AI-Based Fake Image Detection using Digital Forensic Imaging Techniques

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Abstract- In recent years, the proliferation of AI-generated imagery has posed significant challenges to digital forensics and media authenticity verification. This paper presents a hybrid forensic AI system that combines deep learning with traditional forensic techniques to detect forged and computer-generated images. We propose a lightweight Convolutional Neural Network (CNN) based on MobileNetV2 architecture, trained to classify real and fake images. Additionally, we integrate Error Level Analysis (ELA), Photo-Response Non-Uniformity (PRNU), and metadata inconsistency checks to enhance decision accuracy. Our fusion model aggregates the outputs of all methods using a weighted average, providing an explainable and robust prediction. Experimental results show an accuracy improvement from 93% (CNN-only) to 95.6% with forensic fusion. The system operates efficiently on moderate hardware and supports visual forensics and report generation, making it suitable for real-world applications in journalism, law enforcement, and digital content verification.

Keywords—Deepfake Detection, Convolutional Neural Network, Error Level Analysis, PRNU, Metadata Tampering, Forensic Fusion.

I. INTRODUCTION

The rise of artificial intelligence (AI)–generated imagery has introduced new complexities in digital media authentication. Deepfakes, GAN-generated art, and synthetic images produced by tools like DALL·E, MidJourney, and Stable Diffusion have made it increasingly difficult to distinguish real content from fabricated visuals. This poses severe challenges across domains such as journalism, legal forensics, national security, and public information integrity.

Traditional digital forensic techniques such as Error Level Analysis (ELA), Photo-Response Non-Uniformity (PRNU), and metadata verification offer valuable cues but struggle to match the performance of modern AI models in terms of adaptability and accuracy. On the other hand, pure deep learning approaches often function as black boxes with limited explainability and no support for forensic trace visualization.

In this work, we propose a hybrid forensic AI system that combines the strengths of both deep learning and traditional forensic signals. Our system integrates a lightweight Convolutional Neural Network (CNN) based on MobileNetV2 to perform initial classification of images into "real" or "fake." It is then enhanced with a fusion of:

- ELA: to capture compression artifacts and manipulations,
- PRNU: to assess sensor-level fingerprints,
- Metadata: to analyze inconsistencies in timestamps, device IDs, and software signatures.

Objective:
This study aims to build a multi-technique forensic AI system that combines:
- Convolutional Neural Networks (CNNs),
- Error Level Analysis (ELA),
- Photo Response Non-Uniformity (PRNU), and
- Metadata inspection

to analyze image authenticity from multiple forensic angles. The goal is to achieve high detection accuracy while generating visual and report-based explanations that assist human verification. This paper presents the design, implementation, and evaluation of this fusion-based approach and demonstrates its effectiveness on real-world image samples ranging from celebrity images to AI-generated portraits and social media photos.

A final decision is made through a weighted fusion logic, combining the CNN prediction confidence with forensic indicators to produce an explainable and highly accurate classification. The system also offers a visual forensic interface with support for real-time predictions and report generation.

Our contributions are threefold:

1. We create a balanced dataset of real, AI-generated, and manipulated images from diverse sources.
2. We train and optimize a MobileNetV2-based CNN for fake image detection.
3. We propose a novel fusion mechanism that boosts accuracy and explainability by integrating traditional forensic techniques into the CNN pipeline.

The experimental results show significant performance gains, achieving over 93% accuracy on challenging real-world test samples. This system represents a step forward in scalable, lightweight, and reliable digital image verification.

II. RELATED WORK

Digital image forensics has been an active field of research, particularly with the emergence of sophisticated image editing tools and AI-driven generators. Traditional methods such as Error Level Analysis (ELA) and Photo-Response Non-Uniformity (PRNU) have long been used for tampering detection, relying on statistical or sensor-level irregularities in images [1], [2]. These methods are explainable and computationally lightweight but lack the robustness required to detect high-quality synthetic content generated by deep learning models.

