AI IMAGE DETECTOR: LCP, GCLM, YCbCr (DEV LOG 2/10/2026)

Ahmed Ali
Fahim Tanvir

1) Introduction

After launching our application, we began exploring additional ways to strengthen its accuracy and overall performance. We dug into research on alternative algorithms and emerging techniques in AI-generated image detection, eventually uncovering methods that focus on analyzing subtle texture patterns, color inconsistencies, and other visual artifacts commonly found in synthetic images. This opened up new directions for refining our system and guided the next phase of experimentation.

2) Microtexture analysis using LCP

Local Contrast Patterns (LCP) delves into the intricate, fine-grained details of image surfaces to pinpoint the subtle inconsistencies that frequently set AI-generated images apart from authentic photographs. By focusing on how pixel values fluctuate within tiny, localized patches, LCP transforms these minute changes into a distinctive texture signature. This signature exposes the hidden irregularities that generative AI often leaves behind. For example, you might encounter unnaturally smooth areas where the distribution of pixel values lacks the organic variation found in real textures, or you may see repeating motifs and unnatural uniformity, artifacts that arise because current generative models have difficulty replicating the chaotic, non-repetitive nature of actual surfaces. Noise characteristics can also be a giveaway: real images typically exhibit random, sensor-based noise, while synthetic images might display noise that feels off or is distributed in patterns not seen in genuine photos. By systematically charting these local variations, LCP provides a robust, quantitative framework for detecting artifacts that would likely escape the human eye, especially when evaluating images at a glance or under time constraints.

3) Spatial Domain Analysis using GLCM

Spatial domain analysis, particularly with the Gray-Level Co-Occurrence Matrix (GLCM), shifts the focus from individual pixels to how groups of pixels interact to form broader image structures. GLCM extracts a range of statistical features such as contrast, homogeneity, entropy, energy, and correlation that collectively describe the spatial relationships and textural qualities present in an image. These features can reveal whether the underlying structure of an image aligns with the natural patterns typically seen in photographs or if it shows signs of artificial generation. AI-created images often struggle to maintain the subtle, coherent transitions and layered complexity found in real-world scenes. This can result in abrupt changes between regions, unnaturally smooth surfaces with little fine texture, or chaotic, structureless patches, all of which GLCM metrics can capture quantitatively. By highlighting these discrepancies, GLCM becomes a powerful diagnostic tool for uncovering synthetic content, especially in situations where visual inspection alone may not be enough.

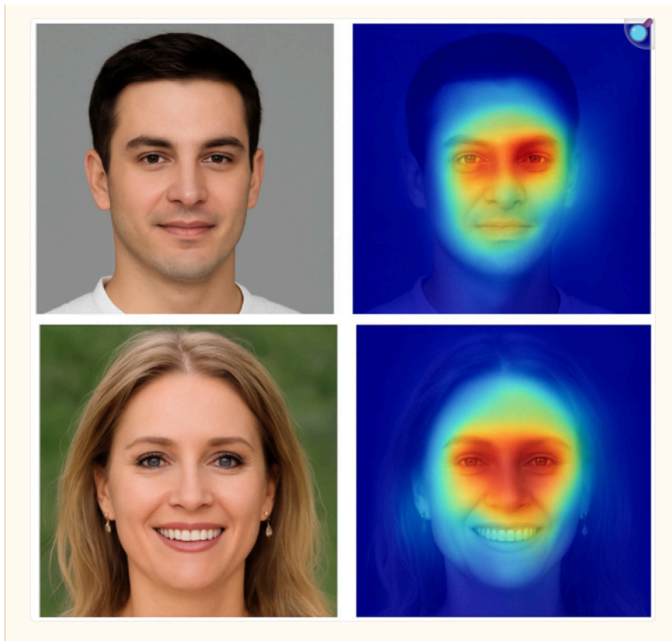

Figure 1: The first 2 methods being used to analyze 2 AI-generated images. It is used to generate a heat map of areas that have AI-generated artifacts(look at the red area).

4) Color Space Analysis with YCbCr

Examining images in the YCbCr color space adds another layer of scrutiny by decomposing the image into its luminance (Y) and chrominance (Cb and Cr) components. This separation allows for a more detailed analysis of how brightness and color information are distributed across the image. Real photos display a natural interplay between light and color, with subtle gradations and blends that reflect the complexities of lighting and material properties. Synthetic images, on the other hand, often show unusual color artifacts such as unnatural transitions, inconsistent shading, or color bleeding that does not match how light interacts with real surfaces. By analyzing each channel independently, YCbCr makes it easier to identify these anomalies, which are especially noticeable in areas like skin tones, shadow transitions, or smooth gradients where generative models frequently struggle. This deeper color analysis uncovers discrepancies that would otherwise remain hidden in the traditional RGB representation.

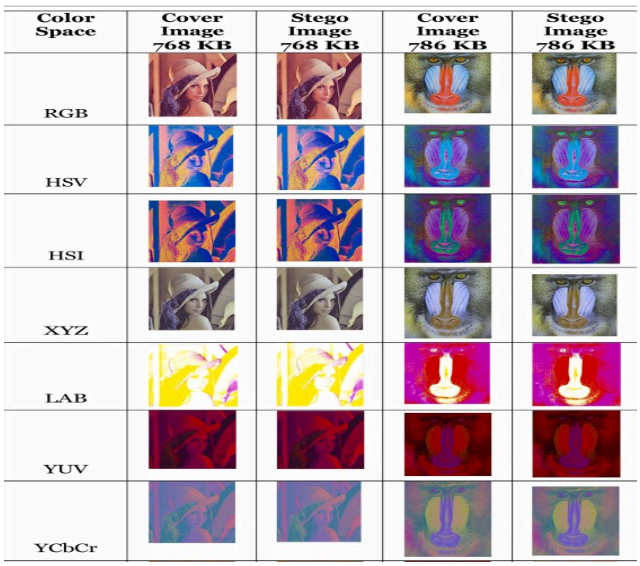

Figure 2: Table of an image that underwent various image filters, including RGB and YCbCr. Comparing both, you can see the latter uses a reddish and grainier filter. Each image is hiding data and the filters are used to perform steganography or how well information is hidden.

