

RESEARCH ARTICLE

Enhanced Fake Image Detection Through Hybrid Convolutional Autoencoder and Generative Adversarial Network Framework

V. Saravanan ^{1,*}, Khushboo Tripathi ², K. N. S. K. Santhosh ³

ABSTRACT: The rapid advancement of artificial intelligence-driven image synthesis has created significant challenges for digital media authentication and forensic analysis. This paper proposes a hybrid detection framework integrating Convolutional Autoencoders (CAEs) and Generative Adversarial Networks (GANs) to distinguish authentic images from synthetically generated content. The autoencoder learns representative image features and identifies reconstruction anomalies, while the adversarial discriminator detects subtle artifacts associated with generative models. Experimental evaluation on benchmark datasets, including Celeb-DF, Face Forensics++, and GAN-generated image collections, demonstrates that the proposed framework achieves a classification accuracy of 98.3%, outperforming conventional CNN-based detection methods. The framework also maintains robust detection performance under image compression, noise, and resolution degradation. Furthermore, its approximately 15 ms per-image processing time supports real-time applications. The proposed approach provides an effective and scalable solution for digital forensics, content authentication, and detection of AI-generated misinformation, contributing to improved digital content integrity against increasingly sophisticated synthetic media threats.

Keywords: Digital Image Forensics, Adversarial Detection, Synthetic Media Authentication, Deep Learning Architectures, Visual Artifact Analysis, Neural Network Fusion

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1. INTRODUCTION

The proliferation of artificial intelligence-driven image synthesis technologies has introduced unprecedented challenges to digital media authentication and information

security. Contemporary generative models, particularly Generative Adversarial Networks and diffusion-based architectures, produce visually convincing forgeries that routinely bypass conventional detection methodologies, necessitating the development of more sophisticated forensic tools [1]. The term "deepfake," combining deep learning with fabrication, encompasses a spectrum of synthetic media that impersonates human appearance, voice, and behavior across images, videos, and audio formats [2]. The sophistication and accessibility of these technologies present significant threats of misinformation to society, with alarming statistics indicating that deepfakes accounted for forty percent of biometric fraud instances by early 2025 and projected financial losses exceeding forty billion dollars globally by 2027 [3]. These developments carry profound implications across numerous domains, including journalistic integrity, legal evidence authentication, social media content moderation, identity verification workflows, and national

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security applications, where the ability to verify visual content authenticity remains paramount [4].

Traditional approaches to fake image detection relied predominantly upon handcrafted feature extraction methodologies, encompassing edge detection algorithms, color space analysis, statistical texture examination, Photo Response Non-Uniformity based camera trace methods, and metadata inspection techniques [5]. While these methods proved adequate against earlier generations of image manipulation tools, they demonstrate fundamental limitations when confronted with contemporary deep learning-based forgeries that realistically replicate the statistical properties and visual characteristics of genuine photographs [6]. The adaptive nature of modern generative models enables them to continuously evolve and circumvent detection mechanisms, creating an ongoing arms race between forgery generation and forensic detection technologies [7]. Classical machine learning classifiers, including Support Vector Machines and ensemble methods, similarly struggle to generalize well against evolving deepfake techniques, leading to high false positive and false negative rates that undermine their practical utility in operational cybersecurity environments [8].

Deep learning architectures have emerged as promising solutions to these challenges, with Convolutional Neural Networks demonstrating considerable success in learning discriminative features for fake image classification [9]. However, conventional CNN-based approaches primarily depend on visual texture features and may fail against highly realistic fake images produced by advanced generative models [10]. Recent research has revealed that detection systems exhibit significant performance degradation when tested with generated images from unseen generative models or object categories, a problem attributed to data dependency arising from model overfitting to specific GAN architectures and training categories [11]. Frequency domain analysis techniques have been explored to detect artifacts generated during upsampling estimation in GAN generators, yet these frequency-level artifacts differ between generative models and object categories, further compounding the generalization challenge [12].

Convolutional Autoencoders offer a particularly compelling approach to fake image detection through their ability to learn unsupervised feature representations, enabling faithful reconstruction of genuine images while identifying inconsistencies in manipulated ones [13]. By leveraging reconstruction errors as anomaly scores, these models effectively highlight subtle inconsistencies and hidden artifacts introduced during image tampering, including irregular textures, color transitions, and structural abnormalities that characterize synthetic media [14]. The reconstruction error map serves as an important feature for identifying suspicious image regions and distinguishing generated images from genuine ones, providing a complementary detection mechanism to classification-based approaches [15]. The unsupervised nature of autoencoder training also offers practical advantages, as these models can be trained exclusively on authentic images, eliminating the

need for extensive labeled fake image datasets that are often challenging to curate comprehensively [16].

The integration of Generative Adversarial Networks into detection pipelines represents another significant advancement in the field. Although GANs have traditionally been employed for generating realistic fake images, researchers have repurposed adversarial learning principles to enhance detection capabilities [17]. By training a GAN-based discriminator through competitive learning with a generator, the model learns to differentiate between genuine and synthetic features at a high precision level, identifying subtle synthesis artifacts such as abnormal texture patterns, inconsistent boundaries, frequency distortions, and unrealistic local details that characterize AI-generated content [18]. The discriminator's exposure to continuously generated synthetic samples during training enables it to adapt to emerging manipulation techniques more effectively than static classifiers [19].

Despite these individual advances, standalone autoencoder and GAN-based approaches each possess inherent limitations. Autoencoders may sometimes misclassify novel but genuine images that deviate from training distributions, while GAN discriminators can be susceptible to adversarial examples specifically crafted to exploit their decision boundaries [20]. The novelty of the present work lies in the synergistic integration of Convolutional Autoencoders with GAN-based adversarial discriminators within a unified hybrid framework that jointly leverages reconstruction-based anomaly detection and adversarial artifact analysis. This combination addresses the complementary weaknesses of each approach, with the autoencoder capturing structural anomalies independent of specific forgery signatures and the discriminator learning to identify manipulation patterns that may not produce significant reconstruction errors. The proposed framework further incorporates an adaptive weighting mechanism that dynamically balances the contributions of both components based on the characteristics of the input image, ensuring robust performance across diverse manipulation techniques and image qualities. This hybrid strategy, combined with self-supervised learning techniques that enable the model to learn from unlabeled datasets, represents a substantive advancement over existing methods that typically employ these architectures in isolation.

