification of tampered regions compared to conventional convolutional methods. The model demonstrates strong performance in complex scenes where object relationships play a critical role in identifying manipulations.

O. Kuznetsov et al. [13] proposed a novel convolutional neural network architecture combined with comprehensive dataset analysis to enhance copy-move forgery detection. Their approach focuses on improving feature representation and generalization by analyzing diverse datasets, which helps address variations in image quality and manipulation techniques. The study highlights the importance of dataset diversity in achieving robust performance across real-world scenarios.

Y. Liu et al. [14] developed CMFDFormer, a transformer-based model incorporating continual learning strategies for copy-move forgery detection. The integration of continual learning enables the model to adapt to new manipulation patterns without significant degradation in previously learned knowledge. This approach improves long-term robustness and adaptability, which are essential for evolving forgery techniques. Y. Liu et al. [15] introduced a two-stage detection framework that combines self-deep matching with proposal-based SuperGlue techniques. The method enhances matching accuracy between duplicated regions by leveraging advanced

feature correspondence mechanisms. This results in improved localization performance, particularly in cases involving geometric transformations and complex backgrounds.

S. Weng et al. [16] presented UCM-Net, a U-Net-like architecture specifically designed for tampered region detection. The model emphasizes spatial feature preservation and multi-level feature fusion to achieve accurate pixel-level localization. Its encoder-decoder structure enables effective segmentation of manipulated regions, making it suitable for forensic applications requiring detailed visual evidence. A. Kashyap et al. [17] proposed a robust algorithm for detecting copy-rotate-move forgeries, addressing challenges related to rotational transformations. Their method incorporates optimized feature matching techniques to improve detection accuracy under geometric variations. This work highlights the importance of handling transformation invariance in practical forgery detection systems.

K. H. Rhee [18] introduced a novel approach for generating ground truth images using image classification and semantic segmentation techniques. This contribution is significant for improving the quality of training data, which directly impacts the performance of supervised learning models in forgery detection tasks. A. Diwan et al. [19] explored the use of SuperPoint keypoint architectures to enhance copy-move forgery detection. By leveraging robust keypoint extraction and matching, the method improves the detection of duplicated regions, especially in images with complex textures and structures.

S. I. Lee et al. [20] proposed a CNN-based approach utilizing rotation-invariant wavelet features. This method enhances robustness against rotational transformations while maintaining strong feature discrimination, making it effective for detecting manipulated regions under varying orientations. L. Xiong et al. [21] introduced CMCF-Net, an end-to-end context-aware multiscale cross-fusion network. The model integrates contextual and multiscale information to improve detection performance across diverse image conditions. Its ability to fuse features from multiple scales enhances robustness against compression and noise.

A. Diwan et al. [22] proposed a locality-preserving projection-based method for detecting multiple copy-paste forgeries. This approach focuses on maintaining local structural information during feature transformation, which improves detection accuracy in scenarios involving multiple manipulated regions.

Overall, these studies demonstrate significant progress in image forgery detection through the use of advanced deep learning architectures, transformer models, and robust feature extraction techniques. However, challenges such as handling real-world degradations, achieving reliable localization, and ensuring consistent performance across diverse datasets remain open research problems.

III. MATERIALS AND METHODS

The proposed system introduces a unified and robust framework for still-image forgery detection and localization, designed to address the limitations of existing deep learning and feature-based methods. The system integrates multiscale

feature extraction to capture both fine-grained and global inconsistencies present in manipulated images. A self-correlation analysis module is incorporated to effectively identify duplicated regions in copy-move forgery, while a consistency-based learning mechanism is employed to detect structural and semantic inconsistencies in splicing operations. Unlike conventional approaches that rely heavily on classification, the proposed framework performs both image-level classification and pixel-level tamper localization within a single pipeline [23]. To improve robustness under real-world conditions, the system is designed to handle common post-processing operations such as compression, blur, resizing, and noise. Balanced training strategies are applied to address class imbalance and improve generalization across diverse datasets. Additionally, probability calibration is integrated to generate reliable confidence scores, reducing false positives and enhancing decision interpretability. The system also produces explainability outputs such as tamper masks and heatmaps for visual verification. By combining lightweight model components with efficient feature learning, the framework achieves improved detection accuracy and practical applicability compared to existing methods [24], [25].