Table 4. Generalized scores for each color space baboon image.

Color Space	Generalized Score
YCbCr	0.87494
HSV	0.8186
LMS	0.81655
RGB	0.81613
HSI	0.81575
XYZ	0.81439
YIQ	0.80834
YUV	0.8083
xyY	0.80473
LAB	0.125

Table 5. Generalized scores for each color space lena image.

Color Space	Generalized Score
YCbCr	0.89024
HSV	0.72689
RGB	0.71852
HSI	0.71123
XYZ	0.69733
LMS	0.67308
xyY	0.63885
YIQ	0.50853
LAB	0.47055
YUV	0.4545

Figure 3: The results for generalization and showcasing YCbCr being the best in generalizing and hiding data.

Our intent was to use the analysis for Figures 2 and 3 to use YCbCr'S hidden data capabilities to make our model aware. Essentially if it can hide data within an image color space, we believe we can combine with LCP to find texture anomalies and to look into the channels where those markers within AI images are hidden.

5) Statistical & Domain Analysis

Statistical and domain analysis combines quantitative feature extraction with insights drawn from domain expertise. On the statistical side, metrics such as pixel value distributions, variance, higher-order moments, and entropy summarize the overall structure and complexity of an image. When these statistics are compared to those typically observed in real-world photography, any deviation can indicate synthetic content. Domain analysis adds further depth by applying knowledge of physical and perceptual behavior, such as how natural lighting creates shadows, how textures vary across materials, or how object boundaries usually appear in real scenes. By integrating these perspectives, analysts can identify artifacts that statistical measures alone might miss, including inconsistencies in how light wraps around objects or the presence of implausible textures in certain contexts. Because AI-generated images rarely match both the statistical norms and the physical realities found in natural images, this combined approach offers a comprehensive method for detecting even subtle and sophisticated forgeries. Through the combination of numerical rigor and domain knowledge, the detection of synthetic images becomes more sensitive and more reliable, making it harder for convincing fakes to go unnoticed.

6) Conclusion

This is our second documentation in conjunction with our first one(the pdf labeled "Math and Science behind it" on Github). Additional development logs and technical updates will follow as we continue researching emerging methods to enhance detection accuracy and overall system performance. The approaches outlined here have been integrated into our application, though evaluation and refinement are still underway. Given the wide range of available techniques and the interconnected nature of many of the methods referenced. There remains substantial opportunity to expand our framework with additional filters and analytical strategies.

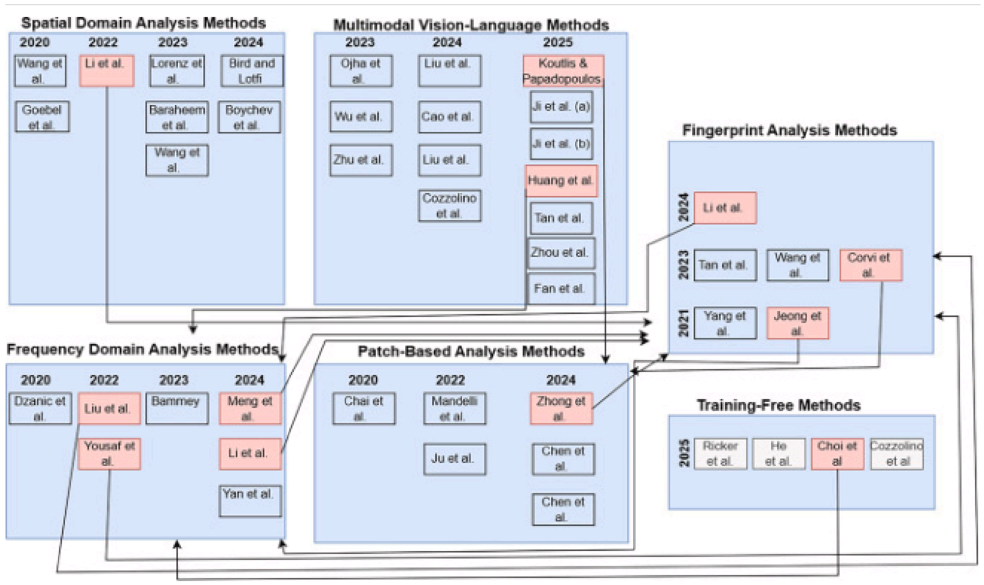

Figure 4: Research timelines of various image detection techniques.

References

[1] Yu H, Xu B. Multi-modal texture fusion network for detecting AI-generated images. Front Artif Intell. 2025, (LCP, GCLM and figure 1) https://pmc.ncbi.nlm.nih.gov/articles/PMC12586049/

[2] Shahad Alharthi, Adnan Gutub, Adjusting image stego practicality via YCbCr color space formation, Journal of Engineering Research, 2025, (YCbCr and figures 2 and 3) https://www.sciencedirect.com/science/article/pii/S2307187725000987

[3] Arpan Mahara, Naphtali Rishe, Methods and trends in detecting AI-generated images: A comprehensive review, Computer Science Review,(Spatial domain and analysis) https://www.sciencedirect.com/science/article/pii/S1574013726000171