

TrueSight: A Multi-Modal Framework for AI Image Authenticity Detection

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Abstract - The rapid advancement of generative artificial intelligence has enabled the creation of highly realistic synthetic images, making it increasingly difficult to distinguish them from real-world photographs. This paper presents **TrueSight**, a multi-modal framework designed for accurate detection of AI-generated images. The system integrates semantic, visual, frequency, and noise-based feature extraction techniques into a unified pipeline. A calibrated XGBoost classifier is used to improve prediction accuracy through feature fusion. In addition, a similar object detection module named **SPOT-IT** is incorporated to identify repeated or duplicated objects within images using hybrid matching techniques. The system is implemented using a modular Flask-based architecture with independent services and centralized routing. Experimental results demonstrate that the proposed framework achieves high accuracy, robustness, and explainability, making it suitable for digital forensics and image verification applications.

Key Words: AI Image Detection, Multi-Modal Learning, Feature Fusion, SPOT-IT, Object Detection, Deep Learning

1. INTRODUCTION

The rapid development of artificial intelligence, particularly generative models such as Generative Adversarial Networks (GANs) and diffusion-based systems, has enabled the creation of highly realistic synthetic images. These images are increasingly used across various domains, making it difficult to verify their authenticity.

The misuse of AI-generated images has raised concerns in fields such as journalism, cybersecurity, and digital forensics. Traditional detection methods based on metadata or visual inspection are no longer reliable due to the advancement of image generation techniques.

To address these challenges, this paper proposes **TrueSight**, a multi-modal framework for detecting AI-generated images. The system combines multiple feature extraction techniques, including semantic, visual, frequency, and noise-based analysis, to improve detection accuracy.

In addition to image authenticity detection, the system integrates a **Similar Object Detection module (SPOT-IT)**, which identifies repeated or duplicated objects within an image. This enhances the system's capability in detecting manipulated or forged content.

The proposed framework is implemented using a modular architecture consisting of a unified Flask router and independent detection modules. This design ensures scalability, flexibility, and efficient processing.

2. SYSTEM ARCHITECTURE

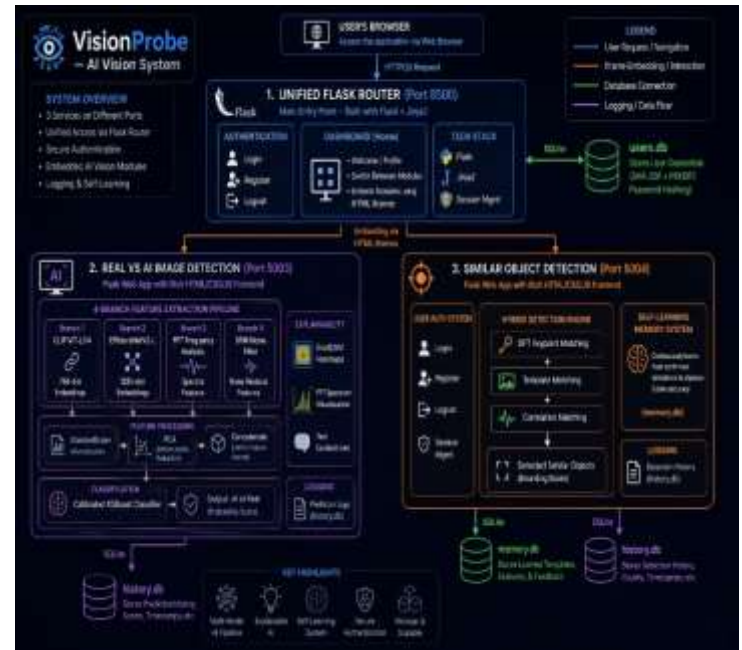


Fig 1. VisionProbe system architecture with unified router and two modules.

2.1 Unified Flask Router (Port 8500)

The system is controlled by a central Flask router that acts as the main entry point.

Functions:

- User Authentication (Login, Register, Logout)
- Dashboard Interface
- Module Switching
- Embedding modules using HTML iframes

Database:

- users.db (SQLite)
- Password hashing using SHA-256 + PBKDF2

2.2 AI Image Detection Module (Port 5003)

This module performs classification of images as real or AI-generated.

Workflow:



Fig 2. Multi-modal AI image detection pipeline.

Feature Extraction (4-Branch Pipeline):

- Branch 1: CLIP ViT-L/14 → Semantic features (768-dim)
- Branch 2: EfficientNetV2-L → Visual features (1280-dim)
- Branch 3: FFT Analyzer → Frequency features
- Branch 4: SRM Noise Filter → Noise residual features

Feature Processing:

- StandardScaler normalization
- PCA dimensionality reduction
- Feature concatenation

Classification:

- Calibrated XGBoost classifier

- Output: Probability score

Explainability:

- GradCAM heatmaps
- FFT visualization
- Text-based explanations

Logging:

- Stored in history.db

2.3 SPOT-IT Similar Object Detection Module (Port 5004)

This module detects repeated or similar objects.



Fig 3. SPOT-IT detection pipeline.

