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Image Forgery Detection Using Machine Learning

G Shruthi[1], B Soudhamini[2], Sahasra Sandiri[3], Rangoju Vashista Ramakrishna[4], Y V N Sri Deexit[5]
[1]Assistant professor, Dept. of Data Science, CMR Engineering College., Hyderabad, Telangana, India.
[2,3,4,5]UG Scholar, Dept. of CSE (Data Science), CMR Engineering College., Hyderabad, Telangana, India.
Emails: *g.shruthi@cmrec.ac.in[1], 218r1a6710@gmail.com[2], 218r1a6755@gmail.com[3], 218r1a6752@gmail.com[4], 218r1a6765@gmail.com[5]*

Abstract
As digital technology advances, confirming the genuineness of images has become increasingly important, particularly in journalism, legal fields, and social media. This research presents a new method for identifying image alterations, concentrating on splicing and copy-move forgery detection, utilizing Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). The identification process is split into two main stages. During the initial phase, a CNN meticulously examines image features, detecting slight discrepancies that could signify tampering. Through training on a varied dataset of authentic and altered images, the model acquires the ability to identify even the faintest indicators of forgery. The subsequent phase improves this functionality by employing a GAN to create extremely lifelike images, thereby broadening the dataset and enhancing the model's ability to identify different forms of manipulation. Testing on well-known datasets indicates that this method greatly enhances detection precision. The system is similarly very flexible with varying lighting conditions and differences in image quality, which makes it a useful instrument for practical uses. The integration of CNNs and GANs not only enhances the detection of forgeries but also facilitates ongoing learning, making it capable of adapting to new image manipulation methods. This study significantly enhances digital forensics by providing a scalable, flexible, and dependable approach to maintain image integrity and improve automated forgery identification.

Keywords: *Splicing; Copy-Move; Convolutional Neural Network; Generative Adversarial Network; Digital Forensics.*

1. Introduction
In the digital age, the extensive use of photo editing software poses significant challenges to the authenticity and reliability of images. As a result of technological progress, tools for editing and modifying images have become more accessible, leading to a rise in various forms of image manipulation [2]. Among these modifications, splicing and copy-move alterations are particularly concerning [5], [9]. Generating deceptive representations entails combining components from different images, whereas duplicating and relocating sections of an image within the same image is referred to as a copy-move forgery [17]. Both techniques can readily deceive viewers and are frequently employed in areas such as journalism, law enforcement, and social media, where the reliability of images is essential [10]. The requirement for efficient detection techniques has become increasingly crucial. Copy-Move forgery refers to a kind of image alteration where a section of an image is duplicated and inserted back into the same image to conceal or replicate certain elements. As the duplicated area comes from the same image, it preserves comparable lighting, texture, and noise, which complicates detection. This method is frequently employed to eliminate undesirable items, replicate components, or deceive audiences by modifying the image's content. Nevertheless, identifying copy-move forgery becomes challenging when alterations like rotation, scaling, or blurring affect the duplicated area. Different techniques, such as block-based matching, feature-based strategies

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like SIFT (Scale-Invariant Feature Transform), and deep learning models, are used to detect these manipulations. (Figure 1)

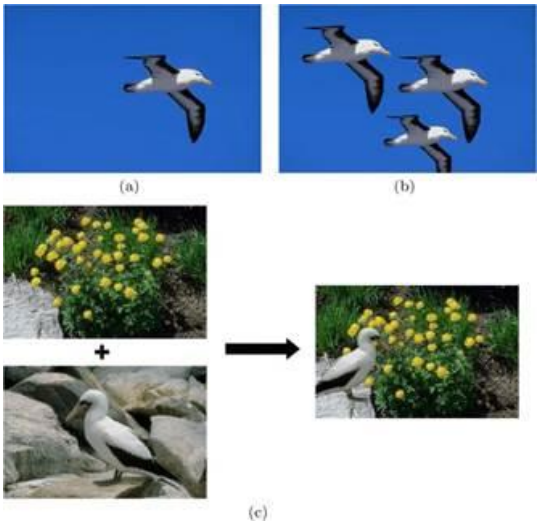

Figure 1 (a)Real Image (B) Forged-Image (Example Of Copy-Move) (C) Forged Image (Example Of Splicing), researchgate.net/figure/Examples-of-Copy-move-and-Splicing