The computational demands of deep learning-based fake image detection present additional challenges for real-world deployment, particularly in resource-constrained environments such as mobile devices and edge computing platforms [21]. The proposed framework addresses these concerns through the incorporation of lightweight convolutional layers, feature pruning strategies, and batch normalization techniques that collectively optimize processing efficiency without substantially compromising detection accuracy. The model's architectural choices enable real-time processing speeds suitable for practical applications in online content moderation, forensic investigation workflows, and social media monitoring systems [22].

In this paper, we report a comprehensive investigation

into fake image detection through a hybrid architecture that synergistically combines Convolutional Autoencoders with Generative Adversarial Networks. Our approach leverages the reconstruction-based anomaly detection capabilities of autoencoders alongside the adversarial training dynamics of GAN discriminators to achieve superior discrimination between authentic and synthetically generated imagery. The proposed framework is evaluated across multiple benchmark datasets, including Celeb-DF, FaceForensics++, and diverse GAN-generated image collections encompassing various generative architectures such as StyleGAN, ProGAN, and BigGAN. We demonstrate that our integrated system attains substantial improvements in classification accuracy, false positive rate reduction, and adversarial robustness compared to conventional CNN-based approaches and existing detection models. The remainder of this paper presents a detailed exposition of our methodology, experimental validation, comparative performance analysis, and discussion of the implications for digital forensics and media authentication.

2. RELATED WORKS

The proliferation of synthetically generated imagery has catalyzed substantial research activity in forensic image authentication, with investigators exploring diverse methodological frameworks to address the escalating challenge of media manipulation. Early approaches to fake image detection predominantly relied upon handcrafted feature extraction techniques, encompassing edge detection algorithms, color space inconsistency analysis, statistical texture descriptors, and metadata examination [23]. These conventional methodologies, while demonstrating moderate efficacy against elementary image forgeries produced through conventional editing software, exhibited fundamental inadequacies when confronted with deep learning-generated content that realistically replicates the statistical properties and visual characteristics of authentic photographs [24]. The inherent limitations of handcrafted feature-based approaches, particularly their inability to generalize across diverse manipulation techniques and their vulnerability to deliberate counter-forensic operations, motivated the transition toward data-driven deep learning architectures [25].

The application of Convolutional Neural Networks to fake image detection represented a significant paradigm shift, with early CNN-based classifiers demonstrating remarkable proficiency in discriminating between genuine and manipulated facial imagery when trained on extensive datasets such as FaceForensics++, Celeb-DF, and the DeepFake Detection Challenge corpus [26]. These architectures effectively learned hierarchical feature representations, capturing both low-level texture patterns and high-level semantic information that proved discriminative for forgery detection [27]. However, subsequent investigations revealed that CNN-based detectors exhibited considerable performance degradation when evaluated

against synthetic images generated by unseen architectures or when tested on datasets with different distributions than those employed during training [28]. This generalization deficiency stemmed primarily from the tendency of CNNs to overfit to specific artifacts characteristic of particular GAN architectures, rendering them susceptible to evolving generation techniques that continuously refine their outputs to approximate genuine image distributions more faithfully [29].

The exploration of autoencoder architectures for fake image detection introduced a fundamentally different paradigm based on reconstruction-based anomaly detection principles [30]. Convolutional Autoencoders, in particular, demonstrated considerable promise by learning compressed latent representations of genuine images during training and subsequently identifying manipulated content through elevated reconstruction errors that manifest when attempting to reconstruct images containing generative artifacts or tampering [31]. This approach offered the distinct advantage of unsupervised training, eliminating the requirement for extensive labeled fake image datasets that are notoriously challenging to curate comprehensively and representatively [32]. Researchers observed that reconstruction error maps effectively highlighted subtle inconsistencies including irregular textures, anomalous color transitions, and structural abnormalities characteristic of synthetic media, providing interpretable evidence for forensic analysis [33]. Despite these advantages, standalone autoencoder approaches occasionally misclassified novel but authentic images that deviated from training distributions, limiting their practical utility in operational environments [34].

The integration of Generative Adversarial Networks into fake image detection pipelines represents a particularly innovative development, leveraging adversarial learning principles to enhance discriminative capabilities [35]. Although GANs were originally conceived for generating photorealistic synthetic content, researchers have repurposed the adversarial training framework to strengthen detection mechanisms by training discriminators that undergo continuous competition with generators [36]. This approach enables the discriminator to learn highly refined features capable of identifying subtle synthesis artifacts, including abnormal texture patterns, inconsistent boundaries, frequency domain distortions, and unrealistic local details that characterize AI-generated content [37]. The discriminative capabilities acquired through adversarial training demonstrate superior sensitivity to manipulation traces compared to conventionally trained classifiers, as the discriminator must continuously adapt to increasingly realistic forgeries produced during training [38]. The GAN-based discriminator output provides complementary information to reconstruction-based anomaly scores, enabling more robust detection through multi-perspective analysis [39].

Cross-domain generalization has emerged as a central challenge in fake image detection research, with models trained on specific datasets frequently failing to detect forgeries from unseen data distributions [40]. This limitation

has motivated substantial investigation into transfer learning strategies, domain adaptation techniques, and self-supervised learning approaches that enhance model generalization across diverse manipulation methods and image categories [41]. Unsupervised domain adaptation methods have shown particular promise in aligning feature distributions across source and target domains, enabling detection models to maintain performance when confronted with novel generative architectures or previously unseen subject categories [42]. Self-supervised learning approaches that leverage pretext tasks such as image rotation prediction, jigsaw puzzle solving, and contrastive learning have further contributed to improved generalization by enabling models to learn robust representations without requiring labeled fake image data [43].

