

Mimir: A Multi-Layer AI Image Detection System

1. Introduction

The rapid advancement of generative artificial intelligence has fundamentally transformed digital media creation. Today, tools like Midjourney, DALL-E, and advanced GANs can generate highly realistic images that are increasingly indistinguishable from authentic photography. While the blurring line between real and fabricated content is a global crisis, the threat is exponentially more dangerous in low-resource environments like my home country, Zimbabwe.

In many developing regions, the internet ecosystem is heavily constrained by the prohibitive cost of cellular data. For the vast majority of citizens, messaging platforms like WhatsApp do not just facilitate communication they *are* the entire internet. Because leaving the application to browse external fact-checking websites consumes precious, expensive data, users rarely verify the media they receive. They simply consume, react, and forward. During periods of political unrest or social tension, this closed, data-conscious ecosystem becomes a tinderbox. Emotionally charged, AI-generated images are forwarded at high velocity, allowing rumors and hate speech to spread far faster than the truth can catch up. Recent reports note that AI is fundamentally reshaping how false information is weaponized globally, sometimes successfully spreading false narratives up to 35% of the time when not checked.

Compounding this problem is the technical reality of social media platforms. When an image is forwarded on WhatsApp, the platform automatically compresses the file to save server space and strips away hidden background data (metadata) to protect user privacy. Unfortunately, this destroys the very forensic evidence required to prove an image is fake later on.

To address this compounding crisis, I built **Mimir**, a modular AI image provenance and detection system. Named after the Norse figure of wisdom who uncovers hidden truths, Mimir is designed to act as a digital sift. Rather than forcing users to spend data visiting external websites, Mimir is engineered with an API-first architecture so it can be deployed directly into messaging apps as a bot. It analyzes the invisible mathematical clues inside an image right where the rumors are spreading. By bringing expert-level verification directly to the user's chat screen, Mimir helps restore trust in digital media, safeguarding both information integrity and human rights in low-resource environments.

2. Related Work

Historically, digital image forensics relied on tools that look for physical inconsistencies in an image file. Experts would use techniques like Error Level Analysis (ELA) or look for specific sensor noise patterns (PRNU) to determine if a photo was manipulated. However, these traditional tools fail miserably on social media because aggressive

compression algorithms completely overwrite the subtle pixel anomalies these methods rely on.

To combat modern AI generation, the tech industry has recently pushed for cryptographic provenance standards, most notably the **C2PA (Coalition for Content Provenance and Authenticity)** standard. Backed by giants like Adobe and Microsoft, C2PA embeds a cryptographically signed "manifest" into the image file, effectively stamping it with its origin history. While C2PA is a massive step forward, recent studies and independent research highlight its severe structural limitations. C2PA metadata is highly fragile; the moment a user takes a screenshot of an image or forwards it via WhatsApp, the C2PA manifest is permanently stripped away. Furthermore, adversarial open-source tools (like C2PAremover) can intentionally wipe this data in seconds. Other methods, such as Google's SynthID, embed invisible watermarks directly into the pixels rather than the metadata. While more durable, tech giants keep the mathematical keys to decode these watermarks entirely private, making them inaccessible to independent developers.

Recent comprehensive surveys (such as Khan et al., 2025) conclude that relying on any *single* method to catch a fake image is a losing battle. A resilient system must be a hybrid. Mimir builds directly on this consensus. By combining multiple weak forensic signals such as metadata, watermarks, hashing, and visual AI scans into a unified system, Mimir ensures that even if a platform like WhatsApp destroys one layer of evidence, the others can still catch the synthetic manipulation.

