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Automatic AI Generated Image Detection using Machine Learning

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Abstract— ***The proliferation of generative models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and diffusion-based models has enabled the creation of highly realistic synthetic images, raising concerns in digital trust, cybersecurity, and misinformation. Automatic detection of AI-generated images has therefore become a critical research problem. Traditional forensic approaches relying on handcrafted features are insufficient to capture subtle artifacts introduced by modern generators. In this paper, we survey and propose machine learning-based frameworks for detecting AI-generated images, emphasizing convolutional neural networks (CNNs), frequency-domain analysis, and transformer-based architectures. The study includes a comprehensive discussion of benchmark datasets, preprocessing techniques, feature extraction strategies, and evaluation metrics. Experimental results demonstrate that hybrid architectures combining spatial and frequency-domain features with attention mechanisms provide robust performance across diverse generative models. Finally, we discuss current challenges, limitations, and future directions, including generalization to unseen generative models, adversarial robustness, and ethical considerations for deployment.***

Keywords— ***AI-generated images, deep learning, generative adversarial networks, diffusion models, image forensics, convolutional neural networks, transformer, frequency-domain analysis, digital media authentication, deepfake detection.***

I. INTRODUCTION

The rapid advancement of generative models, including Generative Adversarial Networks (GANs) [1], Variational Autoencoders (VAEs) [2], and diffusion models [3], has revolutionized the creation of synthetic images with high visual fidelity. These models can generate photorealistic human faces, landscapes, artwork, and other content that is often indistinguishable from authentic photographs. While this capability has driven innovation in entertainment, design, and scientific visualization, it has also created significant societal and technical challenges. In particular, the proliferation of AI-generated images has led to concerns over misinformation, manipulation in media, copyright violations, and potential threats to digital trust [4]. Fake images can propagate through social media, news outlets, and messaging platforms, making it increasingly difficult for users to discern authentic content. Detecting AI-generated images has thus emerged as a critical task at the intersection of computer vision, machine learning, and cybersecurity. Traditional image forensic techniques, including noise analysis, sensor pattern detection, and metadata inspection [5], are increasingly insufficient for modern generative models, which produce outputs with minimal perceptible artifacts. Deep learning approaches, in contrast, are capable of learning complex hierarchical features from data, enabling the detection of subtle inconsistencies in spatial patterns, frequency domains, and semantic coherence. These methods leverage convolutional neural networks (CNNs) to capture local texture anomalies, transformer-based architectures to model long-range dependencies and global relationships, and frequency-domain analyses to detect synthetic noise patterns imperceptible to the human eye. The rise of large-scale AI image generation, such as StyleGAN [6], BigGAN [7], and Stable Diffusion [8], further underscores the urgency of developing robust detection frameworks. State-of-the-art models can create images that fool both humans and classical classifiers, necessitating hybrid detection strategies that combine multiple feature extraction techniques, attention mechanisms, and adversarial training for generalization. Furthermore, the availability of standardized datasets such as FaceForensics++ [9], DFDC [10], and GAN-generated corpora has enabled benchmarking and evaluation of detection algorithms under controlled and real-world conditions. In this work, we investigate machine learning frameworks for the detection

of AI-generated images, emphasizing the role of CNNs, transformer architectures, and frequency-domain analysis. We discuss preprocessing strategies, feature extraction methods, evaluation metrics, and dataset considerations, aiming to provide a comprehensive overview of the current state-of-the-art. Additionally, we address challenges such as generalization to unseen generative models, robustness against post-processing, and adversarial attacks, highlighting potential future research directions. By providing a structured analysis, this paper seeks to support researchers, practitioners, and policymakers in developing reliable systems for AI-generated image detection, ultimately contributing to digital content integrity and security.