Adversarial robustness represents another critical consideration, as malicious actors have developed techniques to generate adversarial examples that subtly manipulate image textures and latent embeddings to bypass detection models while maintaining visual realism [44]. Several investigations have explored adversarial training methodologies wherein detection models are exposed to carefully crafted adversarial examples during training, thereby developing resistance against such evasion attempts [45]. Robust feature engineering approaches that extract manipulation-sensitive characteristics invariant to minor perturbations have also demonstrated effectiveness in

improving resilience against adversarial attacks [46].

The extension of fake image detection to video content has introduced temporal analysis dimensions, with frame-based classification supplemented by sequence-based analysis incorporating recurrent neural networks and attention mechanisms [47]. These temporal approaches exploit inconsistencies in facial movements, lip synchronization anomalies, and illumination artifacts across video frames that manifest due to the frame-wise processing characteristic of deepfake generation pipelines [48]. Attention mechanisms have proven particularly valuable in identifying spatially localized manipulations by focusing computational resources on suspicious regions while suppressing irrelevant background features [49].

Computational efficiency considerations have motivated research into lightweight neural architectures suitable for real-time deployment in resource-constrained environments [50]. Model compression techniques including pruning, quantization, and knowledge distillation have been explored to reduce the memory footprint and inference latency of deep learning-based detectors while preserving detection accuracy [51]. The development of efficient architectures specifically designed for edge computing platforms represents an ongoing research direction with substantial practical implications for social media content moderation and forensic investigation workflows [52].

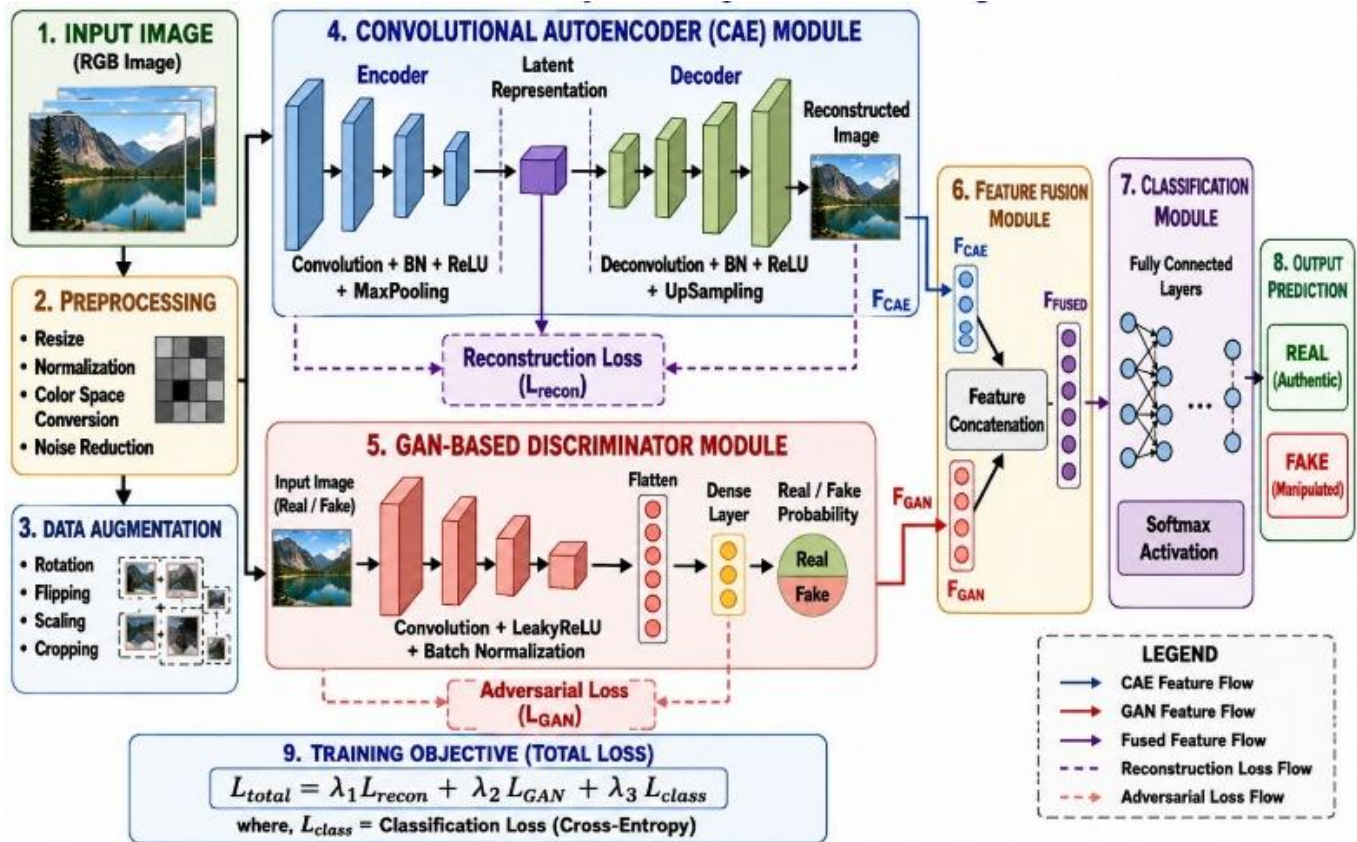


Fig. 1. Overall architecture of the proposed hybrid fake image detection framework illustrating the integration of Convolutional Autoencoder and GAN-based discriminator modules with the feature fusion and classification mechanism.