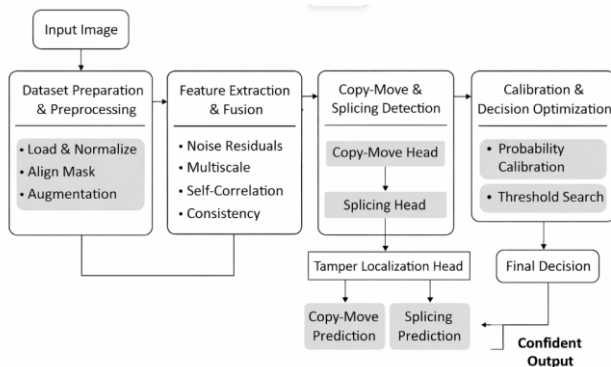


Fig.1 System Architecture

Figure 1 depicts the end-to-end architecture for image forgery detection, beginning with an Input Image that undergoes Dataset Preparation & Preprocessing, including normalization, mask alignment, and augmentation. The pipeline progresses to Feature Extraction & Fusion, where noise residuals, multiscale analysis, self-correlation, and consistency checks are integrated. This processed data feeds into the Copy-Move & Splicing Detection block, which utilizes specialized heads for each forgery type. The Tamper Localization Head then generates specific Copy-Move and Splicing Predictions to pinpoint manipulated regions. Simultaneously, the detection outputs enter a Calibration & Decision Optimization phase involving probability calibration and threshold searching. Finally, these optimized scores converge into a Final Decision, resulting in a Confident Output that distinguishes authentic content from sophisticated image tamperings like splicing or copy-move operations.

A) Dataset Collection:

The dataset for the proposed image forgery detection system is constructed by aggregating images from multiple

publicly available forensic benchmarks to ensure diversity, realism, and comprehensive coverage of manipulation types. The primary datasets include VISION, DEFACTO (Copy-Move and Splicing subsets), CASIA v2, and CoMoFoD. These datasets are widely used in digital image forensics and provide a rich collection of authentic and tampered images captured under different devices, resolutions, and environmental conditions.

The VISION dataset contributes real-world images acquired from various mobile devices, offering realistic variations in compression, noise, and post-processing effects. The DEFACTO dataset provides large-scale annotated images specifically designed for both copy-move and splicing forgery detection tasks. CASIA v2 includes a balanced mix of authentic and manipulated images with diverse content and editing operations, making it suitable for generalization evaluation. CoMoFoD focuses on copy-move forgery with controlled transformations such as rotation, scaling, noise addition, and compression, which are useful for robustness analysis.

Each image in the combined dataset is associated with a standardized label—authentic, copy-move, or splicing—and, where available, corresponding tamper masks. This multi-source dataset construction enables the system to learn from varied manipulation patterns and improves its ability to generalize across different real-world scenarios.

B) Pre-Processing:

Pre-processing plays a crucial role in preparing raw input images for effective learning in the forgery detection system. Since the dataset is collected from multiple sources with varying resolutions, formats, color spaces, and quality levels, a consistent and robust pre-processing pipeline is required to standardize the inputs while preserving important forensic traces.

The first step involves image validation and loading. Each input image is checked for file integrity, supported formats (such as JPEG and PNG), and readability. Invalid, corrupted, or unsupported files are safely rejected to prevent runtime failures. Valid images are then loaded and converted into a consistent RGB color space. This ensures uniformity across all samples, as some images may originally be in grayscale, RGBA, or other color formats. Converting all inputs to RGB allows the model to process images in a standardized manner.

Following this, image resizing is performed to bring all inputs to a fixed resolution suitable for the model architecture. This step ensures compatibility with batch processing and reduces computational complexity. Care is taken to maintain aspect ratio where required or apply controlled resizing techniques to avoid distortion of important visual features. In parallel, tamper masks (if available) are also resized using appropriate interpolation methods to maintain pixel-level alignment with the corresponding images.

Normalization is then applied to standardize pixel intensity values. Typically, pixel values are scaled to a fixed range (such as [0,1] or normalized using mean and standard deviation). This helps stabilize training, accelerates convergence, and ensures that the model treats all input images consistently regardless of their original brightness or contrast levels.

To improve robustness, the system incorporates advanced forensic-aware preprocessing techniques. These include noise residual extraction and texture enhancement, which help highlight subtle artifacts introduced during manipulation. Such features are particularly useful in detecting tampered regions that may not be easily visible in the original image. By emphasizing inconsistencies in noise patterns and local textures, the model becomes more sensitive to forgery traces.