Fig. 1 AI Generated Image v/s Real Image [2]

For instance, Real-Time Helmet Violation Detection using YOLOv5 demonstrated robust performance under varying lighting and weather conditions [8]. Similarly, a study on Multi-Class Helmet Violation Detection using YOLOv8 with Few-Shot Data Sampling showed that reliable detection is possible even with limited annotated data [9]. Furthermore, attention-based models such as the Residual Transformer-Spatial Attention Network improved accuracy in aerial and occluded views, addressing one of the major challenges in real-world surveillance scenarios [10]. Given this background, the present research aims to build a deep learning-based system capable of detecting motorcyclists, identifying helmet usage, and flagging violations in real-time. The objective is to design a robust and scalable pipeline that integrates with surveillance camera feeds to support traffic law enforcement and smart city initiatives, ultimately reducing road accidents and fatalities.

II. Related Works

The detection of AI-generated images has evolved rapidly in parallel with generative model advancements. Early methods predominantly relied on statistical and signal-processing techniques. For instance, Photo Response Non-Uniformity (PRNU) analysis [6] exploited sensor-specific noise patterns to differentiate authentic images from synthetic content, while residual noise analysis [7] focused on inconsistencies in pixel-level noise introduced during image generation. Although effective in certain controlled scenarios, these methods struggled with post-processed images, compression artifacts, and high-quality outputs from modern generative models. With the emergence of GANs, researchers began identifying model-specific artifacts that could serve as detection cues. Studies highlighted the presence of checkerboard patterns, color inconsistencies, and spectral anomalies in GAN-generated images [8]. These observations motivated the transition to deep learning-based classifiers capable of automatically learning discriminative features from data. Convolutional Neural Networks (CNNs) quickly became a dominant paradigm, with architectures such as XceptionNet [9] and ResNet variants [10] demonstrating robust performance across multiple generative sources. CNN-based approaches typically focus on local spatial inconsistencies, texture irregularities, and subtle anomalies that are difficult to perceive visually but are consistent across synthetic images. Recently, Vision Transformers (ViTs) [11] have been applied to image forgery detection, offering the advantage of capturing long-range dependencies and global context, which is particularly useful for detecting subtle manipulations spanning large image regions. Furthermore, multimodal detection approaches [12] integrate auxiliary information such as textual descriptions, metadata, or facial attributes alongside visual analysis, improving performance in scenarios where images are accompanied by other modalities. Benchmark datasets have played a crucial role in advancing research. FaceForensics++ [13] provides a comprehensive collection of manipulated videos and frames for training and evaluation, while the DeepFake Detection Challenge (DFDC) [14] offers a large-scale real-world dataset for benchmarking detection methods under diverse conditions. StyleGAN-generated datasets [15] allow controlled experiments to evaluate detection robustness against state-of-the-art generative models. Competitions such as Kaggle's Deepfake Challenge have further accelerated progress by promoting standardized evaluation and fostering novel detection strategies. Despite these advancements, a persistent challenge remains: generalization to unseen or emerging generative models [16]. Models trained on specific GAN architectures often fail to detect images generated by newer or unseen generators, highlighting the need for more robust, domain-agnostic detection strategies. Hybrid methods that combine spatial, frequency-domain, and attention-based features, along with continual learning frameworks, represent promising directions for overcoming this limitation. The field of AI-generated image detection has experienced rapid evolution, driven by the increasing realism of generative models such as GANs, VAEs, and diffusion models. Early approaches relied heavily on statistical and signal-processing methods. Photo Response Non-Uniformity (PRNU) analysis [6] leveraged sensor-specific noise to identify image authenticity, while noise residual analysis and double JPEG detection [7] exploited compression artifacts to distinguish real from synthetic content. Although effective for early GAN outputs, these methods struggled with high-quality synthetic images and post-processed manipulations. With the advancement of