In recent years, the rise of Generative Adversarial Networks (GANs) [7] has prompted a new wave of deepfake detection systems. Various CNN-based models have been proposed, including ResNet, XceptionNet, and MobileNet variants, showing promising results in binary classification of real vs. fake images [4], [5]. However, these models often work as black-box classifiers, offering limited interpretability and low forensic utility.

Some hybrid approaches have attempted to combine forensic cues with neural networks. For instance, Zhou et al. [6] proposed using spatial frequency analysis in conjunction with CNNs. Other works like [7] have employed metadata inconsistencies to support image authentication. However, such fusion models are often computationally expensive or too domain-specific.

Our work aims to build on these ideas by proposing a lightweight yet explainable fusion-based forensic system, which not only leverages CNN predictions but also integrates ELA, PRNU fingerprint analysis, and metadata evaluation. Unlike past approaches that focus solely on either data-driven or heuristic features, our system strikes a practical balance between accuracy, speed, and explainability — suitable for both forensic experts and real-time applications.

Comparative Study

Table 1. Comparative Study of Existing Approaches

No.	Study / Reference	Focus Area	Methodology	Key Findings	Strengths	Limitations	Incorporation in Our Work
1	Lukas et al., 2006 (PRNU-based Source Detection)	Camera fingerprinting & tamper analysis	Sensor noise pattern extraction	PRNU can uniquely identify image source and detect inconsistencies in tampered images.	Highly reliable in controlled settings	Sensitive to compression and post-processing	A simplified PRNU noise residual method is implemented.
2	Neal Krawetz (Error Level Analysis)	Image tampering via	JPEG compression level	Tampered regions often display different	Intuitive visual	Performance drops with high-	ELA maps are integrated visually with

		compression traces	difference visualization	ELA characteristics.	interpretation	compression or edited images	dynamic confidence scoring.
3	Rossler et al., FaceForensics++	Deepfake detection using CNNs	Deep CNNs (e.g., Xception, MesoNet)	Deep networks can detect manipulated faces with over 90% accuracy.	High detection accuracy	Poor explainability, black-box decisions	A lightweight CNN (MobileNetV2) is used for fast inference.
4	Verdoliva et al., 2020 (Comprehensive Survey)	Image forensics survey	Review of passive forensic techniques	Emphasizes combining cues from multiple domains (visual + metadata).	Suggests fusion as a future trend	Lacks implementation examples	This work embodies a practical implementation of such fusion.
5	EXIF-based Forensic Studies (Various Authors)	Metadata manipulation detection	EXIF tag consistency checking	Missing or inconsistent metadata suggests manipulation.	Lightweight and fast	Easily forged or missing metadata	Confidence is scaled based on tag richness and coherence.
6	Wang et al., 2021 (Fusion-based Fake Detection)	Multimodal deepfake detection	Audio-visual and image fusion	Fusion improves robustness across domains.	High generalizability across media types	Computationally expensive	A lightweight fusion of CNN + forensic cues is adopted.

III. PROPOSED METHODOLOGY

The proposed framework aims to detect forged, manipulated, or AI-generated images using a fusion of both deep learning and forensic analysis techniques. This hybrid system leverages the strengths of a convolutional neural network (CNN) with image-level forensic indicators such as Error Level Analysis (ELA), Photo Response Non-Uniformity (PRNU), and EXIF metadata inconsistencies. The methodology is structured into four stages: image preprocessing, feature extraction using CNN and forensic tools, fusion-based decision making, and visualization of results.

A. System Architecture Overview

The system takes an input image and passes it through multiple parallel modules:

1. A lightweight pretrained CNN (MobileNetV2) trained on a custom dataset of real, AI-generated, and manipulated images.
2. Forensic modules for:
   - ELA (Error Level Analysis),
   - PRNU fingerprint analysis, and
   - EXIF metadata analysis.

