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AI Provenance Tracker: A Hybrid Deep Learning and Heuristic Approach for Detecting AI-Generated Images

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Abstract: *The rapid advancement of generative artificial intelligence has significantly increased the ability to create highly realistic synthetic images, raising serious concerns regarding digital authenticity, misinformation, and cyber fraud. With the emergence of advanced models such as Generative Adversarial Networks (GANs) and diffusion-based techniques, distinguishing between real and AI-generated images has become increasingly challenging for both humans and traditional verification systems. To address this issue, this paper presents an AI Provenance Tracker, an end-to-end hybrid system designed to accurately classify images as real or AI-generated by combining deep learning with heuristic analysis. At the core of the proposed system is a ResNet50-based Convolutional Neural Network (CNN) utilizing transfer learning, which is capable of extracting complex hierarchical features such as edges, textures, and structural inconsistencies from input images. The model is trained on a diverse dataset of approximately 40,000 images, consisting of both real and AI-generated samples, with appropriate preprocessing techniques including resizing, normalization, and data augmentation. The network is optimized using the Adam optimizer and Cross Entropy Loss function, achieving an overall classification accuracy of approximately 90%.*

In addition to the deep learning model, a heuristic analysis module is incorporated to enhance detection robustness by examining non-learned features such as noise distribution, compression artifacts, and metadata irregularities, which are often indicative of synthetic content. The outputs from both the CNN model and the heuristic module are combined using an ensemble strategy based on weighted averaging, improving the system's reliability and reducing false predictions.

The system is implemented using a scalable architecture, where the backend is developed using FastAPI for efficient request handling and model inference, while the frontend is built using Next.js and Tailwind CSS to provide an interactive and user-friendly interface. The complete workflow enables real-time image analysis, making the system suitable for practical deployment in digital content verification scenarios.

Experimental results demonstrate that the proposed hybrid approach outperforms standalone deep learning models in terms of accuracy, generalization, and robustness. The AI Provenance Tracker offers a practical and scalable solution to the growing challenge of detecting AI-generated images, contributing towards enhancing trust and authenticity in digital media ecosystems.

I. INTRODUCTION

The rapid advancement of artificial intelligence, particularly in generative models such as Generative Adversarial Networks (GANs) and diffusion-based techniques, has enabled the creation of highly realistic synthetic images. While these technologies offer significant benefits in fields like design, entertainment, and virtual content generation, they also raise serious concerns related to misinformation, digital forgery, and cybercrime. AI-generated images are becoming increasingly difficult to distinguish from real ones, making authenticity verification a critical challenge in today's digital ecosystem.

Traditional image forensics methods relied on detecting visible inconsistencies such as lighting errors, unnatural textures, or facial distortions. However, modern AI models have significantly reduced these artifacts, rendering conventional detection techniques less effective. As a result, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have gained prominence due to their ability to learn complex visual patterns and identify subtle differences between real and synthetic images.

Despite their effectiveness, deep learning models often face limitations such as poor generalization and sensitivity to unseen data. To address these challenges, this paper proposes an AI Provenance Tracker, a hybrid system that combines a ResNet50-based CNN with heuristic analysis.

The system leverages both learned features and rule-based checks, such as noise patterns and compression artifacts, to improve detection accuracy and robustness.

The proposed solution is designed with a scalable architecture using FastAPI for backend processing and Next.js for frontend interaction, enabling real-time image analysis.

This work aims to provide an efficient and practical approach for detecting AI-generated images, contributing to improved trust and authenticity in digital media.

II. LITERATURE REVIEW

Several researchers have proposed different techniques for detecting deepfake and AI-generated content. The evolution of these techniques over recent years is summarized as follows:

(2021)

Some studies combined Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to capture temporal information across multiple video frames. This approach significantly improved detection accuracy for video-based deepfakes by analyzing both spatial and temporal features.

(2022)

Traditional detection methods proved largely ineffective against highly realistic deepfakes generated by modern Generative Adversarial Networks (GANs). As a result, deep learning became the primary focus. Detection techniques were broadly categorized into:

- Holistic methods: analyzing the entire face
- Feature-based methods: focusing on specific regions such as eyes and lips Popular architectures included CNN, VGG-19, and DenseNet.
- Additionally, ensemble and multi-attention models were introduced to improve generalization and performance.

(2023)

Earlier detection methods relied on visible inconsistencies such as eye blinking, facial artifacts, and head pose variations. However, advancements in deepfake generation significantly reduced these detectable cues, making such approaches less reliable.

(2023)

Advanced techniques such as transfer learning, ensemble learning, and multimodal detection systems were proposed to enhance robustness and generalization. These approaches aimed to improve performance across different datasets and unseen deepfake types.