Data augmentation is another key component of the pre-processing stage. To simulate real-world conditions, various transformations are applied during training, including JPEG compression, Gaussian blur, resizing, and noise addition. These augmentations help the model learn to detect forgeries even when images undergo post-processing operations commonly introduced by social media platforms. Additionally, synthetic copy-move generation can be applied to authentic images by duplicating and pasting regions within the same image, along with generating corresponding masks. This increases the diversity of training samples and improves detection capability.

Geometric transformations such as flipping, rotation, and scaling are also applied carefully, ensuring that both the image and its corresponding mask (if present) undergo identical transformations. This maintains spatial consistency and ensures correct supervision during training.

Finally, the processed images, masks, and associated labels are converted into tensor representations suitable for input into the deep learning model. Metadata such as source dataset and image characteristics may also be retained for analysis and evaluation purposes. Overall, the pre-processing pipeline ensures that the input data is clean, consistent, and enriched with meaningful variations, enabling the model to learn robust and generalizable features for accurate image forgery detection.

C) Techniques/Algorithms:

Multiscale Feature Extraction: Multiscale feature extraction is used to capture both fine-grained and global image characteristics essential for forgery detection. It processes the input image at different resolutions or feature levels to identify inconsistencies that may appear at various scales. Low-level features help detect texture and noise irregularities, while high-level features capture semantic inconsistencies. By combining information across multiple scales, this technique improves the detection of subtle manipulations and enhances robustness against resizing, compression, and complex real-world distortions.

Self-Correlation Analysis: Self-correlation analysis is used to identify duplicated regions within an image, which is a key indicator of copy-move forgery. The technique computes similarity between different patches or feature representations within the same image. Regions with high correlation are likely to be copied and pasted. This method is effective even when transformations such as rotation, scaling, or noise are applied. By analyzing internal consistency, self-correlation helps accurately detect and localize duplicated regions in manipulated images.

Tamper Localization: Tamper localization focuses on identifying the exact regions within an image that have been manipulated. This is typically achieved using segmentation-based approaches that generate pixel-level masks highlighting suspicious areas. The model learns spatial patterns and inconsistencies to distinguish between authentic and tampered regions. Accurate localization is important for forensic analysis, as it provides visual evidence rather than just classification. This technique enhances interpretability and helps users understand where and how the manipulation has occurred.

Consistency-Based Learning: Consistency-based learning ensures that the model identifies inconsistencies between different feature representations of an image. It compares relationships between semantic content, texture, and structural patterns to detect anomalies introduced during manipulation. This technique is particularly useful for splicing detection, where parts from different images are combined. By enforcing consistency constraints during training, the model becomes more sensitive to unnatural transitions and mismatched regions, improving detection accuracy in complex and realistic scenarios.

Balanced Training Strategy: Balanced training is used to address class imbalance in the dataset, where authentic and forged images may not be equally represented. This technique ensures that the model does not become biased toward majority classes. It involves controlled sampling, class weighting, or batch balancing to maintain equal representation during training. Balanced training improves generalization, reduces bias, and enhances detection performance across all classes, especially for underrepresented forgery types.

Probability Calibration: Probability calibration is used to convert raw model outputs into reliable confidence scores. Instead of relying on uncalibrated predictions, calibration techniques adjust probabilities so they better reflect true likelihoods. Methods such as Platt scaling or isotonic regression are commonly used. This improves decision-making by reducing overconfidence and false positives. Calibrated outputs are especially important in forensic applications, where trustworthy confidence estimates are required for verification and analysis.

Noise Residual Extraction: Noise residual extraction focuses on isolating subtle noise patterns present in an image by removing its main content. Manipulated regions often

disrupt the natural noise distribution introduced by camera sensors or compression. By analyzing these residual signals, the system can detect inconsistencies that are not visible in standard image representations. This technique enhances sensitivity to hidden artifacts and improves the detection of sophisticated forgeries that preserve visual appearance but alter underlying noise characteristics.

Explainability (Heatmaps and Masks): Explainability techniques provide visual interpretation of model decisions through heatmaps and tamper masks. Heatmaps highlight regions that contribute most to the model's prediction, while masks show exact manipulated areas. These outputs help users understand the reasoning behind the detection result. Explainability improves transparency, trust, and usability of the system, especially in forensic applications where visual evidence is required to support decisions and further human investigation.