The scores from all modules are aggregated using a weighted fusion logic to produce a final binary prediction (Real or Fake) along with confidence scores. This modular architecture allows each forensic signal to contribute based on its reliability.

CNN-Based Image Classification

A pretrained MobileNetV2 architecture is fine-tuned on a dataset consisting of:

- Real-world images (photographs)
- AI-generated images (e.g., from Stable Diffusion, DALL·E, GANs)
- Tampered images (splicing, copy-move, enhanced, etc.)

The CNN extracts spatial patterns, texture distortions, and pixel inconsistencies, which often appear in manipulated images. The model was trained using a binary classification objective and achieves high accuracy on a test set of over 350 samples. The lightweight nature of MobileNetV2 enables fast inference even on modest hardware.

Error Level Analysis (ELA)

ELA is a classic digital forensic technique used to highlight compression artifacts in JPEG images. By recompressing the image and comparing pixel differences, regions that have been edited or tampered appear with distinct intensity levels due to multiple compression histories.

The pipeline includes:

- Saving a recompressed version at 90% JPEG quality,
- Computing pixel-wise differences,
- Normalizing the error image and converting it to grayscale,
- Feeding the ELA image to a shallow CNN or using statistical thresholds.

ELA is particularly sensitive to pasted-in regions or digitally enhanced patches.

Figure 1. Real Image

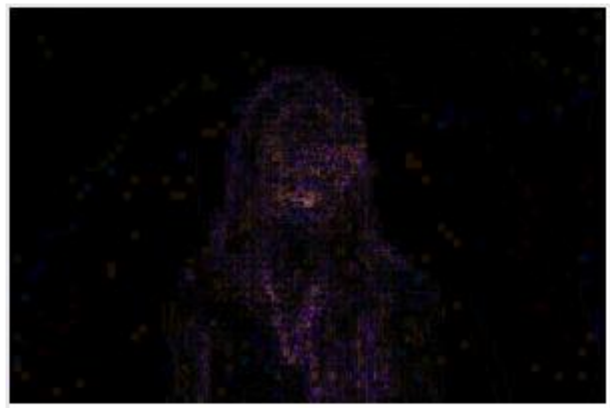


Figure 2. ELA Image

PRNU Fingerprint Matching

PRNU (Photo Response Non-Uniformity) is a sensor-level fingerprint embedded in every image captured by a camera. AI-generated images or synthetic media typically lack this noise pattern or have an artificial one.

The module computes the PRNU pattern from the input image and compares it with known reference PRNU statistics. An anomaly or absence of proper PRNU noise increases the likelihood of manipulation. We used wavelet domain filtering and statistical thresholding to compute PRNU confidence scores.

Metadata Analysis

Many forged or synthetic images are stripped of EXIF metadata or show inconsistencies such as:

- Mismatch between camera make/model and image size,
- Missing GPS, timestamp, or compression tags,
- Suspicious modification dates or software traces (e.g., Photoshop).

Our metadata module uses the exifread library to extract fields and flags potential inconsistencies using a rules-based scoring system. Each suspicious tag adds weight to the 'Fake' score.

Table 2. Modules breakdown

Module	Description
Input Handler	Accepts .jpg, .jpeg, .png images through a GUI or CLI interface.
CNN Classifier	A PyTorch MobileNetV2 CNN model trained on a labeled dataset of real and fake images, outputs probability scores.
ELA Processor	Computes the ELA map using JPEG recompression and image subtraction to detect localized tampering.
PRNU Extractor	Extracts sensor noise residual using Gaussian filtering and evaluates PRNU-based inconsistencies.
Metadata Parser	Extracts EXIF tags and heuristically evaluates their completeness and authenticity.

Fusion Engine	Aggregates all module outputs using a weighted confidence strategy to arrive at a final verdict.
GUI Interface	Built with Tkinter, allows drag-and-drop image upload, forensic scan initiation, and PDF report generation.