(2024)

Recent research primarily focuses on deep learning-based approaches, especially CNN models, for extracting spatial features from images and video frames. These models analyze complex visual patterns to classify content as real or manipulated with improved accuracy.

(2025)

Early deepfake detection methods based on physical cues like eye blinking and facial movement have become ineffective against advanced AI-generated content. Current

research emphasizes the use of advanced CNN architectures such as XceptionNet and EfficientNet for spatial feature extraction. For video analysis, RNN and LSTM models

are used to detect temporal inconsistencies across frames. Additionally, research is focusing on addressing challenges such as adversarial attacks and improving computational efficiency for real-time detection systems

III. AI PROVENANCE: KEY INNOVATIONS

1) Innovation 1: Hybrid Detection Model

Unlike existing systems that rely only on deep learning, our approach combines ResNet50 CNN + heuristic analysis to improve detection accuracy and robustness.

2) Innovation 2: Diverse Dataset Training

The model is trained on a large dataset (~40,000 images) including multiple sources such as CIFAKE and Kaggle datasets, ensuring better generalization across different AI-generated images.

3) Innovation 3: Heuristic Feature Analysis

The system analyzes additional features like noise patterns, compression artifacts, and metadata inconsistencies, which are often ignored by traditional CNN models.

4) Innovation4: Ensemble Decision System

Instead of relying on a single model, outputs from deep learning and Heuristic modules are recombined using a weighted ensemble method for more reliable predictions.

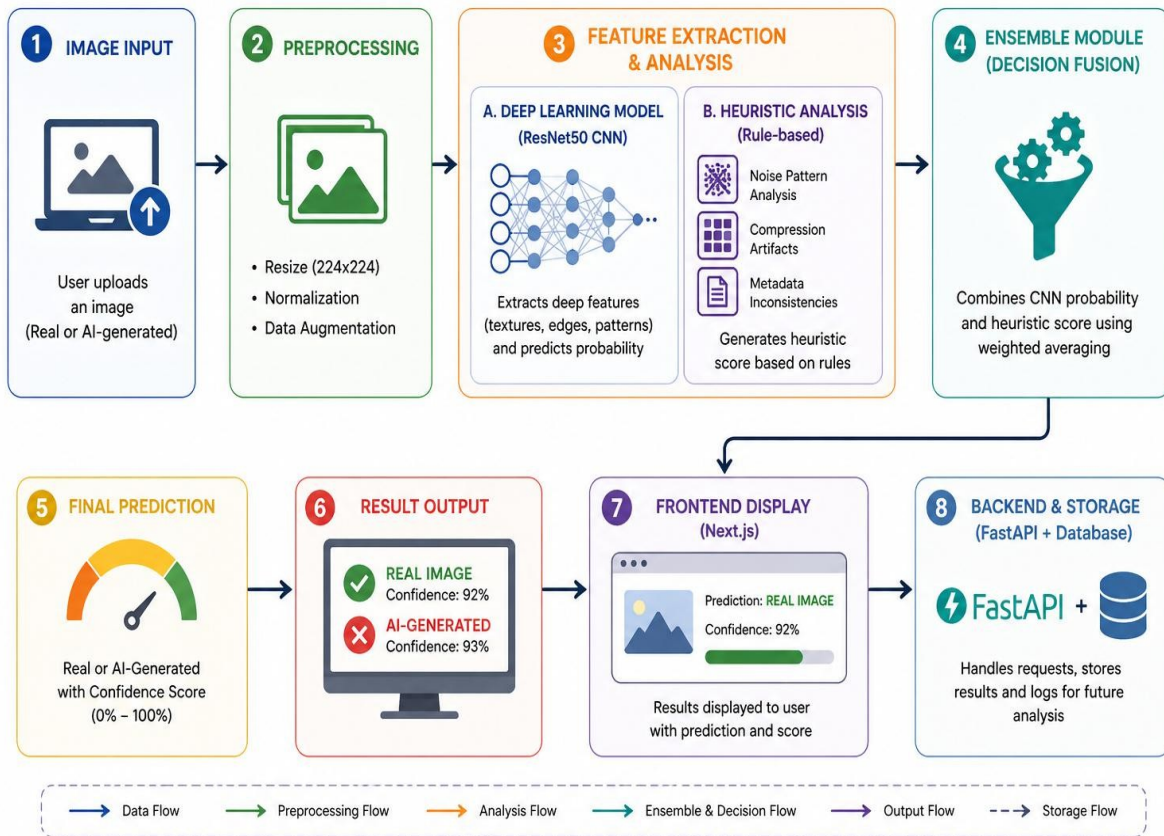
5) Innovation5: Real-Time Web-Based Detection

The system supports real-time detection through a Next.js frontend and FastAPI backend, allowing users to upload images and get instant results.