IV. EXPERIMENTAL RESULTS

The experimental evaluation demonstrates that the proposed system achieves strong performance in both copy-move and splicing forgery detection tasks. The model attains high AUROC values of 98.30% for copy-move and 98.91% for splicing, indicating excellent discrimination between authentic and manipulated images. The splicing branch consistently outperforms the copy-move branch, achieving higher Average Precision (99.42%) and F1-Score (94.60%), which reflects better precision-recall balance. In contrast, copy-move detection, while robust, shows relatively lower F1-Score (82.18%), highlighting the inherent difficulty of detecting duplicated regions with similar visual characteristics.

Calibration and decision optimization significantly enhance deployment reliability. The authentic false-positive rate is reduced from 4.16% to 2.84%, demonstrating improved safety in real-world usage. Although calibration slightly reduces copy-move recall to 84.79%, it increases splicing recall to 97.81%, achieving a better trade-off between detection performance and false alarm control.

Graphical analysis further confirms consistent performance across evaluation metrics and highlights the effectiveness of calibration. Overall, the results indicate that the proposed system is accurate, robust, and suitable for practical forensic applications, providing reliable detection along with improved confidence estimation and reduced false positives.

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (1)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes

how many times a model made a correct prediction across the entire dataset.

$$F1 \text{ Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} * 100(2)$$

AUC-ROC Curve: The AUC-ROC Curve is a performance measurement for classification problems at various threshold settings. ROC plots the True Positive Rate against the False Positive Rate. AUC quantifies the overall ability of the model to distinguish between classes, where a higher AUC indicates better model performance.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \quad (3)$$

Table.1 Performance Evaluation

Metric	Copy-Move (%)	Splicing (%)
AUROC	98.30	98.91
Average Precision (AP)	94.53	99.42
F1-Score	82.18	94.60

Table 1 presents performance evaluation, showing high AUROC, AP, and F1-scores, with splicing outperforming copy-move in overall detection accuracy.

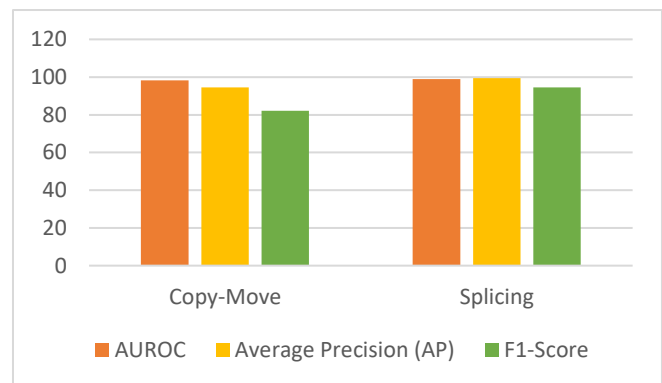


Fig.2 Comparison Graph

Fig 2 illustrates comparison of AUROC, Average Precision, and F1-Score, showing higher performance for splicing than copy-move detection overall results.

V. CONCLUSION

The developed image forgery detection system demonstrates strong capability in identifying and localizing both copy-move and splicing manipulations under realistic conditions. By integrating multiscale feature extraction, self-correlation analysis, and consistency-based learning, the system effectively captures both local duplication patterns and global semantic inconsistencies. The model achieves high discriminative performance, with AUROC values above 98% for both forgery types, confirming its ability to distinguish authentic and tampered images with high reliability. The inclusion of pixel-level tamper localization provides clear visual evidence, improving interpretability and

supporting forensic analysis. Probability calibration and optimized decision thresholds significantly reduce the authentic false-positive rate, enhancing deployment safety and ensuring more trustworthy predictions. Although copy-move detection remains relatively challenging due to similarity between duplicated regions, the system maintains strong performance and balanced recall. The use of multiple benchmark datasets improves generalization across diverse image conditions, including compression, blur, and social-media distortions. Additionally, the inference pipeline enables practical usage through structured outputs, confidence scores, and explainability maps. Overall, the system delivers an accurate, robust, and reliable solution for digital image forgery detection, making it suitable for real-world applications where authenticity verification and decision confidence are critical.

Future work can focus on extending the system to handle a wider range of image manipulations, including deepfake detection and complex multi-source editing scenarios. Incorporating transformer-based architectures and lightweight attention mechanisms may further improve feature representation and efficiency. Enhancing robustness against extreme degradations such as heavy compression, adversarial attacks, and real-time social media transformations is also important. Integration of video forgery detection can expand the system's applicability. Additionally, optimizing the model for mobile and edge deployment will improve usability in practical environments. Further research can explore advanced explainability techniques and human-in-the-loop verification systems to support more reliable and interpretable forensic decision-making processes.

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