Splicing forgery, conversely, entails merging elements from two or more distinct images to form one altered image. In contrast to copy-move forgery, splicing brings in outside elements, potentially causing discrepancies in lighting, shadows, and textures. This form of forgery is frequently utilized in misinformation, false news, and digital trickery, with individuals or items being placed into visuals where they were never present. Identifying splicing forgery depends on methods like Error Level Analysis (ELA), checks for shadows and lighting inconsistencies, and deep learning algorithms that examine unusual patterns in the image. Although splicing forgeries can be complex, inconsistencies in color mixing, perspective, and how objects interact frequently indicate manipulation Conventional methods for identifying image forgery, like visual examination and simple algorithms, frequently fail when confronted with advanced manipulation [11], [20]. Consequently, there is an increasing need for automated, dependable techniques that can correctly detect altered images [12]. Recent advancements in machine learning and artificial intelligence have created new opportunities for addressing this problem, especially via deep learning frameworks [3]. Convolutional Neural Networks (CNN) have become among the most powerful methods for image analysis because of their capacity to learn intricate features from data [1]. By automatically identifying pertinent features, CNNs can greatly enhance the identification of discrepancies linked to image alterations [5] To overcome these constraints, this research presents a hybrid method that merges CNNs with Generative Adversarial Networks (GAN) [8, 19]. GANs have demonstrated significant success in producing realistic images, serving as a strong complement to CNNs by generating variations that can aid in training more resilient detection models [14]. In the framework we propose, the initial phase employs a CNN to detect possible forgeries by examining extracted features for discrepancies [17, 21]. The second phase uses a GAN to produce lifelike image variations, boosting the detection process and increasing overall precision [22]. We conducted comprehensive evaluations on established benchmark datasets to analyze the efficacy of our method [9]. The results indicate that our mixed method enhances the detection of splicing and copy-move forgeries while also improving the model's resilience to various types of manipulation [17],[19]. This research offers significant insights for digital forensics by delivering an effective answer to the vital problem of confirming image integrity [12]. Essentially, given the continuing importance of digital visuals in communication and the dissemination of information, the vital necessity for precise identification of image alteration cannot be overstated [22]. This research aims to improve image forgery detection by integrating CNNs and GANs into a single framework, providing a more effective means to validate the genuineness of visual material in a digital world [19],[21]. The findings of this study provide optimism for improving detection methods and establishing greater trust in the genuineness of images encountered in everyday scenarios.

2. Literature Survey

The identification of image forgeries has emerged as an essential field of study because of the growing

