ProofPols: Making trust inspectable

Team The Strongest

Abstract

We present ProofPols, a trust infrastructure for the age of synthetic media that independently evaluates content authenticity and claim credibility. By separating origin assessment from factual verification and grounding both in multi-signal evidence with conservative uncertainty, ProofPols enables users to make informed trust decisions without relying on opaque or overconfident systems.

Track

Track 1 — Restoring Trust in the Age of Synthetic Media

1 Problem Context

Advances in generative AI have made it trivial to create realistic text, images, audio, and video. This has eroded a fundamental pillar of the digital world: trust. Synthetic media enables misinformation, impersonation, scams, and reputational harm at scale[1].

Current solutions are fragmented, opaque, and often overconfident[3, 2]. They typically conflate two different questions:

- Where does this content come from?
- Are the claims in this content factually reliable?

These must be treated as independent dimensions.

2 From Detection to Inspectable Trust

Generative models have made realistic synthetic content cheap and widely accessible, while verification remains difficult for non-experts. This asymmetry increases the risk of misinformation, fraud, and impersonation across remote and digital interactions.

ProofPols addresses this gap by combining provenance, multimodal analysis, and retrieval-based verification into a single interpretable system that separates origin assessment from factual credibility and emphasizes uncertainty over binary judgments[14].

3 Product Concept

ProofPols is a trust infrastructure that independently assesses:

1. **Authenticity** — whether content is real, AI-generated, or edited.
2. **Credibility** — whether explicit claims associated with content are supported by evidence.

ProofPols does not attempt to decide what users should believe. Instead, it provides interpretable evidence, conservative confidence, and explicit uncertainty to support informed human judgment.

4 Flagship Use Case: Remote Hiring Verification

In remote hiring, employers increasingly receive digital resumes, portfolios, and interview recordings that may be synthetic or misleading. ProofPols helps assess whether submitted materials are authentic and whether stated credentials are supported by external evidence, reducing both fraud risk and unjust exclusion.

5 User Flow

1. User uploads content (text, image, audio, or video) and optional claim context.
2. The system detects modality and preprocesses the input.
3. The Authenticity Engine evaluates origin and integrity.
4. If a textual claim is present, the Truth Engine evaluates its credibility.
5. Results are displayed as two independent panels with explanations and limitations.

6 System Architecture

Figure 1 shows the modular processing pipeline of ProofPols. User input is first classified by modality and preprocessed, after which available cryptographic provenance metadata (e.g., C2PA) is verified. The Authenticity Engine then analyzes the content using physical and signal-level constraints, generative-behavioral tests, and limited contextual signals to assess origin and integrity.

In parallel, textual claims are extracted from the content and passed to the Truth Engine, which uses a

Retrieval-Augmented Generation (RAG) pipeline to retrieve external evidence and compare claims against it. Signals from both engines are combined in an evidence fusion layer using conservative Bayesian aggregation, followed by confidence calibration to produce bounded trust estimates. The final results are presented to the user through an explainable interface that surfaces verdicts, evidence, and explicit limitations.

7 Authenticity Engine

The Authenticity Engine assesses whether content is:

- Likely Real
- Likely AI-Generated
- Likely Edited / Mixed
- Uncertain

It uses converging evidence from:

- Cryptographic provenance (C2PA, content credentials)[4]
- Physical and signal constraints (camera physics, audio acoustics)
- Temporal consistency (video)[7, 8]
- Generative-prior behavioral tests (diffusion reconstruction stability)[5, 6]
- Limited contextual signals

Evidence is fused using Bayesian accumulation with capped likelihood ratios and conflict dampening. Confidence is conservatively bounded per modality.

8 Truth Engine

The Truth Engine evaluates the credibility of explicit or implicit textual claims associated with content.

Pipeline

1. Claim extraction and decomposition[9]
2. Evidence retrieval using Retrieval-Augmented Generation (RAG)[10] from:
   - Wikipedia / Wikidata
   - News APIs
   - Government and scientific datasets
3. Cross-source agreement analysis
4. LLM-based comparison between claims and retrieved evidence
5. Conservative scoring with uncertainty

Truth is never assigned directly to images, audio, or video — only to claims expressed about them.

9 Outputs

Each analysis produces:

- Verdict
- Confidence score (bounded)
- Evidence summary
- Known limitations

Why Bounded Confidence

Binary labels encourage over-trust and misinterpretation. ProofPols instead reports bounded confidence to reflect uncertainty and reduce automation bias[15].

10 User Experience

- Drag-and-drop upload interface
- Two-panel trust display (Authenticity and Credibility)
- Visual confidence indicators
- Expandable evidence explanations
- Explicit uncertainty messaging

Designed for non-technical users.