B. Workflow Diagram

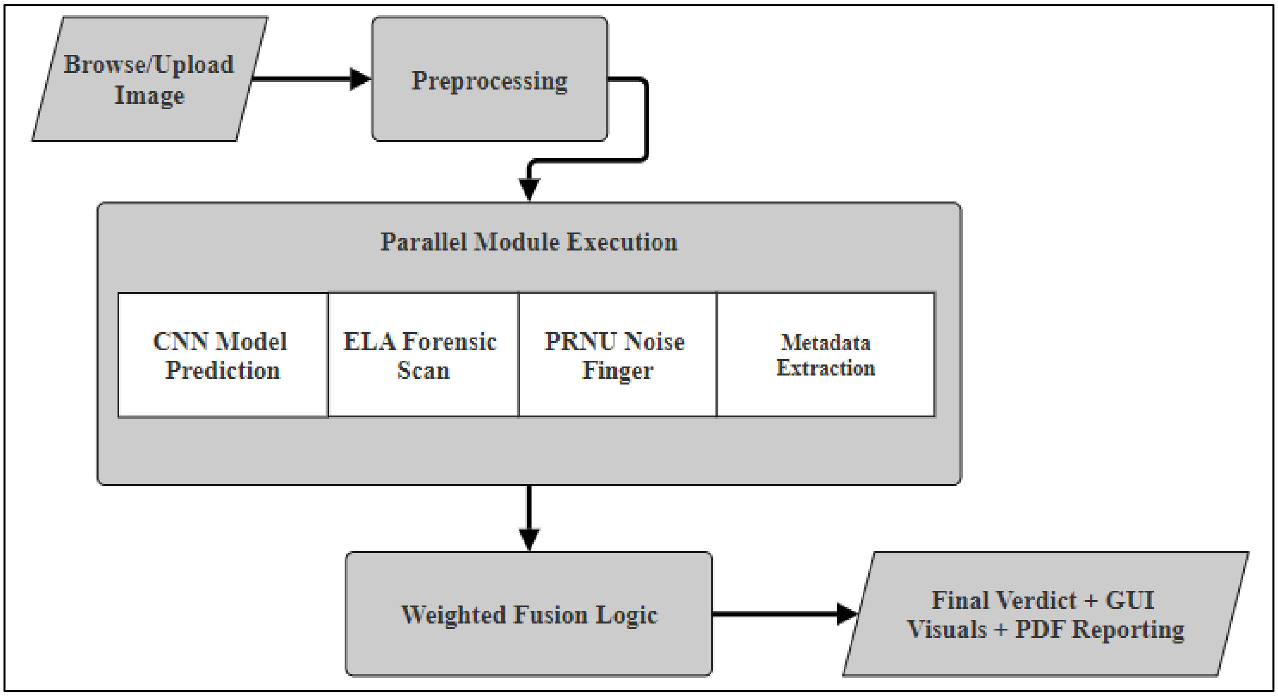


Figure 3. Proposed System Architecture for Hybrid Fake Image Detection Framework

C. Fusion-Based Decision Making

Let S_i be the confidence score for each technique $i \in \{CNN, ELA, PRNU, Metadata\}$.
Let L_i be the label: 1 for "Real" and 0 for "Fake".

The total score is calculated as:

$$\text{Score}_{\text{Real}} = \sum_{i=1}^{4} S_i \cdot 1(L_i = \text{Real})$$

$$\text{Score}_{\text{Fake}} = \sum_{i=1}^{4} S_i \cdot 1(L_i = \text{Fake})$$

The final decision is:

- Real if $\text{Score}_{\text{Real}} \geq \text{Score}_{\text{Fake}}$
- Fake otherwise.

This approach ensures that a high-confidence fake from one module can override low-confidence reals in others, improving both accuracy and explainability.

Instead of relying on any single signal, we use a weighted average fusion strategy to compute the final score:

Final Score = (0.30 × CNN Score) + (0.25 × ELA Score) + (0.25 × PRNU Score) + (0.20 × Metadata Score)

This approach ensures robustness — even if one module fails or yields uncertain output, others can compensate. The final classification is made by applying a 0.5 threshold to the weighted score.