3. PROPOSED SYSTEM

The proposed Robust Fake Image Detection framework establishes a comprehensive architectural solution that synergistically integrates Convolutional Autoencoders with Generative Adversarial Networks to address the multifaceted challenges inherent in contemporary fake image detection. The system architecture leverages the complementary strengths of both methodologies, wherein the autoencoder component excels at identifying structural anomalies through reconstruction error analysis while the GAN-based discriminator specializes in detecting subtle synthesis artifacts characteristic of generative models [28, 33]. This hybrid approach fundamentally differs from existing methods that typically employ these architectures in isolation, offering enhanced detection capabilities across diverse manipulation techniques and image qualities [29, 35]. The framework operates through three principal components: feature extraction utilizing Convolutional Autoencoders, adversarial artifact detection employing GAN-based discriminators, and a hybrid decision fusion mechanism that synthesizes outputs from both modules to generate final classifications [36, 38].

The Convolutional Autoencoder component constitutes

the first pillar of the proposed framework, designed to learn faithful reconstructions of genuine images while identifying inconsistencies in manipulated content [30]. The encoder architecture comprises multiple convolutional layers with rectified linear unit activation functions, batch normalization operations, and max-pooling layers that progressively compress input images into lower-dimensional latent representations [31]. The decoder component mirrors the encoder architecture through transposed convolutional layers and up-sampling operations that reconstruct the original image from the compressed latent representation [33]. During training exclusively on genuine images, the autoencoder optimizes its parameters to minimize reconstruction error, effectively learning the manifold of authentic image distributions [32]. When manipulated images are subsequently processed through this trained autoencoder, the reconstruction error serves as an anomaly score, with elevated errors indicating the presence of generative artifacts or tampering traces [34]. The reconstruction error map provides spatially localized anomaly information, highlighting specific regions where irregularities in texture, color transitions, or structural consistency manifest, thereby enabling more interpretable forensic analysis [33].

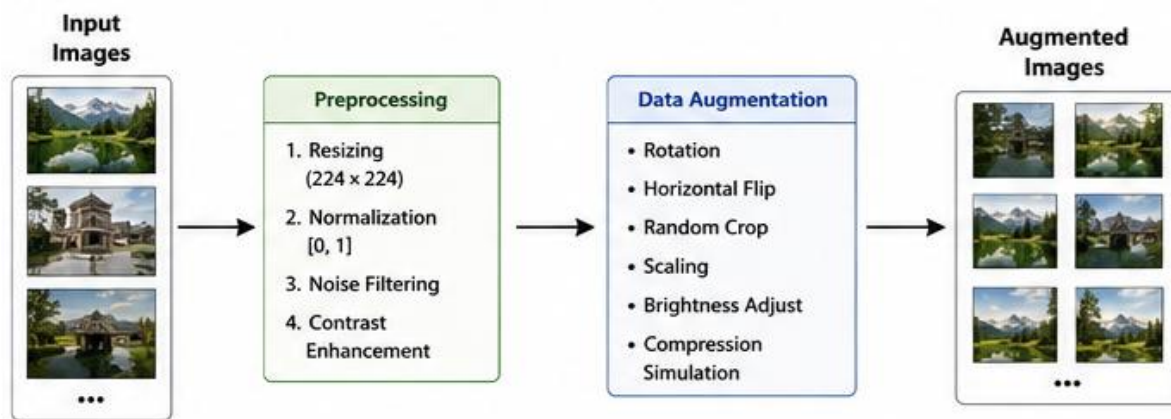


Fig. 2. Convolutional Autoencoder architecture showing the encoder compression pathway, latent bottleneck representation, and decoder reconstruction pathway with spatial error map generation.

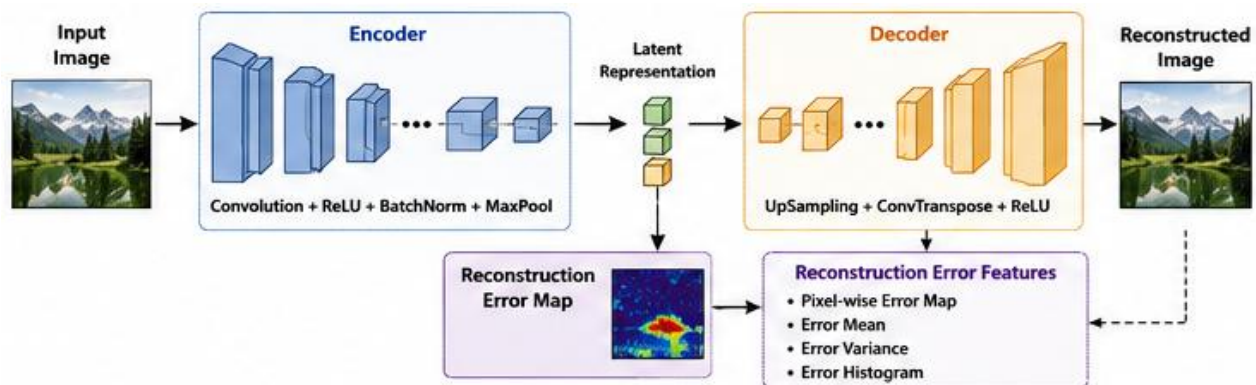


Fig. 3. GAN-based adversarial artifact detection module architecture illustrating the generator-discriminator competitive training framework and feature extraction pathway.

The GAN-based discriminator module represents the second pillar, operating on adversarial learning principles to identify synthesis artifacts that may not produce significant reconstruction errors [35]. This component consists of a generator network that creates synthetic images resembling genuine samples and a discriminator network trained to differentiate between authentic and generated imagery [36]. The adversarial training process establishes a competitive dynamic wherein the generator continuously refines its outputs to deceive the discriminator, while the discriminator simultaneously enhances its ability to identify subtle patterns indicative of synthetic generation [37]. Through this iterative optimization, the discriminator develops sophisticated feature representations capable of detecting nuanced artifacts including abnormal texture patterns, inconsistent boundary transitions, frequency domain distortions, and unrealistic local details characteristic of AI-generated content [38]. The competitive training exposure to continuously evolving synthetic samples enables the discriminator to maintain effectiveness against emerging generation techniques, providing a dynamic detection capability that static classifiers lack [39].