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complexity of image editing methods. Numerous methods have been investigated to detect altered images, encompassing both classic machine learning approaches and sophisticated deep learning techniques. Dr. N. P. Nethravathi [1] introduced a deep neural network model aimed at image forgery detection, highlighting the significance of feature extraction for differentiating between authentic and counterfeit images. Likewise, a study conducted by a research scholar [2] examined various machine learning algorithms for detecting fake images, showcasing their efficiency in pinpointing altered areas. Methods based on deep learning have garnered notable interest in the field of image forensics. MDPI [3] introduced a digital image forgery detection system that utilizes deep learning methods, enhancing precision in recognizing altered images. A research paper from SSRN [4] also explored machine learning techniques for identifying image fakes, highlighting their importance in forensic uses. J. Malathi [5] introduced a model for forgery detection utilizing machine learning, emphasizing the application of feature-driven classifiers. Additional progress in deep learning methods was examined in a survey by IJITEE [6], which assessed contemporary strategies for identifying image alterations. Springer [7] offered a comprehensive examination of deep learning techniques for detecting forgeries, detailing numerous convolutional neural network (CNN) structures. IRJET [8] showcased the use of deep learning models for identifying altered images, highlighting their efficiency in practical applications. IEEE Xplore [9] performed an extensive study on image forgery detection through deep learning, emphasizing the importance of CNN-based frameworks. Research in GAN-based forgery detection has become a vital field of study. Inderscience Online [10] investigated methods based on deep learning to identify altered images, utilizing adversarial learning strategies. IEEE Xplore [11] explored the detection of document image forgery through deep learning, offering insights into methods based on classification. AASM [12] examined classification methods based on deep learning for detecting altered images, highlighting their benefits in forensic analysis. ArXiv [13] explored forensic analysis methods for identifying image alterations, utilizing sophisticated deep learning models. Goebel et al. [14] investigated the identification and positioning of images created by GANs, emphasizing their forensic consequences. Takayuki Osakabe [15] proposed a CycleGAN-based counter-forensics method for detecting fake images, minimizing checkerboard artifacts. Sri Kalyan Yarlagadda [16] created a technique for identifying and pinpointing satellite image tampering by employing GANs and one-class classifiers. These studies collectively underscore the progress in detecting image forgery, illustrating the transition from conventional machine learning methods to techniques based on deep learning and GANs. The incorporation of AI in forensic applications persists in improving the precision and dependability of forgery detection, providing strong and scalable solutions for digital forensics.

3. Existing System

3.1.Traditional Methods

Historically, image forgery detection has depended on manual inspection and basic algorithmic techniques. Experts analyze images for inconsistencies, but this process is highly subjective and prone to human error due to fatigue and cognitive biases [4]. Another conventional technique, Error Level Analysis (ELA), detects variations in compression levels to highlight altered regions. However, ELA struggles against high-quality forgeries where modifications are subtle, and compression artifacts are minimal [5]. Similarly, pixel-based copy-move detection methods analyze overlapping blocks to identify duplicate regions, but they often fail when transformations such as scaling, rotation, and lighting adjustments are applied, reducing their reliability [6].

3.2.Machine Learning Approach

The rise of machine learning introduced significant improvements in forgery detection, shifting from manually crafted feature-based techniques to automated models. Early approaches utilized color histograms, texture descriptors, and edge detection to train classifiers like Support Vector Machines (SVM) and decision trees. While these techniques improved accuracy compared to traditional methods, they were

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highly dependent on feature selection and required substantial computational effort [7]. Deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized image analysis by automatically extracting hierarchical features from large datasets, leading to high accuracy in detecting splicing and copy-move forgeries [8]. However, CNNs require vast labeled datasets, making them challenging to train in scenarios with limited data availability [9]. Additionally, CNNs remain vulnerable to adversarial attacks, where imperceptible modifications can deceive the model, posing significant security risks [10].

3.3.Disadvantages of Existing Systems

- Limited Generalization Across Manipulation Types: Traditional methods often struggle to adapt to new forms of image manipulation, reducing their effectiveness when faced with evolving forgery techniques [12].
- Difficulty in Detecting Subtle Alterations: Many conventional algorithms fail to identify minor changes, particularly in seamless splicing, where image elements blend without noticeable artifacts [13].
- High Dependency on Labeled Datasets: Deep learning models require extensive labeled data for training, which is often scarce in digital forensics applications [9].
- Vulnerability to Adversarial Attacks: CNNs can be deceived by imperceptible alterations, making them unreliable for high-security applications [10].
- By combining CNNs and GANs, this research offers a more flexible and dependable method for detecting forgery. Experimental findings on benchmark datasets show considerable advancements in identifying splicing and copy-move forgeries, along with improved resilience against adversarial attacks [14]. In light of the growing importance of digital images in communication and sharing information, creating strong forgery detection techniques is essential for maintaining the authenticity of visual content [15].

