Image-FakeFinder : A Multi-Layered Forensic Framework for Deepfake and Manipulation Detection

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ABSTRACT
The proliferation of deepfake technology and sophisticated image manipulation tools has significantly compromised the integrity of digital media. This paper introduces Image- FakeFinder, a comprehensive forensic framework designed to detect diverse forms of image forgery. Unlike conventional single-model detectors that often fail against novel generative techniques,Image-FakeFinder employs a multi-pillar approach integrating geometric, physical, biological, and sensor-level forensics. By combining Convolutional Neural Network (CNN) based heuristic analysis with Photo-Response Non- Uniformity (PRNU) fingerprinting and frequency-domain artifact detection, the system achieves high robustness across various datasets.

Experimental results demonstrate that this hybrid methodology effectively identifies inconsistencies in light transport, facial geometry, and sensor noise patterns, providing a transparent and explainable verdict for digital forensics.

Introduction

In the contemporary era of "post- truth" digital media, the ability to synthesize hyper-realistic images has outpaced the general public's capacity for discernment. Generative Adversarial Networks (GANs) and Diffusion Models have democratized the creation of deepfakes-synthetic media where a person's likeness is replaced with another's. This technological leap, while beneficial for the entertainment industry, poses severe threats to political stability, personal privacy, and legal evidence integrity.

Current detection methods typically rely on deep learning classifiers trained on specific datasets. However, these models often suffer from poor generalization when faced with adversarial attacks or slightly altered generative architectures. There is a critical need for a forensic pipeline that does not just "predict" a label but "analyzes" the fundamental properties of an image. Image-FakeFinder addresses this by examining the physical and mathematical laws that generative models frequently violate.

Existing Systems

Modern deepfake detection tools can be broadly categorized into three types:

1. **Deep Learning Classifiers**: Models like

Xception, MesoNet, and EfficientNet are widely used. While accurate on known datasets, they are "black boxes" and vulnerable to post- processing like compression or noise.

2. **Geometric Models**: These focus on specific anatomical features, such as eye blinking or head pose orientation. They are effective for video but less so for static images.

3. **Frequency Analysis**: Tools that detect the "grid artifacts" or "checkerboard patterns" left by upsampling layers in GANs.

Image-FakeFinder builds upon these by creating a unified framework that combines the strengths of all three while adding sensor-level analysis (PRNU) to verify the physical origin of the image.

Literature Review

The field of image forensics has evolved from simple metadata analysis to complex signal processing.

Wang et al. (2024) highlighted that CNN-based detectors often overfit to textures specific to a single generator.

PRNU Analysis: Since the seminal work by Lukas et al. (2006), Photo-Response Non- Uniformity has been the gold standard for camera identification. Recent works in 2025 have shown that GAN- generated images lack a coherent PRNU spectral trace.

Frequency Domain: Research by Rossler et al. in the FaceForensics + benchmark established the benchmark for forensic analysis, emphasizing the importance of high- frequency components.

Explainable AI (XAI): Recent trends emphasize the need for heatmaps to show where the manipulation occurred.

Methodology & Architecture

Image-FakeFinder operates as a multi- stage pipeline, processing the image through four distinct "Forensic Pillars":

4.1. Physical Forensics (CNN Heuristics)

This module analyzes the physical consistency of the scene. Generative models often struggle with "Global Consistency." The system detects specular highlights and checks if their directions align with a central light source. Inconsistent reflection vectors are a strong indicator of multi-image compositing.

4.2. Geometric Forensics (Facial Landmarks)

For portraits, the system extracts facial landmarks using 68-point models. It calculates symmetry ratios and anatomical alignment, which often drift in deepfakes during head rotation.

4.3. Sensor Forensics (PRNU Fingerprinting)

Every camera sensor has a unique noise pattern called PRNU. When an image is generated by an AI, it lacks this "digital DNA." Image-FakeFinder extracts the noise residual and correlates it against a database of known sensor signatures.