11 Ethics and Privacy

- Stateless analysis
- No biometric storage
- No author fingerprinting
- No opaque trust scores
- Explicit uncertainty and limitations[12, 13]
- Human review encouraged for high-stakes use

Handling Uncertainty and False Positives

When signals conflict or are weak, the system reports uncertainty rather than forcing a decision, ensuring outputs remain advisory rather than authoritative[15].

12 Impact and Metrics

Impact

- Reduced misinformation spread
- Lower scam and impersonation success
- Improved user awareness and caution

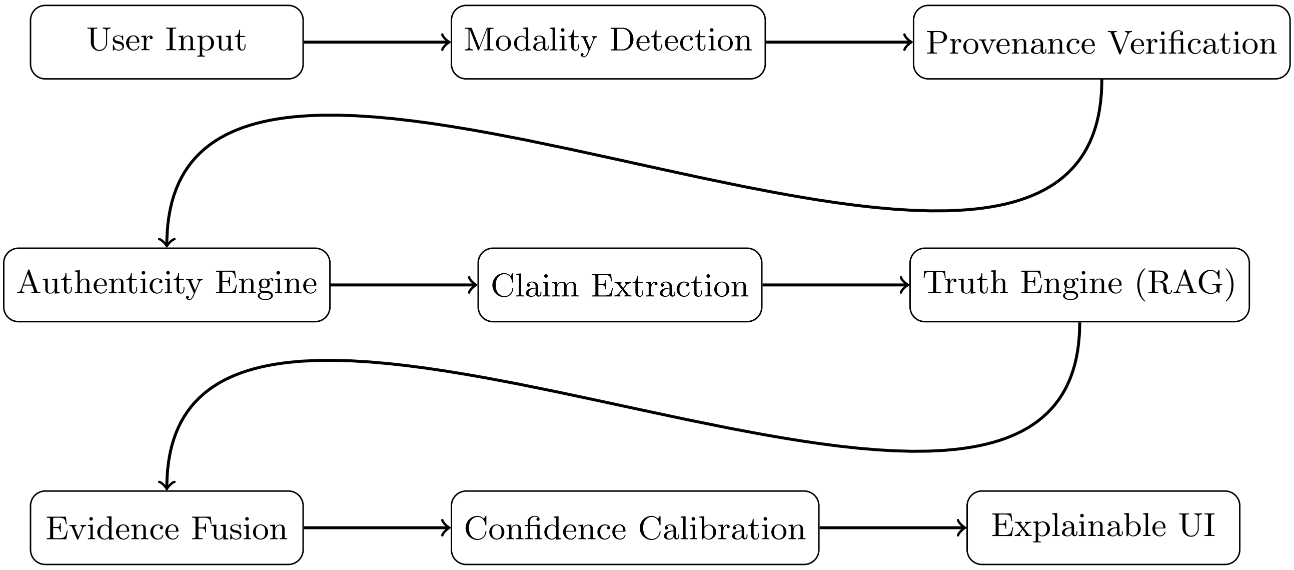

Figure 1: ProofPols system architecture pipeline.

Metrics

- Calibration accuracy[11]
- False positive rate
- User comprehension surveys
- Reduction in blind sharing behavior[16]

13 Scalability

- Modular pipeline per modality
- Cloud and edge deployable
- Extendable to new content types and platforms

14 Prototype / Demo

We provide a web-based demo that:

- Accepts all media types
- Shows dual trust panels
- Uses mock and real backend endpoints
- Demonstrates realistic user interaction

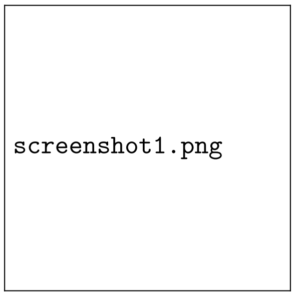

Figure 2: Prototype upload and input interface.

15 Technical Stack

Backend

- Django (core backend and orchestration)
- REST APIs for forensic services
- Modular services for each analysis pipeline

ML and Forensics

- PyTorch for model inference
- OpenCV for image/video processing
- librosa / torchaudio for audio
- Diffusion-based behavioral testing

`screenshot2.png`

Figure 3: Prototype results interface showing authenticity and credibility panels.

Truth Engine

- Retrieval-Augmented Generation (RAG)
- Vector search (FAISS / similar)
- LLM for comparison only

Frontend

- HTML, CSS, JavaScript
- Professional, minimal UI

16 Conclusion

ProofPols restores trust not by making strong claims, but by providing clear evidence, conservative confidence, and explicit uncertainty. It enables users to navigate a world saturated with synthetic media without relying on blind faith or opaque systems.

References

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