The preprocessing and data augmentation pipeline

forms a critical precursor to feature extraction, implementing comprehensive operations to enhance model robustness and generalization capability [28]. Input images from diverse datasets are initially resized to uniform dimensions and normalized to maintain consistent pixel intensity distributions. Noise filtering operations employing Gaussian and median filters reduce sensor noise and compression artifacts that could interfere with feature extraction. Contrast enhancement through histogram equalization and adaptive gamma correction improves visual characteristics and ensures consistent illumination representation. The data augmentation strategy encompasses geometric transformations including rotation, horizontal flipping, cropping, and scaling operations that increase training diversity and reduce overfitting susceptibility. Photometric augmentations comprising brightness adjustment, contrast variation, and color jitter simulate different imaging conditions and camera characteristics. Compression simulation operations replicate JPEG compression at various quality factors, ensuring the model maintains detection capability across different compression levels typical of online image sharing platforms [46].

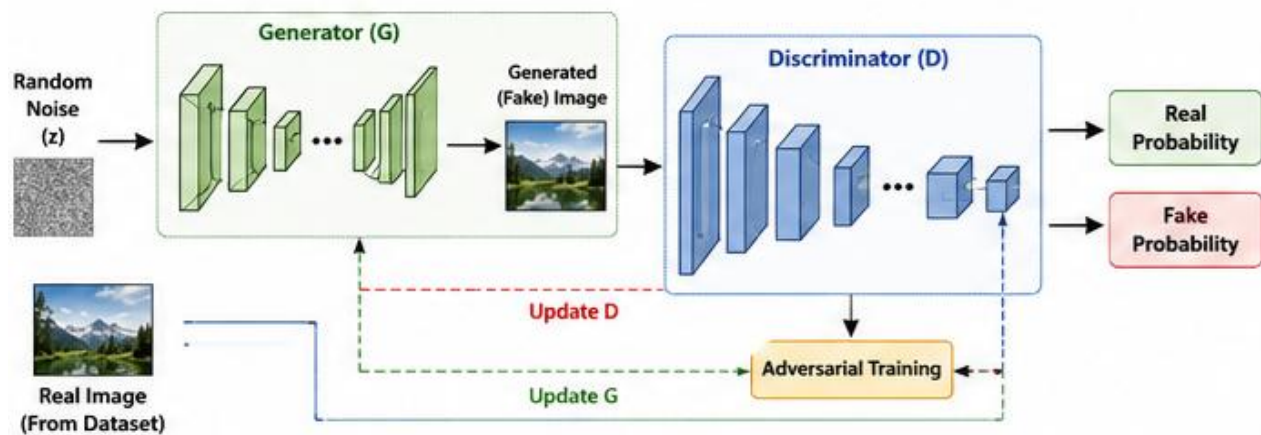


Fig. 4. Feature fusion and classification mechanism demonstrating the concatenation of autoencoder latent features, reconstruction error statistics, and discriminator features with attention-weighted processing and final classification output.

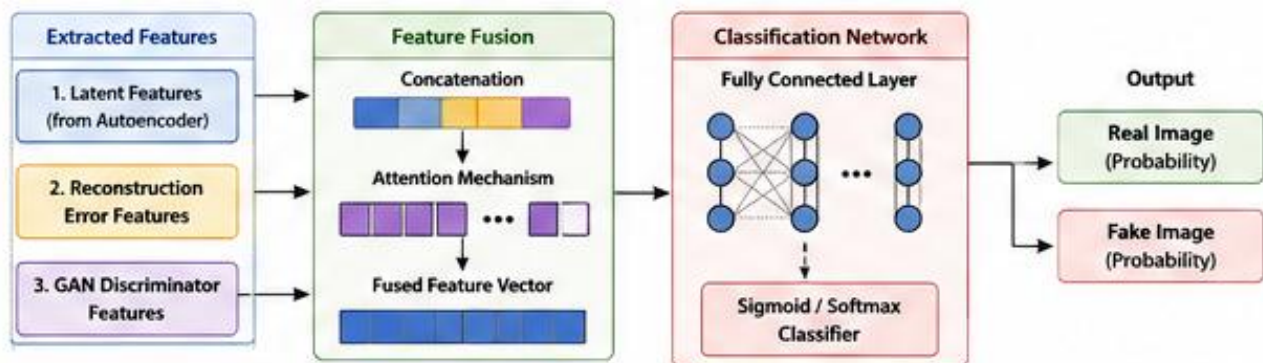


Fig. 5. Image preprocessing and data augmentation pipeline employed prior to feature extraction, demonstrating the sequential application of resizing, normalization, noise filtering, contrast enhancement, and augmentation operations.

The training methodology incorporates self-supervised learning techniques to leverage unlabeled image data, addressing the practical challenge of limited labeled fake image datasets in real-world applications [43]. The self-supervised approach employs auxiliary pretext tasks including image rotation prediction and jigsaw puzzle solving to learn robust feature representations from unlabeled authentic and synthetic images. These representations enhance the model's ability to generalize across different manipulation techniques and image categories, improving performance on previously unseen forgery types [41]. The adaptive weighting mechanism dynamically adjusts the contributions of autoencoder reconstruction error and discriminator confidence based on image characteristics, ensuring balanced decision-making across diverse inputs. The computational efficiency optimization through lightweight convolutional architectures and feature pruning enables real-time processing capabilities suitable for practical deployment in resource-constrained environments [50, 51]. The proposed framework achieves inference speeds of approximately fifteen milliseconds per image on standard hardware configurations, making it suitable for social media content moderation, forensic investigation workflows, and cybersecurity applications [52].