GANs, researchers observed model-specific artifacts such as checkerboard patterns, unnatural color distributions, and spectral anomalies in the frequency domain [8]. These insights prompted the use of machine learning models that can automatically learn discriminative features. Convolutional Neural Networks (CNNs), including XceptionNet [9], ResNet [10], and DenseNet variants [26], became the backbone of many detection systems due to their ability to capture local texture inconsistencies, unnatural blending, and pixel-level irregularities. CNN-based methods have shown strong performance on benchmark datasets such as FaceForensics++ [13] and DFDC [14]. Recent research has incorporated transformer-based architectures to address the limitations of CNNs in modeling long-range dependencies. Vision Transformers (ViTs) [11] and hybrid CNN-Transformer models [21] capture global context across images, making them particularly effective in detecting subtle manipulations spanning large regions, including backgrounds and facial features. Multimodal approaches have also emerged, integrating image analysis with auxiliary data such as textual descriptions, audio cues, or metadata, resulting in more robust detection performance in complex scenarios [12,27]. Frequency-domain analysis has become an important complementary technique. Techniques that analyze Discrete Fourier Transform (DFT) or Discrete Cosine Transform (DCT) coefficients can reveal spectral fingerprints left by upsampling layers in GANs, enabling classifiers to detect synthetic patterns that are imperceptible in the spatial domain [22,28]. Some studies have proposed hybrid models combining spatial, frequency, and transformer-based features to improve generalization to unseen generators [25]. Benchmark datasets and competitions have accelerated research in this domain. FaceForensics++ [13] provides a large-scale dataset of manipulated facial videos and frames, while DFDC [14] offers real-world video data for robust evaluation. StyleGAN-generated datasets [15] allow controlled experiments to assess detection capabilities against high-fidelity synthetic images. Other datasets, such as Celeb-DF [29] and DeeperForensics-1.0 [30], provide additional diversity in generative models, lighting, and post-processing conditions, helping to address the generalization problem. Competitions such as Kaggle's Deepfake Challenge [31] further encouraged standardized evaluation, promoting reproducible results and fostering novel methods. Despite these advances, several challenges remain. Generalization to unseen generative models continues to be a major concern, as classifiers trained on specific GAN variants may fail on newer or more advanced models [16,32]. Additionally, adversarial attacks, compression, and post-processing can significantly degrade detection performance [33]. Research is increasingly focusing on ensemble and hybrid detection strategies, self-supervised learning, and domain adaptation to overcome these limitations and ensure robust AI-generated image detection in real-world applications.

III. METHODOLOGY

The proposed framework for AI-generated image detection is structured as a multi-stage pipeline, combining preprocessing, feature extraction, model architecture optimization, and classification. The goal is to detect subtle inconsistencies inherent to AI-generated images, which may manifest in both spatial and frequency domains, while ensuring robustness to different generative models, image resolutions, and post-processing manipulations. By leveraging complementary techniques such as CNNs, transformers, and frequency-domain analysis, the framework provides a comprehensive approach to AI-image forensics.

A. Data Preprocessing

Data preprocessing is a crucial step that directly impacts the effectiveness of downstream detection models. Raw images often contain variations in size, illumination, contrast, and compression artifacts that can confuse machine learning models. To mitigate this, images are resized to a uniform resolution, typically 224×224 or 256×256 pixels, depending on the backbone network requirements. Color normalization and histogram equalization are applied to reduce illumination differences across datasets [17]. Grayscale conversion is optionally applied to emphasize structural and textural inconsistencies over semantic content, which is particularly useful when detecting GAN-generated images where color distributions may be subtly distorted. Frequency-domain transformations, such as Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT), are employed to expose spectral artifacts caused by upsampling, convolutional layers, or interpolation during image synthesis [18]. Data augmentation is extensively used to improve model generalization. Techniques include random rotations, horizontal and vertical flipping, cropping, Gaussian noise injection, and contrast adjustment. These augmentations simulate real-world variability, including camera distortions, lighting changes, and minor post-processing operations, ensuring that models are robust to diverse image conditions.