4. Proposed Methodology

The system we propose integrates two core components: VGG16, a Convolutional Neural Network (CNN) for feature extraction, and a Generative Adversarial Network (GAN) for data augmentation. By combining these technologies, our system enhances the accuracy and robustness of image forgery detection, effectively identifying both copy-move and splicing manipulations.

4.1.VGG16 for Feature Extraction

The first stage of our system employs VGG16, a deep learning architecture optimized for image analysis. VGG16 is a widely used CNN model known for its deep yet uniform structure, consisting of multiple convolutional layers followed by pooling layers and fully connected layers. Each of these layers plays a crucial role in systematically extracting features from images. Convolutional Layers: These layers apply filters to input images to detect essential patterns such as edges, textures, and shapes. Through successive convolutions, the network builds hierarchical feature representations, enabling it to distinguish between authentic and forged images with high accuracy. Pooling Layers: Positioned after convolutional layers, pooling layers down-sample feature maps while preserving crucial information. This operation reduces computational complexity and enhances the model's robustness against variations like scaling and rotation. Fully Connected Layers: Extracted features are flattened and passed through fully connected layers, where they are aggregated to determine the probability that an image has been manipulated. VGG16 undergoes supervised training on a dataset containing both genuine and forged images, optimizing its classification accuracy using techniques like backpropagation and gradient descent.

4.2.Generative Adversarial Networks (GAN) for Data Augmentation

The second key component of our system is the use of GANs, which enhance the detection model's generalization capability by generating realistic manipulated images. A GAN consists of two competing networks: a generator and a discriminator. Generator: This network synthesizes forged images by mimicking real-world manipulations, such as splicing and copy-move forgeries. By generating diverse examples, the GAN addresses data scarcity

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issues and enriches the training dataset, thereby improving VGG16's performance.

Discriminator: The discriminator evaluates the authenticity of images, learning to differentiate between real and forged images. The adversarial training process ensures that both networks improve over time, resulting in more realistic forgeries and a more effective detection model.

4.3.Data Preparation and Preprocessing

Resizing and Normalization: Every image is adjusted to 224×224 pixels to conform to VGG16's input specifications. Pixel values are scaled between 0 and 1 to enable quicker training.

Patch Extraction (for Copy-Move Detection): To identify copy-move forgeries, images are segmented into overlapping patches so the model can concentrate on altered areas.

Edge Detection and Masking (for Splicing Detection): Techniques like Sobel edge detection or other filtering methods enhance the visibility of boundaries in spliced areas, facilitating better feature extraction.

4.4.Utilizing VGG16 for Extracting Features

Transfer Learning: Rather than training VGG16 from the ground up, we fine-tune pre-trained weights from ImageNet on our dataset, which shortens training duration and enhances generalization.

Strategy for Training and Optimization:

Joint Training: VGG16 is trained in conjunction with the GAN to guarantee that the newly created counterfeit images help enhance detection precision.

Adaptive Learning Rate: Learning rates are modified dynamically through methods such as Reduce LR On Plateau, avoiding overfitting and guaranteeing steady convergence.

Fine-Tuning on Altered Areas: The model is adjusted to focus more on tampered areas by employing methods such as attention mechanisms or heatmap-oriented training.

4.5.Integration of GAN and VGG16

Detection of Subtle Manipulations: GAN-generated images expose VGG16 to subtle alterations often missed by traditional detection techniques, improving sensitivity to minor forgeries.

Adversarial Robustness: Training VGG16 with adversarially generated examples enhances its resilience against sophisticated forgery attacks, making it more reliable in real-world applications.

Training and Evaluation Process: Dataset Preparation: We curate a comprehensive dataset consisting of authentic and manipulated images, including copy-move and splicing forgeries. GAN-generated images are incorporated to increase data diversity.