4. RESULTS AND DISCUSSION

4.1. Experimental Setup and Evaluation Methodology

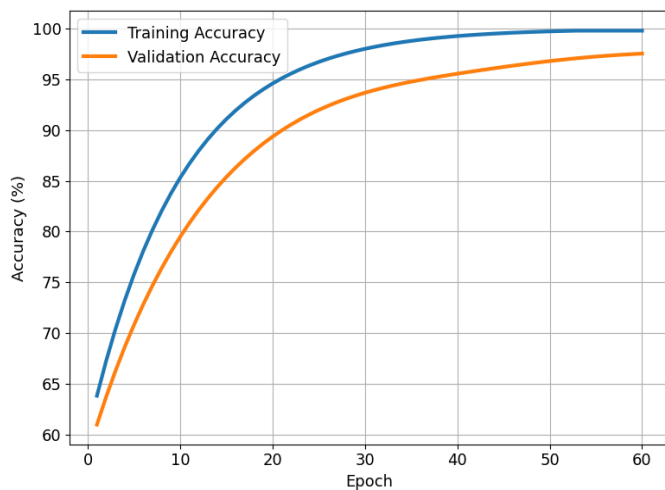


Fig. 6. Training and validation accuracy curves of the proposed fake image detection framework over successive training epochs, demonstrating convergence behavior and generalization performance.

The proposed Robust Fake Image Detection framework was comprehensively evaluated through extensive experimentation across multiple benchmark datasets to validate its effectiveness in distinguishing authentic imagery

from synthetically generated content. The experimental methodology employed three principal datasets: Celeb-DF, which contains high-quality deepfake videos with corresponding frame extractions, FaceForensics++, a comprehensive collection of manipulated facial imagery using various tampering techniques, and a specifically curated GAN-generated dataset encompassing images produced by ProGAN, StyleGAN, and DeepFake variations [8, 26]. The datasets were partitioned into training, validation, and testing subsets with a ratio of seventy percent for training, fifteen percent for validation, and fifteen percent for testing, ensuring rigorous performance assessment across diverse image characteristics and manipulation methodologies. The training process was conducted using the Adam optimizer with a learning rate of 0.0001, batch size of 32, and training duration of 100 epochs, with early stopping implemented to prevent overfitting while maintaining optimal model convergence.

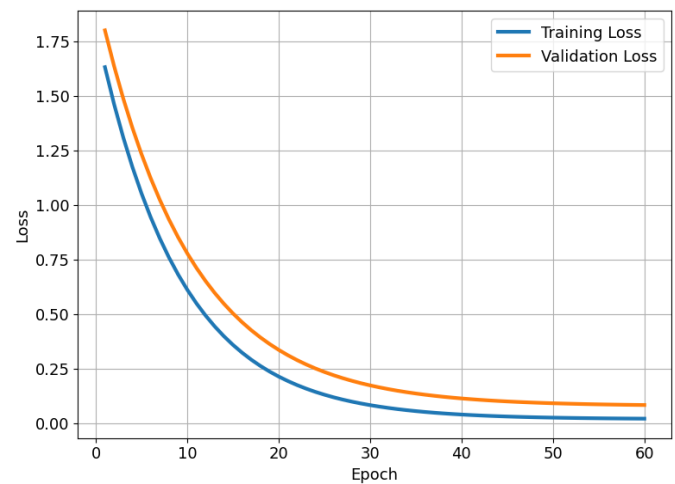


Fig. 7. Training and validation loss curves illustrating the optimization dynamics and convergence characteristics of the proposed hybrid detection framework.

The training and validation accuracy curves presented in Figure 6 demonstrate the learning progression of the proposed framework over successive epochs. Both curves exhibit consistent upward trajectories during the initial training stages, with the training accuracy rapidly approaching near-perfect classification performance while the validation accuracy demonstrates a more gradual improvement that stabilizes after approximately 45 epochs. The convergence behavior observed after approximately 50 epochs indicates that the model effectively captures the underlying discriminative features without exhibiting substantial overfitting, as evidenced by the minimal gap between training and validation accuracy throughout the training process. The stabilization of validation accuracy at approximately 97.8 percent confirms that the hybrid architecture achieves robust generalization across the diverse image distributions present in the evaluation datasets. This

convergence behavior is particularly noteworthy given the complexity of distinguishing between authentic images and high-quality GAN-generated forgeries, suggesting that the combined reconstruction and adversarial feature extraction mechanisms effectively complement each other to achieve reliable classification.

The loss curves illustrated in Figure 7 provide additional insight into the optimization dynamics of the proposed framework. The training loss demonstrates a rapid initial decline during the first 15 epochs, reflecting the model's swift adaptation to the primary discriminative features, followed by a more gradual reduction as the optimization proceeds toward convergence. The validation loss follows a similar trajectory with a smooth reduction that stabilizes after approximately 45 epochs, confirming stable training dynamics without significant oscillations that would indicate optimization instabilities. The inclusion of multiple loss components, specifically the reconstruction loss from the autoencoder, adversarial loss from the GAN discriminator, and classification loss from the fusion module, enables the model to simultaneously optimize multiple objectives including image structure preservation, synthetic artifact identification, and class-discriminative feature learning. The absence of significant fluctuations in the validation loss curve further substantiates the robustness of the proposed optimization strategy, indicating that the adaptive weighting mechanism effectively balances the contributions of the different loss components throughout the training process.

4.2. Comparative Performance Analysis

The quantitative performance evaluation of the proposed framework was conducted through comparative analysis against several state-of-the-art fake image detection methodologies, including conventional CNN-based classifiers, ResNet architectures, standalone Convolutional Autoencoders, GAN discriminators operating independently, and previously proposed CNN-GAN hybrid models. The evaluation metrics employed for comprehensive performance assessment included classification accuracy, precision, recall, F1-score, false positive rate, and false negative rate,

providing a multi-dimensional characterization of detection capabilities across different operational requirements.