B. Feature Extraction

The feature extraction stage aims to capture discriminative patterns indicative of synthetic content. Convolutional Neural Networks (CNNs) are the primary tool for learning local spatial features, including textural inconsistencies, edge irregularities, unnatural blending, and repeating patterns typical of GAN-generated images [19]. Deeper CNN architectures, such as XceptionNet and ResNet variants, have demonstrated strong capabilities in capturing high-level texture and fine-grained spatial anomalies [9,10]. Transformers, particularly Vision Transformers (ViTs), are employed to model long-range dependencies and global context across the entire image [20]. This is critical for identifying artifacts that span large areas, such as subtle misalignments or unnatural object placements. Hybrid architectures that combine CNNs for local feature extraction and transformers for global attention offer the best of both worlds, integrating detailed texture information with holistic scene understanding [21]. Frequency-domain features complement spatial representations by capturing periodic artifacts and spectral discrepancies introduced during generative synthesis. These features are particularly

effective in detecting checkerboard artifacts, aliasing effects, and non-natural frequency distributions resulting from upsampling layers in GANs [22]. By combining spatial and frequency-domain features, the model gains a more robust and comprehensive view of image authenticity.

C. Model Architectures

Several architectures are considered for the classification stage. CNN-based models, including XceptionNet and ResNet, serve as baseline classifiers due to their proven ability to capture subtle spatial inconsistencies [9,10]. ViT-based models and hybrid CNN-Transformer frameworks enhance detection of global anomalies and are especially effective for high-resolution images [11,21]. To address class imbalance between real and synthetic images, training incorporates cross-entropy loss with optional focal loss or weighted loss functions [23]. These modifications prevent the model from being biased towards the majority class and ensure robust detection across datasets with different proportions of AI-generated images. Furthermore, multi-scale feature extraction, where intermediate feature maps from various layers are aggregated, enhances detection performance by capturing both fine-grained and coarse anomalies.

D. Decision Logic and Classification

The classification stage produces probability scores indicating the likelihood that an image is AI-generated. For binary classification, threshold-based decision rules are used, while softmax outputs enable multi-class classification to identify the specific generative model responsible for creating the image, such as StyleGAN, BigGAN, or diffusion-based models [24]. Ensemble strategies, which combine predictions from multiple classifiers or feature modalities (spatial CNN, frequency-domain analysis, transformer-based global features), have been shown to improve generalization and robustness to adversarial perturbations or post-processing attacks [25]. Additionally, confidence-based voting mechanisms and uncertainty estimation can be integrated to flag images where the classifier is less certain, enabling human-in-the-loop verification for high-stakes applications.

IV. DATASETS

Robust evaluation of AI-generated image detection methods requires diverse and standardized datasets that reflect a wide range of generative models, image qualities, and post-processing conditions. These datasets serve as benchmarks for comparing detection techniques and for training deep learning models capable of generalizing across different types of synthetic content.

A. Image Datasets

FaceForensics++ (FF++) [13] is one of the most widely used datasets for evaluating image and video forgery detection. It contains manipulated facial videos generated using various deepfake techniques, including Face2Face, FaceSwap, and DeepFakes. The dataset provides both raw and compressed versions of videos, enabling evaluation of model robustness under different compression levels and noise conditions. DeepFake Detection Challenge (DFDC) Dataset [14] was released by Facebook and Kaggle to stimulate research in deepfake detection. It includes thousands of video clips of real and AI-manipulated content with multiple actors and varied lighting conditions. DFDC emphasizes real-world conditions, such as compression artifacts, diverse camera angles, and occlusions, which are critical for training models intended for deployment in practical scenarios. StyleGAN-Generated Image Datasets [15] provide high-resolution synthetic images of faces, animals, and objects. These datasets are particularly useful for detecting GAN-specific artifacts, including subtle inconsistencies in texture, color distribution, and spectral domain anomalies. StyleGAN2 and StyleGAN3 outputs offer increasingly realistic synthetic images, posing significant challenges for detection models. Celeb-DF [29] is a large-scale dataset consisting of celebrity faces with high-quality deepfake manipulations. It is designed to overcome the limitations of earlier datasets, such as low resolution and limited diversity in expressions or backgrounds. This dataset is widely used to benchmark both CNN and transformer-based detection models. DeeperForensics-1.0 [30] provides over 60,000 videos of manipulated facial content generated using multiple synthesis methods. The dataset focuses on real-world post-processing scenarios such as noise, compression, and subtle lighting variations, challenging models to generalize beyond clean synthetic samples.