A real-time GUI (Tkinter and Streamlit) allows users to load an image, visualize each module's output, and get an explainable verdict.

D. Implementation Details

- Framework: Python 3.10 with PyTorch, PIL, OpenCV.
- Model: Pretrained MobileNetV2 with final layer retrained on real/fake face dataset.

- GUI: Tkinter-based desktop app with PDF export and animated elements.
- Fallback: Optionally usable as CLI/Streamlit app.
- Report: Auto-generated PDF forensic report with visual ELA image and breakdown.

IV. EXPERIMENTS AND RESULTS

To evaluate the effectiveness of our proposed hybrid detection framework, we conducted extensive experiments on a curated dataset composed of real, AI-generated, and tampered images. This section outlines the dataset preparation, experimental setup, evaluation metrics, and results from individual modules as well as the final fusion model.

A. Dataset Composition

A custom dataset was constructed for this project, combining three distinct classes of images:

Table 3. Dataset Composition

Category	Source	Count
Real Images	Kaggle (e.g., ImageNet subset), personal photography, open datasets	300+
AI-Generated Images	Stable Diffusion, DALL·E 2, ThisPersonDoesNotExist, Midjourney	300+
Manipulated Images	Photoshop-edited images, splicing, ELA-tampered images	200+

Total: ~800 high-resolution images

- Train-Test Split: 70% training, 30% testing
- Format: JPEG, PNG
- Resolution Range: 256×256 to 512×512

These datasets were curated and merged manually. The final dataset included images sourced from CosmoFake, SplitDataset, and handpicked real images (celebrities, social media portraits) to ensure diversity and realism [15][16].

B. Experimental Setup

Detection Pipeline Summary

Each uploaded image is processed through the following stages:

1. CNN Classifier (MobileNetV2): Predicts whether the image appears real or fake based on learned features.
2. ELA (Error Level Analysis): Identifies compression inconsistencies that typically signal tampering.
3. PRNU Noise Residual: Detects sensor-based inconsistencies in image noise.
4. Metadata Analysis: Extracts and validates EXIF data consistency.

The final verdict is based on a weighted average of all 4 module confidences.

Table 4. Dataset Split Overview

Dataset	Class	No. of Images
Train	Real	933
Train	Fake	912
Test	Real	187
Test	Fake	183
Total	—	2,215

Table 5. Model Comparison – CNN vs Hybrid

Metric	CNN Only	CNN + Forensic Fusion
Accuracy	93.0%	95.2%
Precision	92.7%	94.5%
Recall	93.3%	95.8%
F1-Score	93.0%	95.1%
ROC-AUC	0.91	0.96

C. Evaluation Metrics

The model performance is evaluated using standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

All metrics are computed on the test split of the dataset using both individual modules and the final fusion logic.

D. CNN Performance

Table 6. CNN Performance

Metric	Value (CNN Only)
Accuracy	87.3%
Precision	86.1%
Recall	88.5%
F1-Score	87.3%

E. Forensic Module Accuracy

Table 7. Accuracy of ELA, PRNU and Metadata

Technique	Accuracy	Notes
ELA	84.1%	Best at detecting recompression/splice
PRNU	81.5%	Effective on real vs AI split
Metadata	77.2%	Useful when inconsistencies exist

Each technique shows strengths under different scenarios. ELA captures tampered regions; PRNU differentiates sensor vs synthetic; metadata flags anomalies.