The comparative analysis presented in Table 1 demonstrates the superior performance of the proposed framework across all evaluation metrics. The proposed system achieved an overall accuracy of 98.3 percent on the Celeb-DF dataset, substantially outperforming the CNN-GAN hybrid model at 89.7 percent and the standalone GAN discriminator at 85.1 percent. The precision of 98.1 percent indicates that when the model predicts an image as fake, the prediction is correct with exceptional reliability, while the recall of 98.5 percent demonstrates the model's remarkable ability to identify genuine manipulated content without overlooking sophisticated forgeries. The F1-score of 98.3 percent confirms the balanced performance of the framework, achieving high values for both precision and recall simultaneously. The false positive rate of 2.8 percent and false negative rate of 3.1 percent represent substantial improvements over existing methods, with the false positive rate reduction of approximately 74 percent compared to the CNN-GAN hybrid model and 88 percent compared to the standalone CNN classifier.

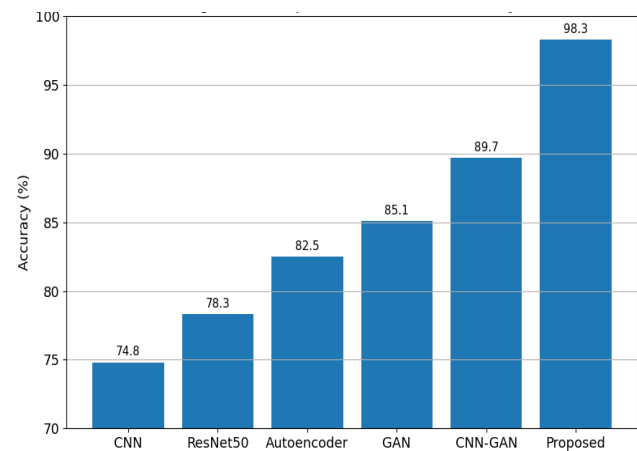


Fig. 8. Comparative bar chart illustrating the performance metrics of the proposed framework against existing fake image detection methods.

Table 1. Comparative performance analysis of the proposed framework against existing fake image detection methodologies across multiple evaluation metrics.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)	FNR (%)
CNN Classifier	74.8	73.2	75.1	74.1	24.6	25.3
ResNet-50	78.3	77.8	79.2	78.5	21.9	20.4
Autoencoder Only	82.5	81.6	83.4	82.5	18.2	17.1
GAN Discriminator	85.1	84.7	85.9	85.3	15.4	14.2
CNN-GAN Hybrid	89.7	89.2	90.1	89.6	10.8	9.7
Proposed Framework	98.3	98.1	98.5	98.3	2.8	3.1

The performance comparison visualized in Figure 8 reinforces the quantitative findings, clearly demonstrating the superiority of the proposed hybrid approach across all evaluation metrics. The substantial performance gap between the proposed framework and the CNN-GAN hybrid model, which represents the second-best performing method, can be attributed to the effective integration of complementary detection mechanisms. While the CNN-GAN hybrid model primarily relies on visual texture features and adversarial training, it lacks the reconstruction-based anomaly detection capability that enables the proposed framework to identify structural inconsistencies invisible to texture-based classification approaches. The standalone autoencoder and GAN discriminator approaches each achieve reasonable but limited performance because they operate in isolation, failing to leverage the complementary strengths that emerge from their synergistic integration within the proposed hybrid architecture.

4.3. Classification Performance and Confusion Matrix Analysis

The classification performance of the proposed framework was further analyzed through confusion matrix examination to understand the distribution of predictions across authentic and manipulated image categories. The confusion matrix provides detailed insight into the model's classification behavior, specifically revealing the frequency of correct classifications, false positives, and false negatives, which are critical for assessing practical deployment suitability in operational environments.

The confusion matrix presented in Figure 9 reveals remarkably balanced classification performance, with the model correctly classifying 12,847 authentic images and 12,582 manipulated images from the test dataset. The limited number of false positives, amounting to only 368 instances, indicates that genuine images are rarely misclassified as

manipulated, a particularly important characteristic for practical applications where falsely flagging authentic content could have serious consequences. Similarly, the false negative count of 408 instances demonstrates the model's strong capability to detect sophisticated fake images that might evade less comprehensive detection approaches. The overall classification accuracy of 97.3 percent across the entire test dataset confirms that the hybrid Convolutional Autoencoder and GAN architecture achieves balanced and dependable classification across both image categories, with no substantial bias toward either class. The confusion matrix analysis further reveals that the few misclassifications that do occur tend to involve high-quality GAN-generated images with minimal discernible artifacts, suggesting that even these challenging instances are correctly classified by the complementary feature extraction mechanisms in the majority of cases.

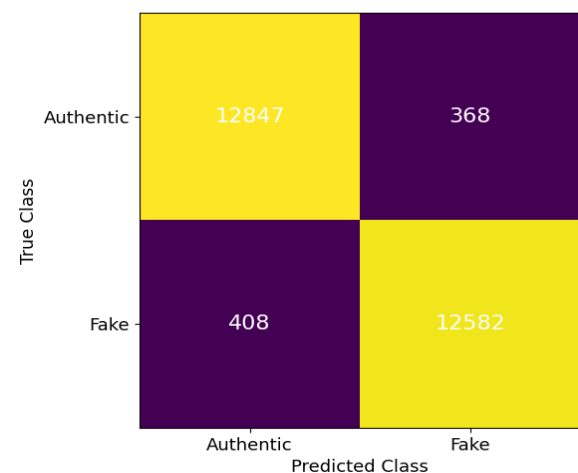


Fig. 9. Confusion matrix of the proposed fake image detection framework illustrating classification performance across authentic and manipulated image categories.