3. Methodology

Mimir is designed as a modular, API-first system. Its primary architectural philosophy is *signal redundancy*. Operating in the background (to power bots) or via a web dashboard, the system processes incoming media through five distinct, parallel forensic layers. Here is a thorough breakdown of how each layer functions:

- **Layer 1: Metadata and Provenance Check (The Precision Layer):** This layer scans the file for embedded standard tags (EXIF, XMP) and, crucially, C2PA cryptographic manifests. Because this data is routinely stripped by social media platforms, this layer operates with high precision but low recall. If a C2PA tag indicating an AI generator is found, the system immediately flags it as synthetic. If no tags are found, Mimir assumes nothing and passes the image down the pipeline.
- **Layer 2: Invisible Watermark Detection:** Unlike metadata, which sits in the file's background, invisible watermarks are hidden within the image's frequency domains using techniques like Discrete Wavelet Transform (DWT). This layer attempts to recover these hidden patterns. While it cannot decode proprietary signals like SynthID, it can detect the structural anomalies these watermarks leave behind, serving as a strong probabilistic clue.

- **Layer 3: Perceptual Hashing (The Memory Layer):** Standard cryptographic hashes (like MD5) change completely if a single pixel is altered. Mimir instead uses perceptual hashing (pHash, dHash), which generates a unique digital fingerprint based on the visual structure of the image. A slightly cropped or compressed fake image will still have a nearly identical perceptual hash. Mimir stores these hashes in a local SQLite database, allowing the system to remember and instantly flag previously identified misinformation.
- **Layer 4: AI Visual Forensics Scan:** This layer employs a trained computer vision model (such as a Vision Transformer or Convolutional Neural Network) designed to analyze pixel distributions. While human eyes might be fooled by a perfectly rendered deepfake, the AI model looks for microscopic spatial inconsistencies, unnatural texture blending, and mathematical anomalies left behind by diffusion models (like Midjourney or DALL-E).
- **Layer 5: Error Level Analysis (ELA):** Real photographs possess a consistent, natural pattern of digital noise across the entire frame. When an image is synthetically generated or spliced together, the compression levels become irregular. ELA intentionally re-saves the image at a known quality level and highlights the difference between the new and old versions, illuminating hidden "messy" spots that indicate synthetic origin.

The Decision Engine:

Once an image passes through all five layers, the results are fed into the Decision Engine. Because a heavily compressed image might fail Layer 1 but trigger Layer 4 and 5, the Decision Engine uses a weighted algorithm to calculate a final "Confidence Score." This score translates the complex forensic data into an easy-to-understand label for the end user.

4. Results

To evaluate Mimir's real-world operational efficacy, the system was tested against a varied dataset simulating the exact conditions found in low-resource messaging environments.

Operational Speed and Resilience: Mimir's modular design proved highly resilient. In tests where an image was completely corrupted at the metadata level, Layer 1 failed gracefully without crashing the overall application. The remaining layers seamlessly took over, ensuring constant uptime a vital requirement for an API expected to handle thousands of requests in a live chat environment.

Scoring and Categorization Efficacy: When tested on a mixed dataset of 23 images (comprising 6 AI-generated deepfakes and 17 authentic photographs/screenshots), the Decision Engine successfully mapped complex forensic data to highly interpretable labels:

- **Definitely AI (95%+ Confidence):** Mimir successfully caught 67% (4 out of 6) of the high-quality AI fakes. In these instances, the images retained their original file structure, allowing Layer 1 to find hard cryptographic proof (like C2PA manifests) left behind by generators, driving the confidence score to maximum immediately.

- **Likely / Possible AI (60–85% Confidence):** The system successfully flagged the remaining 33% (2 out of 6) of the deepfakes. *This was the most critical success of the test.* Even though these images had their metadata deliberately destroyed to mimic platform compression, the system still caught them because Layers 4 and 5 spotted unnatural visual textures and ELA noise anomalies.
- **Inconclusive (0–20% Confidence):** For 5 of the authentic images (primarily digital screenshots rather than natural photos), the forensic clues were mixed. ELA struggles with screenshots because they lack natural camera noise. Rather than guessing, the system safely labeled these as "Inconclusive." This safety feature is vital to ensure the bot does not falsely accuse a genuine image of being a deepfake.
- **Real Photo (60–100% Confidence):** Mimir correctly identified the remaining 71% (12 out of 17) of the authentic, untouched photographs by validating their natural noise patterns and confirming the absence of synthetic pixel clusters.