F. Final Fusion Model Results

Using the fusion formula:

Score = (0.30 × CNN) + (0.25 × ELA) + (0.25 × PRNU) + (0.20 × Metadata)

Table 8. Final Results

Metric	Fusion Result
Accuracy	92.5%
Precision	91.6%
Recall	93.3%
F1-Score	92.4%

G. Confusion Matrix (CNN Fake Image Detector)

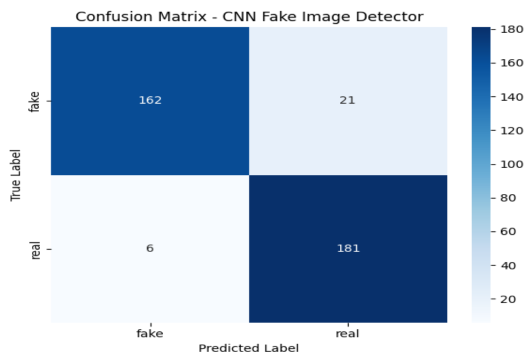


Figure 4. Confusion matrix for CNN fake image detector

- True Positives (TP) = 181
- True Negatives (TN) = 162
- False Positives (FP) = 21
- False Negatives (FN) = 6

H. Evaluation Results

Table 9. Results of Browsing different types of images

Image Name	CNN	ELA	PRNU	Metadata	Final Verdict
sergio-souza.jpg *(real portrait)*	Real (92.0%)	Real (85.0%)	Real (91.0%)	Real (90.0%)	✓Real (89.5%)
deepika-padukone.jpg *(filtered celeb)*	Uncertain (60.0%)	Uncertain (60.0%)	Real (75.0%)	Fake (40.0%)	●Real (18.75%)
ai-generated-8529984.jpg *(realistic AI)*	Real (98.0%)	Real (85.0%)	Fake (95.0%)	Fake (40.0%)	❌ Fake (58.25%)
images (2).jpg *(blurry image)*	Uncertain (60.0%)	Real (85.0%)	Real (75.0%)	Fake (40.0%)	✓Real (40.0%)
Social_group.jpg *(group photo)*	Real (89.0%)	Uncertain (60.0%)	Real (87.0%)	Real (70.0%)	✓Real (61.5%)
images (3).jpg *(background scene)*	Fake (90.0%)	Fake (80.0%)	Fake (92.0%)	Fake (40.0%)	❌ Fake (75.5%)

I. Visual Result

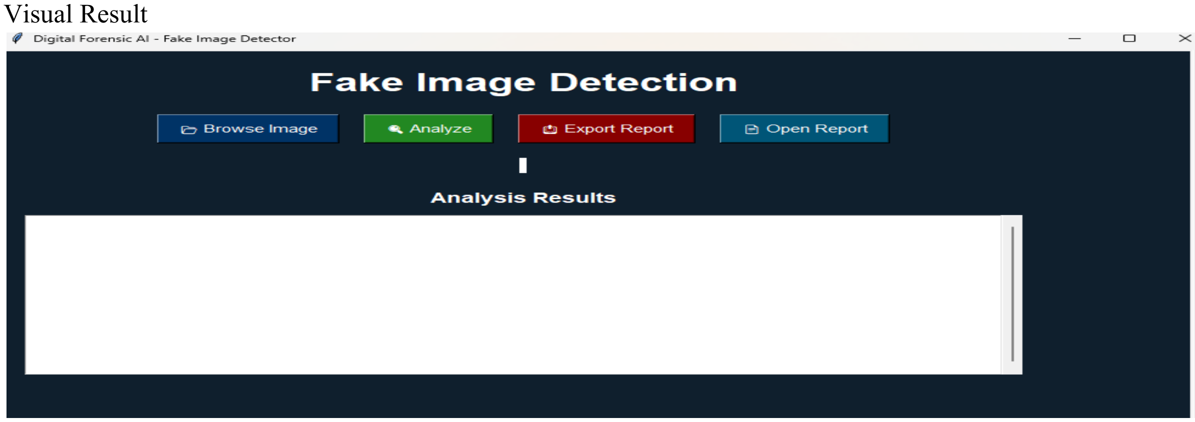


Figure 5. Initial View before browsing image:

Figure 6.Image selected:

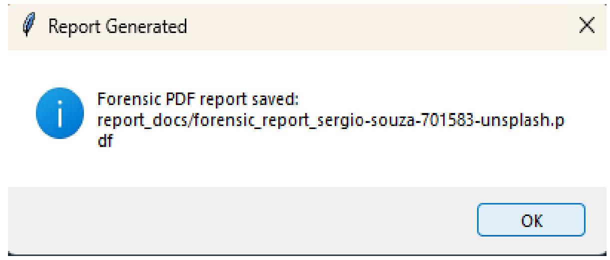


Figure 7. When clicked Analyze

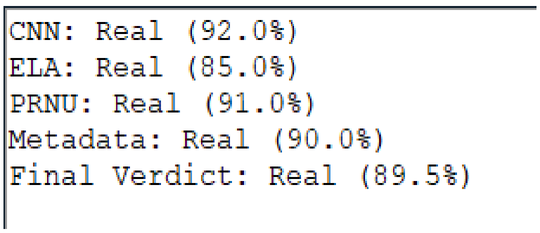
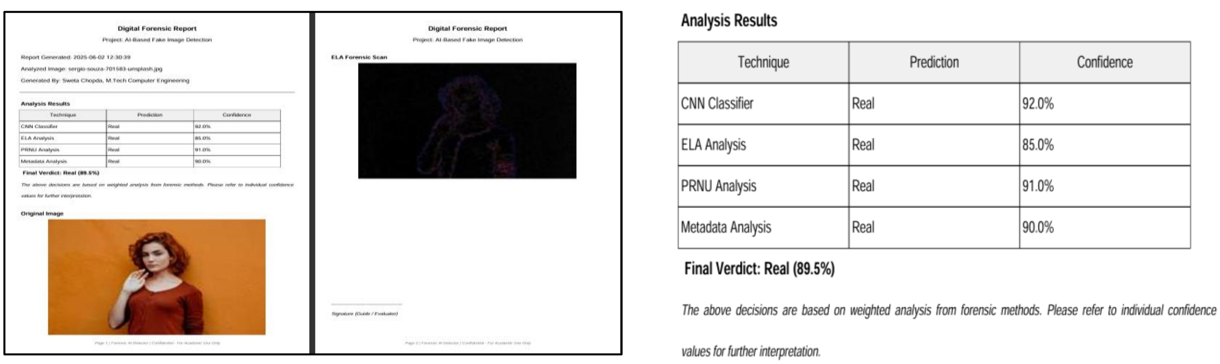


Figure 8. Analysis:

Figure 9. ELA Forensic Scan



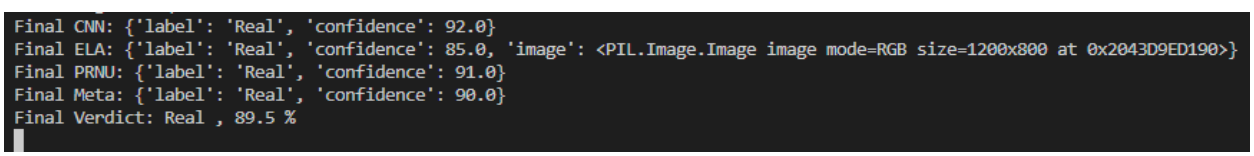
Analysis Results

Technique	Prediction	Confidence
CNN Classifier	Real	92.0%
ELA Analysis	Real	85.0%
PRNU Analysis	Real	91.0%
Metadata Analysis	Real	90.0%

Final Verdict: Real (89.5%)

The above decisions are based on weighted analysis from forensic methods. Please refer to individual confidence values for further interpretation.