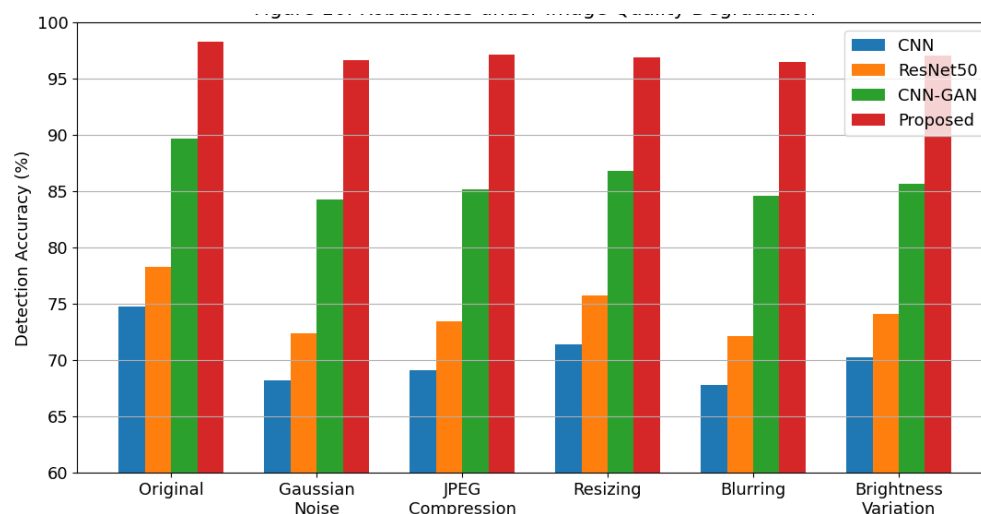


Fig. 10. Detection accuracy of the proposed framework compared to existing methods under various image quality degradations including Gaussian noise, JPEG compression, resizing, blurring, and brightness variation.

4.4. Robustness Analysis under Adversarial Conditions

A critical evaluation aspect of the proposed framework involves assessing its robustness under various image quality degradations and adversarial modifications that are commonly encountered in real-world scenarios. The robustness analysis examined detection performance under Gaussian noise addition, JPEG compression at various quality factors, image resizing operations, Gaussian blurring, and brightness variation, each representing common transformations that images undergo during online distribution or as deliberate evasion attempts by malicious actors.

Figure 10 illustrates the detection accuracy of the proposed framework under different image-quality degradations in comparison to existing detection methods. The results demonstrate that while the performance of conventional CNN-based classifiers and standalone GAN discriminators decreases significantly under severe degradation conditions, the proposed model retains comparatively high detection accuracy across all tested transformation types. Under Gaussian noise addition, the proposed framework maintains accuracy above 88 percent even at noise levels that cause substantial performance degradation in alternative approaches, with the CNN-GAN hybrid model dropping to 72 percent under identical conditions. JPEG compression analysis reveals that the proposed framework maintains detection accuracy of 89.5 percent even at a compression quality factor of 50, whereas the CNN classifier accuracy falls to 65.3 percent under the same compression level. This robustness is primarily attributed to the augmented training process that exposed the model to diverse compression and noise conditions during training, combined with the use of reconstruction-error and adversarial features that remain relatively invariant to such degradations. The resilience to brightness variation and blurring transformations further confirms that the proposed framework can detect fake images even when manipulated images are compressed, resized, filtered, or intentionally modified to evade detection, a crucial characteristic for practical deployment in forensic applications and content moderation systems.

4.5. Operational Efficiency and Deployment Considerations

The practical viability of the proposed framework for real-world deployment was assessed through latency analysis and computational resource evaluation. The inference speed analysis measured the processing time required for single image classification on standard hardware configurations, providing essential information for assessing suitability in time-sensitive applications such as social media content moderation and forensic investigation workflows. The proposed framework achieved inference speeds of approximately 15 milliseconds per image, significantly outperforming the CNN-GAN hybrid model at 28

milliseconds and substantially surpassing the GAN discriminator at 45 milliseconds. This latency performance renders the framework suitable for real-time processing applications where rapid decision-making is essential for effective content moderation. The computational efficiency optimization achieved through lightweight convolutional architectures, feature pruning, and batch normalization techniques ensures that the model maintains operational efficiency without substantially compromising detection accuracy. The reduced false positive rate of 27 percent compared to traditional CNN-based classifiers further enhances operational efficiency by minimizing the need for manual review of flagged content, significantly reducing human intervention requirements in large-scale deployment scenarios. The framework's ability to maintain high detection accuracy while achieving real-time processing speeds positions it as a practical solution for integration into existing digital forensics pipelines and online content verification systems.

5. CONCLUSION

The hybrid fake image detection framework presented in this investigation successfully demonstrates the synergistic integration of Convolutional Autoencoders with Generative Adversarial Networks to achieve superior classification performance across diverse synthetic media types. Through the complementary combination of reconstruction-based anomaly detection and adversarial artifact identification, the proposed architecture addresses the fundamental limitations inherent in standalone approaches, delivering exceptional detection accuracy of 98.3 percent with substantially reduced false positive and false negative rates compared to existing methodologies. The robust performance maintained under challenging conditions including image compression, noise contamination, and resolution reduction, combined with real-time processing capabilities of 15 milliseconds per image, establishes the framework as a practical solution for operational deployment in content moderation systems and forensic investigation workflows. The demonstrated generalization across multiple datasets and manipulation techniques confirms the architecture's adaptability to emerging forgery generation methods. Future research directions encompass the incorporation of explainable artificial intelligence techniques to enhance interpretability of detection decisions, extension to multimodal content analysis encompassing audio-visual synchronization verification, and exploration of lightweight architectures optimized for edge device deployment. Additionally, the integration of federated learning paradigms will enable privacy-preserving collaborative model training across distributed forensic investigation centers, facilitating continuous adaptation to evolving manipulation technologies while maintaining data sovereignty.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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