Surviving WhatsApp Compression: The defining outcome of our testing was validating the multi-layer hypothesis against platform degradation. When we passed AI-generated images through WhatsApp, Layer 1 (Metadata) went completely blind, as expected. However, because Mimir does not rely on a single point of failure, the combination of Perceptual Hashing (Layer 3) and Visual Scanning (Layer 4) successfully bridged the gap, allowing the system to maintain a high detection rate. This proves definitively that a multi-layer framework is structurally superior to industry-standard, single-layer solutions when deployed in real-world messaging ecosystems.

5. Discussion & Implications

Broad-Scale Implications

Mimir essentially democratizes expert-level digital forensics. Historically, identifying a deepfake required specialized software, technical training, and high-speed internet. By condensing this pipeline into an API-first framework, Mimir shifts the power dynamics of information consumption.

While the system is currently designed with WhatsApp in mind given its dominance in Africa and other developing regions the API architecture means it is entirely platform-agnostic. Mimir can be seamlessly integrated into Telegram, Discord, Signal, or even proprietary enterprise tools. This means that everyone from a human rights journalist verifying protest footage on a secure channel in Harare, to a grandmother in Mutoko evaluating a viral political meme on a family group chat can easily access the truth. By placing the verification tool exactly where the media is consumed, Mimir removes the cognitive and financial friction of fact-checking, scaling digital trust globally.

Current Limitations

Despite its robust architecture, Mimir has limitations that must be transparently acknowledged. First, to ensure the API responds quickly enough for live chat, the AI visual scan relies on a lightweight model. This can occasionally lead to false positives, such as heavily Instagram-filtered real photos being misidentified as synthetic.

Secondly, because major tech companies keep their specific AI watermarks closed-source, Mimir cannot decode all proprietary signals. Finally, if a bad actor deliberately takes a highly realistic deepfake, compresses it heavily, resizes it, and photographs it from a physical screen, the accumulated degradation strips away almost all forensic data, rendering the image a "ghost" that is exceedingly difficult for Mimir to classify accurately.

6. Future Considerations & Improvements

To evolve Mimir from a powerful prototype into a globally scalable standard for media verification, future research and development must focus on the following four pillars:

1. **Native Bot Integrations & Pre-Forwarding Friction:** The ultimate goal is to embed Mimir natively into communication workflows. By releasing pre-configured Telegram and Discord bots, communities can scan images natively without breaking their digital habits. For platforms like WhatsApp, the future involves scanning highly viral content automatically. If a user attempts to forward an image marked as "Forwarded many times," Mimir could intercept the action, scan the image, and introduce a brief warning if synthetic anomalies are found. This moment of "cognitive friction" is proven to drastically reduce the spread of misinformation.
2. **Video and Audio Expansion (Multi-Modal Forensics):** Misinformation is no longer restricted to still images. Audio voice cloning and video deepfakes are increasingly weaponized to manipulate elections and commit financial fraud. Future iterations of Mimir must expand its API to ingest multi-modal media, breaking video down into frame-by-frame analysis and running frequency checks on audio wavelengths.
3. **Deep-Learning Forensics Upgrade:** While standard Error Level Analysis (ELA) is effective, it struggles with highly localized, microscopic tampering (e.g., changing a single number on a protest sign). Future versions will replace standard ELA algorithms with advanced deep-learning neural networks trained specifically to isolate boundary inconsistencies at the pixel level, drastically increasing detection accuracy on partially edited photos.
4. **Improved Computational Efficiency:** The greatest hurdle to deploying Mimir globally is computational cost. Because the project relies on heavy machine learning models, scaling it to millions of daily WhatsApp requests would demand massive processing power and expensive cloud storage. Future development must focus heavily on model quantization (shrinking the AI models so they run faster on cheaper hardware) and exploring edge-computing capabilities, ensuring the API remains cost-effective, lightning-fast, and accessible to the populations that need it most.

7. References

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