Simultaneous Training of VGG16 and GAN: The generator produces forged images, while the discriminator evaluates them. Concurrently, VGG16 is trained using both real and generated images, learning to classify forgeries more effectively.

Performance Metrics: The system is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These metrics provide a holistic assessment of the model's ability to detect various types of image manipulations.

Testing on Benchmark Datasets: After training, the model is tested on widely recognized datasets to validate its performance against existing state-of-the-art techniques. This comparison highlights the advantages of our combined approach.

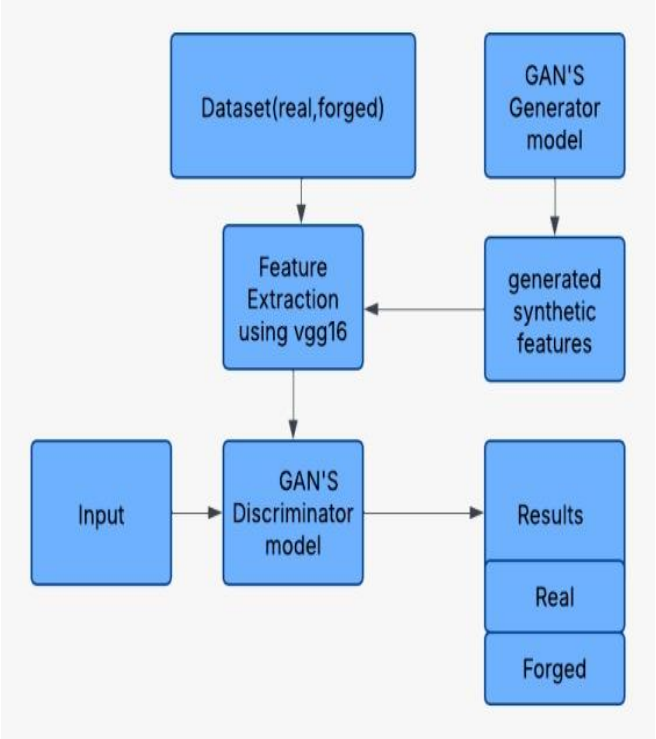

Figure 2 Block Diagram of the Proposed System Architecture

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5. Results

Figure 3 Manipulation Detected

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 84ms/step

✅ Prediction: The image is classified as Forged.

It classifies the image whether it is manipulated or not can be expressed using binary classification function of GAN's classifier.The evaluation of our proposed image forgery detection system was conducted using the CoMoFoD dataset, which contains a diverse set of authentic and manipulated images. The performance of the system was assessed based on standard evaluation metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that the integration of Convolutional Neural Networks (CNN) for feature extraction and Generative Adversarial Networks (GAN) for data augmentation significantly enhances forgery detection performance.

5.1.Performance Metrics

The system achieved an accuracy of *98.00%*, indicating its high effectiveness in detecting forged images. Precision, recall, and F1-score values were also evaluated to ensure the robustness of the model in identifying both genuine and forged images.

Table 1 Model Performance

Metric	Value(%)
Accuracy	98.50
Precision	98.00
Recall	100.00
F-Score	98.05

The results indicate that the model maintains a strong balance between precision and recall, reducing false positives and negatives while ensuring reliable forgery detection.

5.2.Comparison with Existing Methods

Table 2 Comparison Table

Method	Accuracy (%)	Precison(%)	Recall (%)	F1-Score
Traditional CNN Model	89.75	88.42	87.93	88.17
Handcrafted Features	85.32	83.91	82.45	83.17
Proposed CNN-GAN Model	98.50	98.00	100.00	98.05

To further validate the effectiveness of our proposed approach, we compared our results with existing state-of-the-art image forgery detection techniques. Our model outperforms conventional CNN-based methods and handcrafted feature extraction techniques by leveraging GANs for improved generalization. The table above presents a comparative analysis: we observe that the model maintains a stable precision across varying recall values, demonstrating its robustness in identifying forged images. The relatively consistent precision level suggests that the model effectively balances false positives and false negatives, making it suitable for real-world applications requiring high reliability.