6) Innovation6: Scalable and Deployable Architecture

The architecture is designed to be lightweight, scalable, and easily deployable for real-world applications such as social media verification and digital forensics.

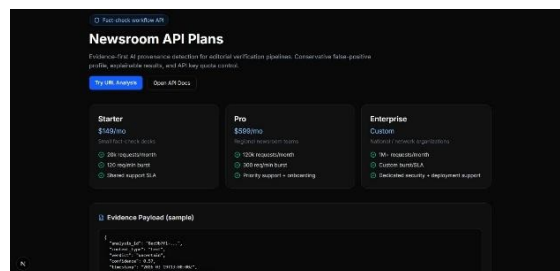
AI PROVENANCE TRACKER – SYSTEM PIPELINE



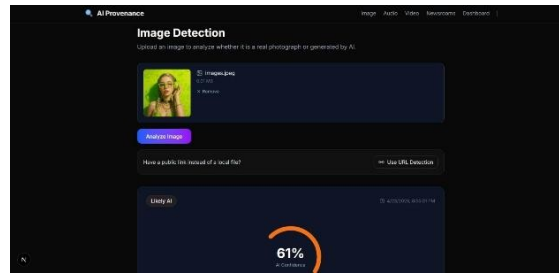
Photos:

User Interface:

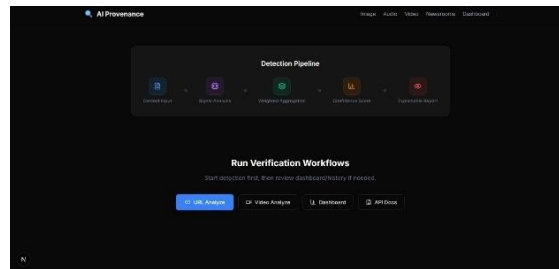
- NewsRoom API Plans



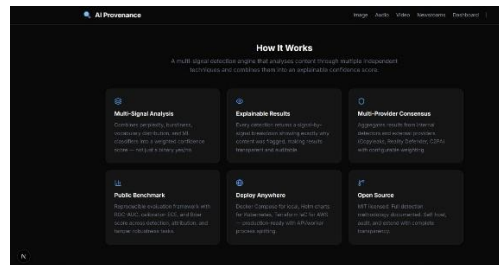
- ImageDetection



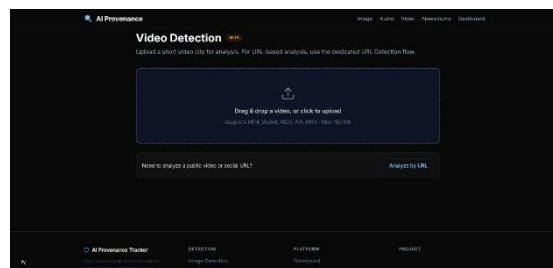
- DetectionPipeline



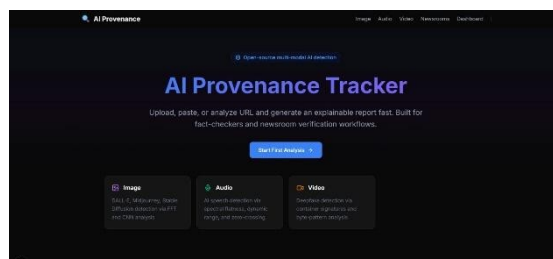
- Working



- FileUploader



- Dashboard



- Accuracy

```
model.eval()
correct = 0
total = 0

with torch.no_grad():
    for images, labels in val_loader:
        images = images.to(device)
        labels = labels.to(device)

        outputs = model(images)
        _, predicted = outputs.max(1)

        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print("Accuracy:", correct / total)

*** Accuracy: 0.9
```

IV. CONCLUSION

This paper presented the AI ProvenanceTracker, a hybrid system designed to detect whether an image is real or AI-generated. By combining a ResNet50-based deep learning model with heuristic analysis, the proposed approach effectively captures both learned visual patterns and rule-based inconsistencies such as noise and compression artifacts.

The system achieved an accuracy of approximately 90%, demonstrating improved performance compared to standalone methods. The use of an ensemble mechanism further enhanced reliability and reduced false predictions. In addition, the scalable architecture built using FastAPI and Next.js enables real-time detection, making the system suitable for practical applications.

Overall, the proposed solution provides a robust, efficient, and deployable approach for AI-generated image detection. It contributes toward improving trust, authenticity, and verification in digital media, addressing the growing challenges posed by advanced generative technologies.



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