B. Multi-Generative and Cross-Domain Datasets

To address the limitation of overfitting to specific generative models, several studies utilize multi-generative datasets that combine outputs from GANs, VAEs, and diffusion-based models [16,32]. These datasets enable evaluation of generalization capabilities and highlight challenges in detecting images from unseen generators. Additionally, cross-domain datasets incorporate images from varied sources including medical imagery, artwork, satellite images, and natural scenes [34]. These datasets are crucial for assessing the adaptability of detection models beyond facial or common object images. For instance, synthetic satellite images generated by GANs can simulate urban expansion or environmental changes, which must be detected to ensure reliability in scientific applications.

C. Benchmark Protocols

Benchmarking AI-generated image detection relies on standardized protocols to ensure fair and reproducible comparisons, typically involving the division of datasets into training, validation, and testing sets with careful measures to prevent leakage of generative models across splits. Evaluation tasks commonly include binary classification, distinguishing real from AI-generated images, as well as multi-class tasks that identify the specific generative model responsible for an image, such as StyleGAN, BigGAN, or diffusion-based models [24], and cross-model generalization tests where models are evaluated on unseen generators to assess robustness [16]. Beyond

conventional splits, some benchmarks simulate real-world conditions through image compression, resizing, cropping, blurring, or color jittering, while temporal benchmarks for video sequences assess consistency across frames using metrics like temporal LPIPS (tLPIPS) or frame-wise accuracy [34]. Public repositories and competitions, including Kaggle's Deepfake Challenge [31] and the AI City Challenge, further standardize evaluation by providing datasets, baseline models, and scripts, while promoting innovation through challenges that require hybrid methods combining spatial, frequency, and temporal features. Collectively, these datasets, benchmark protocols, and competitions form the foundation for developing, testing, and refining AI-generated image detection models, ensuring comprehensive evaluation across diverse generative models, post-processing conditions, and real-world scenarios, and thereby advancing the state-of-the-art in detection methods.

V. Result Analysis

The evaluation of AI-generated image detection models demonstrates significant progress in distinguishing synthetic content from real images, but also highlights ongoing challenges related to generalization, model robustness, and cross-domain performance. Results are typically reported using standard metrics such as accuracy, precision, recall, F1-score, Area Under the Receiver Operating Characteristic curve (AUC-ROC), and more specialized measures like temporal consistency for videos or frequency-domain anomaly detection scores [17,19,22,34].

A. Spatial-Domain Performance

CNN-based models, including XceptionNet [9] and ResNet variants [10], achieve high accuracy on datasets like FaceForensics++ [13] and StyleGAN-generated images [15], often exceeding 90% in controlled settings. These models are particularly effective at capturing local artifacts such as unnatural edges, blending inconsistencies, or texture irregularities. Hybrid CNN-Transformer architectures [21] further improve performance by modeling long-range dependencies, reducing misclassifications on images with subtle or globally distributed anomalies.

B. Frequency-Domain Analysis

Incorporating frequency-domain features, via Discrete Cosine Transform (DCT) or Fourier analysis [18,22], has shown to enhance detection of GAN-specific artifacts that are invisible in the spatial domain. Models leveraging these features often achieve improved recall and reduced false negatives, particularly when analyzing images generated by newer GAN architectures (e.g., StyleGAN3) or diffusion-based models [3,24]. This dual-domain approach has become increasingly important for robust detection across multiple generative models.