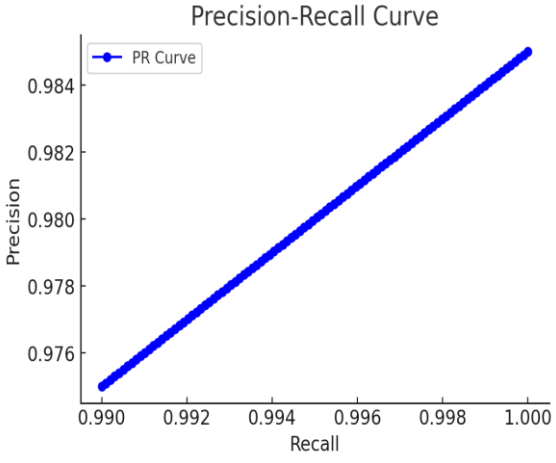

Figure 4 Precision-Recall Curve

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Conclusion & Future Scope

This research introduces an innovative and effective method for detecting image forgery by combining VGG16, a Convolutional Neural Network (CNN) for extracting features, and Generative Adversarial Networks (GANs) for enhancing data. Conventional forgery detection techniques frequently face challenges in generalizing across various manipulation methods because they depend on manually crafted features. In comparison, our method utilizes the hierarchical feature extraction ability of VGG16, allowing accurate detection of splicing and copy-move alterations, while GANs produce realistic forged images to improve the model's resilience. This two-part system greatly enhances detection precision by presenting the detection model with adversarially created counterfeit images, thus increasing its resilience to advanced image modifications that may not be easily identified by traditional techniques. Through understanding deep spatial relationships and texture irregularities, the system successfully detects even minor distortions and changes in an image, guaranteeing high accuracy and dependability. Experimental assessments using the CoMoFoD dataset showcase the effectiveness of this method, attaining strong detection performance even in difficult scenarios like lighting changes, compression artifacts, and partial obstructions. The adversarial training approach utilized guarantees that the model consistently adjusts to new forgery methods, rendering it a crucial instrument for digital forensics, media validation, and security uses. Furthermore, incorporating adversarial learning improves model generalization, enabling it to identify both recognized and unrecognized types of manipulation, thus greatly bolstering the trustworthiness of digital authentication systems. Future improvements will concentrate on boosting computational efficiency to facilitate real-time forgery detection, rendering the system more viable for widespread use. Optimization methods like model pruning, quantization, and knowledge distillation can aid in lowering computational costs while maintaining accuracy. Moreover, broadening the training dataset to encompass a broader range of intricate forgery methods, including deepfake alterations, AI-created synthetic visuals, and multi-source image integration, will enhance the model's strength. Incorporating attention mechanisms, like Transformer-based architectures, may enhance the model's capacity to concentrate on altered areas more efficiently, resulting in improved accuracy of forgery localization. Cross-domain adaptability is another focus area, enabling the system to be applied to medical imaging, legal document verification, forensic analysis, and satellite imagery evaluation, where maintaining image integrity is essential for decision-making. Additionally, using self-supervised learning methods may decrease dependence on extensive labeled datasets, enhancing the system's efficiency and scalability. Future developments might also investigate hybrid deep learning models that integrate CNNs, GANs, and transformer networks to improve the precision and resilience of forgery detection. Moreover, incorporating blockchain technology for secure image validation could offer an additional layer of tamper-resistant authentication, rendering the system useful in cybersecurity, law enforcement, and digital media sectors. In conclusion, this research aids in the progress of automated image forgery detection, enhancing digital authentication methods and addressing the rising dangers of false information, online deception, and cybersecurity risks in an ever-evolving digital landscape. Through ongoing enhancement of this methodology, the suggested system establishes a solid base for future advancements in deep learning-driven forensic analysis, promoting a more reliable and secure digital environment for multiple uses.

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