FROM PIXELS TO PROVENANCE: HARNESSING SOURCE CAMERA FINGERPRINTS TO DETECT AI-CREATED IMAGES

ABSTRACT

The rapid advancement of generative artificial intelligence (AI) has revolutionized digital media creation, enabling the synthesis of highly realistic images that are virtually indistinguishable from authentic photographs. While these technologies empower creativity, they also pose significant challenges to digital forensics, misinformation detection, and intellectual property validation. This study introduces a Source Camera Fingerprint (SCF)-based Forensic Framework for detecting AI-generated images through intrinsic sensor pattern analysis. The proposed model leverages convolutional neural networks (CNNs) to extract photo-response non-uniformity (PRNU) patterns from authentic images and compares them with residual noise inconsistencies typical of generative models. Experimental results demonstrate that the SCF framework achieves 96.8% accuracy in distinguishing AI-created content from real photographs while maintaining interpretability through gradient-based visualization. This research bridges the gap between digital provenance verification and AI image forensics, ensuring authenticity in an increasingly synthetic visual world.

Keywords: AI Forensics, Image Authentication, Source Camera Fingerprint, Deep Learning, PRNU Analysis, Generative Models, Synthetic Media Detection.

EXISTING SYSTEM

Existing forensic systems primarily rely on content-based feature analysis or deepfake detection algorithms that focus on visible artifacts such as texture irregularities or color discrepancies. While these approaches perform adequately on older generative models, they falter when confronted with high-resolution diffusion-generated images that exhibit realistic sensor-like noise. Moreover, conventional methods depend heavily on large labeled datasets for training, limiting scalability across diverse generative architectures.

In many current systems, deep learning models such as CNNs or autoencoders are employed to classify images as real or fake. However, these models lack physical interpretability since they do not consider the sensor-level properties that differentiate AI images from camera-captured photographs. As a result, they often misclassify post-processed or compressed images and are vulnerable to adversarial manipulations designed to conceal synthetic origins.

Additionally, the absence of visualization or interpretability limits forensic transparency. Security professionals and law enforcement agencies require verifiable reasoning to support authenticity claims. Without explainable evidence—such as feature maps or fingerprint correlations—AI-based classifiers cannot meet the standards of forensic validation required in investigative or judicial environments.

Disadvantages of Existing System

- 1. Lack of Physical Basis: Most models rely on visual features instead of intrinsic sensor characteristics, reducing detection reliability.
- 2. Poor Generalization: Existing classifiers fail to adapt to new or unseen AI generative architectures.
- 3. Opaque Decision-Making: Absence of interpretability prevents validation and hinders trust in forensic outcomes.

PROPOSED SYSTEM

The proposed Source Camera Fingerprint (SCF)-Based Forensic Framework offers a robust and interpretable solution for detecting AI-generated images by combining physical sensor fingerprinting with deep learning-based pattern analysis. The system leverages Photo-Response Non-Uniformity (PRNU)—a unique sensor-specific noise pattern inherent to every digital camera—to establish the provenance of an image. Since AI-generated images lack such optical signatures, deviations in noise distribution can serve as definitive indicators of synthetic origin.

The architecture comprises three major stages. The first stage performs noise residual extraction using wavelet-based denoising filters to isolate the PRNU signal from image content. The second stage employs a Convolutional Neural Network (CNN) trained on genuine and synthetic PRNU residuals to identify characteristic discrepancies. The third stage integrates Grad-CAM visualization to highlight areas where the model detects inconsistencies, providing interpretable evidence of image authenticity.

To enhance resilience against compression and scaling, the system incorporates an adaptive preprocessing pipeline that normalizes image resolution and illumination. A hybrid loss function combining binary cross-entropy and texture similarity ensures that both classification accuracy and PRNU consistency are optimized during training. This allows the model to generalize effectively across different datasets and generative models, including GANs and diffusion-based architectures.

Experimental results demonstrate that the proposed SCF framework achieves 96.8% classification accuracy, outperforming existing CNN-based detectors by a notable margin. The Grad-CAM heatmaps clearly visualize the specific pixel regions where sensor inconsistencies occur, providing transparent justification for the model's decisions. This interpretability not only enhances forensic reliability but also enables human experts to corroborate the findings with physical evidence.

Advantages of Proposed System

- 1. Physically Grounded Detection: Utilizes camera-specific PRNU signatures, ensuring robust distinction between real and AI-generated images.
- 2. High Accuracy and Adaptability: Combines statistical fingerprinting with CNN learning to maintain accuracy across multiple generative models.
- 3. Explainable Forensic Insight: Employs Grad-CAM visualizations to provide interpretable, verifiable evidence of authenticity.

SYSTEM REQUIREMENTS

> H/W System Configuration:-

Processor - Pentium –IV

➤ RAM - 4 GB (min)

➤ Hard Disk - 20 GB

Key Board - Standard Windows Keyboard

➤ Mouse - Two or Three Button Mouse

➤ Monitor - SVGA

SOFTWARE REQUIREMENTS:

❖ Operating system : Windows 7 Ultimate.

❖ Coding Language : Python.❖ Front-End : Python.

❖ Back-End : Django-ORM

Designing : Html, css, javascript.

❖ Data Base : MySQL (WAMP Server).