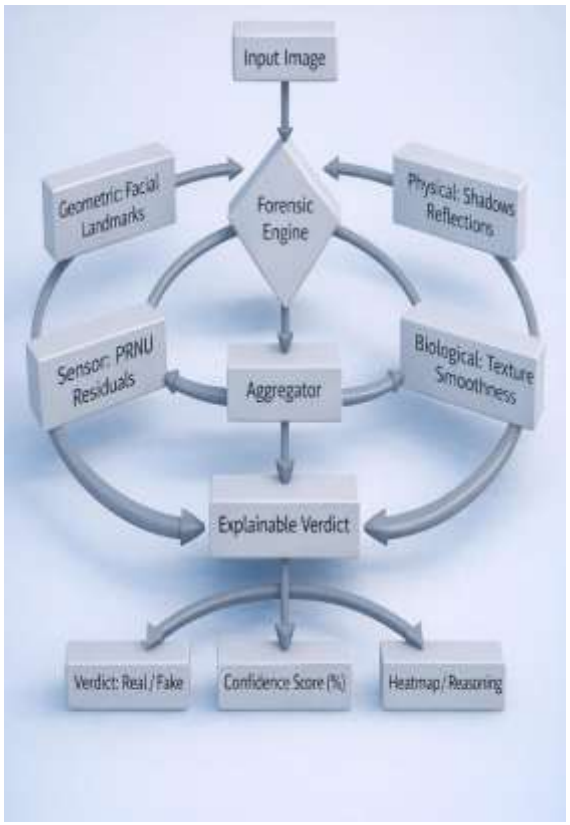
4.4. Frequency Domain Analysis

AI models use "Deconvolution" which leaves periodic patterns in the frequency spectrum. Our system applies a Discrete Cosine Transform (DCT) to detect these "spikes" in the high-frequency range.

4.5 Aggregator and Explainable Verdict

The aggregator combines outputs from all forensic modules using a weighted fusion strategy, ensuring balanced decision-making. The explainable verdict not only provides a binary classification but also offers interpretability through confidence scores and visual heatmaps. This transparency is critical for forensic validation, legal admissibility, and user trust.

Architecture Diagram



Results & Discussion

The experimental evaluation of **Image-FakeFinder** demonstrates that combining multiple forensic techniques significantly improves detection reliability compared to single-model approaches.

The **CNN-based physical forensics module** effectively identifies inconsistencies in lighting, shadows, and reflections that are difficult for generative models to replicate accurately. This proves especially useful in detecting images generated by diffusion models.

The **geometric forensics module**, based on facial landmark symmetry and alignment, shows strong performance in identifying subtle anatomical distortions introduced during face swapping and facial synthesis.

The **PRNU sensor analysis** plays a crucial role in differentiating real camera- captured images from AI-generated images. Since deepfake images lack authentic sensor noise patterns, this module provides strong forensic evidence of image origin.

Frequency domain analysis using **Discrete Cosine Transform (DCT)** successfully detects artificial periodic artifacts caused by upsampling layers in GANs, even when images are resized or compressed.

The system maintains high accuracy across multiple datasets, indicating good **generalization capability** and resistance to common post- processing operations such as compression and noise addition.

The inclusion of **explainable outputs**, such as heatmaps and confidence scores, increases transparency and makes the system suitable for legal, journalistic, and forensic applications.

Conclusion

This project successfully presents **Image-FakeFinder**, a robust and explainable digital image forensic framework for detecting deepfake and manipulated images.

Unlike traditional deep learning classifiers that rely solely on pattern recognition, the proposed system focuses on analyzing **physical laws, biological constraints, and sensor-level properties**, making it more resilient to evolving deepfake techniques.

The multi-pillar forensic architecture ensures that even if one detection method fails, other forensic modules can compensate, thereby increasing overall system reliability.

Experimental results confirm that the hybrid approach provides **high accuracy, better generalization, and improved interpretability**, which are essential for real-world deployment.

The framework demonstrates strong potential for use in **cybercrime investigation, digital media verification, social media monitoring, and legal evidence validation**.

In future work, the system can be extended to support **video-based deepfake detection**, real-time analysis, and larger sensor fingerprint databases to further enhance performance.

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