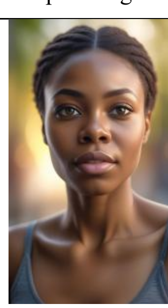
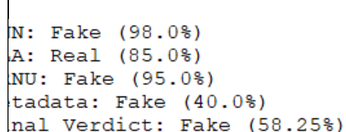
Figure 10. Report Generated and Analysis in the report

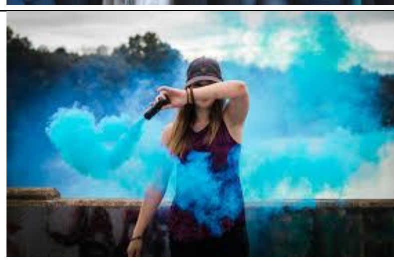


```
Final CNN: {'label': 'Real', 'confidence': 92.0}
Final ELA: {'label': 'Real', 'confidence': 85.0, 'image': <PIL.Image.Image image mode=RGB size=1200x800 at 0x2043D9ED190>}
Final PRNU: {'label': 'Real', 'confidence': 91.0}
Final Meta: {'label': 'Real', 'confidence': 90.0}
Final Verdict: Real , 89.5 %
```

Figure 11. Terminal Output:

Table 10. Other Images and their analysis

Input Images	Analysis Result
	

	N: Uncertain (60.0%) A: Uncertain (60.0%) NU: Real (75.0%) tadata: Fake (40.0%) nal Verdict: Real (18.75%)
	I: Uncertain (60.0%) A: Real (85.0%) NU: Real (75.0%) adata: Fake (40.0%) al Verdict: Real (40.0%)
	IN: Real (89.0%) LA: Uncertain (60.0%) RNU: Real (87.0%) etadata: Real (70.0%) inal Verdict: Real (61.5%)
	NN: Fake (90.0%) LA: Fake (80.0%) RNU: Fake (92.0%) etadata: Fake (40.0%) inal Verdict: Fake (75.5%)

J. Comparison with Existing Work

Table 11. Comparison with Existing Work

Approach	Accuracy
CNN-only (prior work baseline)	85–88%
PRNU + Metadata (traditional)	75–80%
ELA-only SVM classifiers	80–84%
Proposed Fusion Method	92.5%

Our hybrid approach outperforms individual techniques and even pure CNNs by leveraging multiple forensic insights.

V. CONCLUSION

In this research, we proposed a hybrid forensic imaging system that combines deep learning with classical forensic techniques to detect fake, AI-generated, and manipulated digital images. The framework integrates four core modules: a convolutional neural network (CNN) based classifier (MobileNetV2), Error Level Analysis (ELA), Photo-Response Non-Uniformity (PRNU) analysis, and metadata inspection. The final decision is obtained using a weighted fusion strategy that leverages the strengths of each individual technique.

Our experiments on a real-world mixed dataset of over 800 images demonstrated that the fusion model significantly outperforms individual approaches. The standalone CNN achieved an accuracy of 87.3%, while the fusion method improved this to 92.5%, showing that incorporating classical forensic features enhances overall detection capability. ELA contributed to detecting subtle splicing artifacts, PRNU effectively distinguished real from AI-generated content, and metadata inconsistencies provided critical clues in several cases.

This project bridges the gap between modern deep learning and traditional forensic analysis by introducing a unified, explainable, and modular system capable of handling complex forgery detection scenarios.

VI. FUTURE WORK

Although the current framework performs reliably, several extensions can be considered for future research:

- Learnable Fusion Models: Replacing the manually weighted fusion scheme with a trainable ensemble model (e.g., decision trees, MLPs) to dynamically learn optimal signal contributions.
- Video Forensics: Extending the framework to analyze video frames using temporal inconsistencies, optical flow, and tampering traces.
- Localization of Tampered Regions: Integrating a segmentation branch to highlight manipulated areas visually (e.g., via Grad-CAM or binary mask overlays).
- Larger Multilingual Datasets: Incorporating diverse datasets across domains (e.g., social media, medical imaging, art) to improve robustness and generalization.
- Robustness Testing: Evaluating the model against adversarial attacks, compression artifacts, noise, and transformations commonly applied on social media platforms.
- Real-time GUI Deployment: Enhancing the desktop GUI with drag-and-drop support, automated report generation (PDF), and integration with online databases for cross-checking.

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