Phase 1: SIFT Keypoint Detection

- Extract keypoints and descriptors
- Optional template extraction

Phase 2: Hybrid Matching

- SIFT Matching (FLANN)
- Template Matching
- Correlation Matching

Decision:

- Template provided → Template matching
- Else → Auto detection

Post Processing:

- Non-Maximum Suppression (NMS)
- Confidence threshold filtering

Memory System:

- Uses memory.db
- Learns patterns over time

Output:

- Bounding boxes
- Object count
- Confidence score

3. METHODOLOGY**3.1 AI Detection Workflow**

The system processes input images through multiple stages:

1. Image Upload
2. Preprocessing
3. Feature Extraction
4. Feature Fusion
5. Classification
6. Output Generation

3.2 Object Detection Workflow**SPOT-IT performs:**

1. ROI Selection
2. Feature Extraction
3. Matching
4. Filtering
5. Annotation

3.3 Mathematical Model**Feature fusion:**

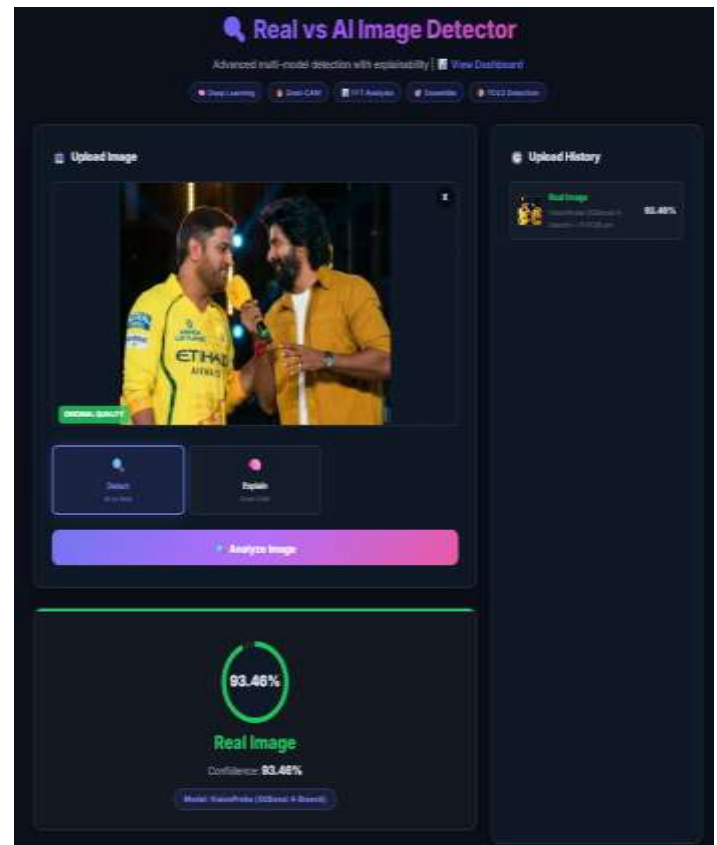
$$F = [F_{CLIP} + F_{CNN} + F_{FFT} + F_{SRM}]F = [F_{CLIP} + F_{CNN} + F_{FFT} + F_{SRM}]$$

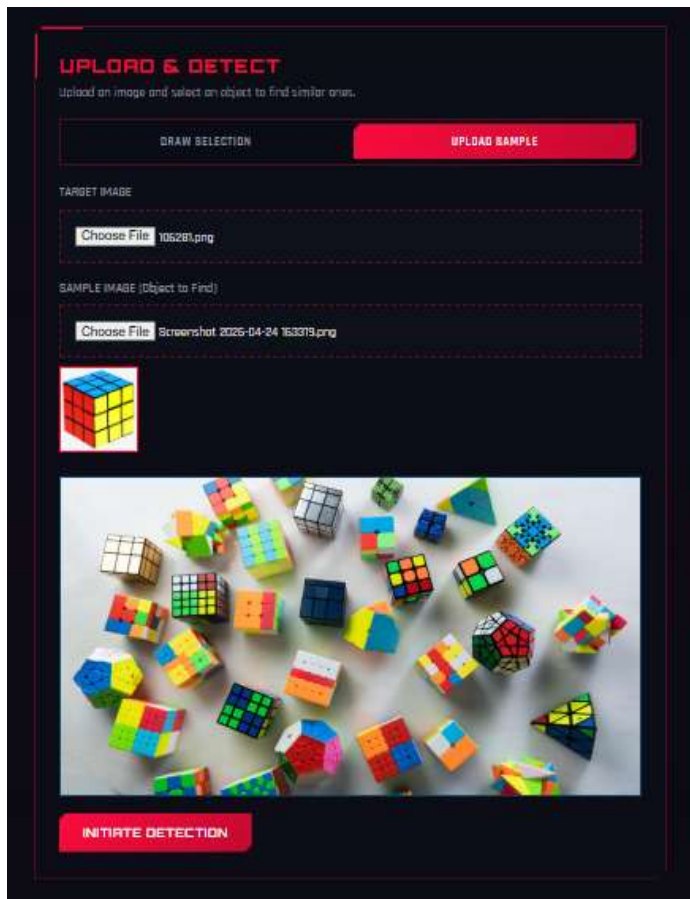
Classification:

$$y = \sigma(WF + b) y = \sigma(WF + b)$$

4. RESULTS AND ANALYSIS**4.1 Accuracy Comparison**

Model	Accuracy
CNN	78%
CLIP	82%
FFT	75%
TrueSight	91%

4.2 Output Visualization



4.3 Observations

The proposed TrueSight framework achieves higher accuracy by combining semantic, visual, frequency, and noise-based features. Feature fusion and the XGBoost classifier improve prediction stability and reduce misclassification. The explainability module enhances interpretability through GradCAM and FFT visualization. The SPOT-IT module effectively detects repeated objects using hybrid matching techniques. Non-Maximum Suppression ensures precise detection, while the memory system improves performance over time. However, advanced AI-generated images and computational complexity remain challenges.

4.4 Performance Insights

The proposed TrueSight framework demonstrates consistent performance across different datasets, effectively distinguishing real and AI-generated images. Real images exhibit natural noise and frequency distributions, while AI-generated images show smoother textures and irregular spectral patterns, which are successfully captured by the multi-modal approach. The SPOT-IT module performs efficiently in detecting repeated objects under variations in scale and orientation. The system maintains balanced accuracy with low false predictions, making it suitable for real-world image forensics applications.

4.5 Explainability Analysis (GradCAM)

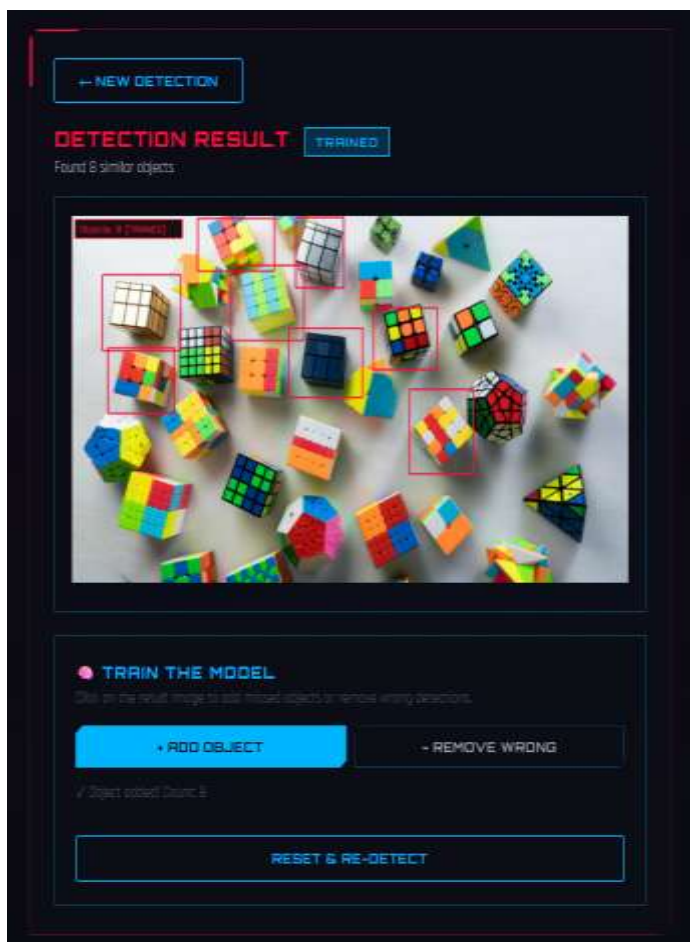
The GradCAM analysis provides insight into the internal decision-making process of the model. It highlights the regions of the image that contribute most to the classification outcome. For real images, the model typically focuses on meaningful structural features such as edges and object boundaries. In contrast, for AI-generated images, attention is often directed toward irregular textures, unnatural patterns, and inconsistent regions.

This behavior indicates that the model effectively learns discriminative features rather than relying on random patterns. The use of GradCAM improves interpretability and transparency, making the system more reliable for applications in digital forensics and image verification.

4.6 Confusion Matrix Analysis

The confusion matrix is used to evaluate the classification performance of the proposed system. It provides a detailed breakdown of correctly and incorrectly classified instances. A high number of true positives (AI images correctly identified) and true negatives (real images correctly identified) reflects strong model accuracy.

The relatively low number of false positives and false negatives indicates that the system maintains balanced performance across both classes. This balance is essential for real-world applications, as it minimizes incorrect predictions and ensures reliable detection of AI-generated content.



5. DISCUSSION

The integration of multi-modal learning and hybrid detection improves system performance. The SPOT-IT module adds a new dimension by detecting repeated patterns. Challenges include handling highly advanced synthetic images and optimizing real-time performance.

6. CONCLUSION

This paper presented TrueSight, an integrated AI vision system combining deep learning and hybrid object detection. The system achieves high accuracy and provides explainable results.

Future work includes real-time optimization and video analysis.

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