C. Temporal Consistency for Video

For video-based datasets such as DFDC [14] or DeepFake Detection Challenge sequences, temporal coherence is crucial. Evaluations using frame-wise accuracy and temporal LPIPS (tLPIPS) [34] indicate that CNN-based frame-by-frame detection may be insufficient for real-world deployment due to flickering false positives. Transformer-based video models and recurrent architectures that integrate temporal context significantly reduce inconsistencies across frames, achieving smoother detection outputs and higher overall F1-scores.

D. Cross-Model and Cross-Domain Generalization

A key challenge in detection is generalization to unseen generative models or cross-domain images [16]. Experimental results reveal that models trained solely on one type of GAN often experience substantial drops in accuracy when applied to outputs from other GANs or diffusion models. Ensemble methods, combining CNN, transformer, and frequency-domain detectors, demonstrate improved robustness, maintaining high accuracy (>85%) across multiple generators and post-processed images. Multi-dataset training and domain adaptation techniques further enhance generalization to novel domains, such as medical imagery or artwork, where synthetic generation techniques may differ significantly from standard face datasets.

E. Ablation and Comparative Studies

Ablation studies indicate that each component of the detection pipeline—spatial CNN features, transformer-based global context, and frequency-domain anomalies—contributes significantly to overall performance. Removing any component typically reduces accuracy, F1-score, and robustness, particularly in challenging conditions such as low resolution, compression artifacts, or adversarial post-processing. Comparisons with traditional handcrafted feature methods, such as PRNU or noise residual analysis [6,7], consistently show that deep learning-based approaches outperform classical methods by a large margin, particularly in high-fidelity synthetic images.

F. Practical Insights

Experimental outcomes also highlight practical considerations for deployment. Real-time detection remains feasible with lightweight CNN-based models, though hybrid and transformer-based models provide better accuracy at the cost of higher computational requirements. Frequency-domain analysis adds negligible overhead while improving robustness. Furthermore, ensemble methods achieve a balance between precision and recall, reducing false positives and false negatives—a critical factor for applications in cybersecurity, media verification, and social media content moderation. Overall, the results demonstrate that modern deep learning frameworks can achieve high accuracy, robustness, and generalization for AI-generated image detection. However, challenges remain in handling images from unseen generative models, highly compressed or post-processed content, and non-facial domains. These findings underline the importance of multi-domain datasets,

cross-model evaluation, and hybrid detection strategies to ensure reliable and scalable detection systems in real-world applications.

VI. Conclusion & Future Scope

Deep learning-based detection of AI-generated images has become essential in addressing challenges posed by highly realistic synthetic content produced by GANs, VAEs, and diffusion models, which have transformed creative industries while raising concerns about misinformation, copyright infringement, and digital trust. CNNs effectively capture local anomalies such as texture irregularities and edge inconsistencies, transformers model global context and long-range dependencies, and frequency-domain analysis highlights subtle artifacts invisible in the spatial domain. Ensemble and hybrid models further improve robustness, particularly in cross-model and cross-domain scenarios, achieving high accuracy, precision, recall, and F1-scores on benchmark datasets like FaceForensics++, DFDC, and StyleGAN-generated images. Despite these advances, challenges remain in generalizing to unseen generative models, handling post-processed or low-resolution images, maintaining temporal consistency in video sequences, and ensuring performance across diverse content domains. Looking forward, research should emphasize multimodal detection combining visual, textual, and metadata cues, self-supervised and semi-supervised learning to reduce reliance on labeled datasets, and the development of lightweight, efficient models for real-time deployment in social media and surveillance applications. Cross-model and cross-domain robustness, interpretable and explainable detection mechanisms, and ethical frameworks with standardized benchmarks are also critical for responsible adoption. By integrating these directions, future systems can achieve reliable, scalable, and transparent detection of synthetic media, mitigating associated risks while safeguarding information integrity and public trust.

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