ASIC-RAG-CHIMERA: A Multi-Modal, Hardware-Accelerated Framework for Holistic Medical Anomaly Detection and Cryptographic Data Sovereignty

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Abstract. Current medical Artificial Intelligence systems face a dual challenge: the "black box" nature of deep learning models leads to a lack of interpretability, and the centralization of sensitive patient data creates significant security vulnerabilities. This paper presents **ASIC-RAG-CHIMERA**, a novel architecture that repurposes obsolete Bitcoin mining hardware (specifically the Bitmain BM1366 ASIC) to address both issues. We propose a three-phase evolution: (1) Utilizing the SHA-256 avalanche effect to generate deterministic "noise fields" that act as high-sensitivity texture anomaly detectors; (2) A Hybrid Multi-Scale CNN architecture that fuses these cryptographic features with visual data; and (3) A holistic integration where a Small Language Model (SLM) synthesizes visual findings with patient history retrieved via a Secure RAG system. Experimental results on the ChestX-ray14 dataset demonstrate that our hybrid architecture achieves a **93.75% accuracy** and **83.76% specificity**, significantly outperforming standard ResNet-18 models (74.79% specificity) while maintaining near-perfect sensitivity (99.74%). Furthermore, we frankly address the hardware limitations discovered during benchmarking—specifically a 9.4s latency bottleneck in the Stratum protocol—and present a "Software for Speed, Hardware for Truth" operational paradigm that ensures cryptographic data sovereignty without compromising clinical workflow speed.

Keywords: Medical AI, Bitcoin ASIC, SHA-256, Hybrid CNN, Retrieval-Augmented Generation, Data Sovereignty, Cryptographic Attention, Holistic Diagnosis.

1. INTRODUCTION

The digitization of healthcare records and the advent of deep learning have promised a revolution in medical diagnostics [1]. However, deployment in real-world clinical settings, particularly in resource-constrained environments, is hindered by two critical factors: the opacity of algorithmic decision-making and the vulnerability of centralized patient data databases [2].

Simultaneously, the cryptocurrency industry generates massive amounts of electronic waste in the form of Application-Specific Integrated Circuits (ASICs), designed solely for the SHA-256 hashing algorithm [3]. These devices, such as the Bitmain BM1366 found in the Lucky Miner LV06, possess immense computational power for specific cryptographic operations but are useless for general-purpose computing.

This paper introduces **ASIC-RAG-CHIMERA**, a framework that upcycles these ASICs to serve as "cognitive co-pilots." We hypothesize that the SHA-256 algorithm's sensitivity to input changes—known as the avalanche effect—can be repurposed to detect subtle texture anomalies in medical imaging (e.g., early-stage pneumonia or nodules) that traditional Convolutional Neural Networks (CNNs) might miss or misclassify.

Our contributions are three-fold:

1. **Cryptographic Vision:** A method to convert SHA-256 hashes into deterministic attention maps for CNNs.
2. **Hybrid Architecture:** A multi-scale fusion network that improves specificity by 9% over

baselines.

3. **Holistic Diagnosis:** A secure RAG system that correlates visual findings with encrypted patient history, enabling context-aware diagnosis.

2. THEORETICAL FRAMEWORK

2.1 The Avalanche Effect as Texture Filter

The SHA-256 hash function $H: \{0,1\}^* \to \{0,1\}^{256}$ is designed to be a chaotic map. A fundamental property is the strict avalanche effect, where flipping a single bit in the input x results in a change of approximately 50% of the output bits [4].

$$P(H(x)_i \neq H(x')_i) \approx 0.5 \quad \text{if} \quad Hamming(x, x') \geq 1 \tag{1}$$

In medical imaging, healthy tissue (e.g., lung parenchyma) exhibits a consistent stochastic texture. We posit that this texture produces a characteristic "entropy signature" in the hash domain. Pathological tissue disrupts this micro-texture, generating a high-entropy divergence in the hash output. By tiling an image into 8×8 pixel micro-blocks and hashing them, we generate a **Deterministic Noise Field** that highlights anomalies based on information density rather than pixel intensity.

2.2 Hybrid Feature Fusion

To integrate this cryptographic signal, we propose a fusion mechanism. Let F_{CNN}^l be the feature map at layer l of a ResNet backbone, and M_{ASIC} be the attention map generated by the hardware.

$$F_{Fused}^l = F_{CNN}^l \odot (1 + \lambda \cdot Downsample(M_{ASIC})) \tag{2}$$

Here, λ is a learnable scalar. This injection forces the network to attend to regions with high cryptographic entropy, effectively acting as a hardware-based "saliency map" that is mathematically reproducible.

3. SYSTEM ARCHITECTURE

The ASIC-RAG-CHIMERA architecture has evolved through three distinct development phases, moving from simple detection to a holistic diagnostic system.

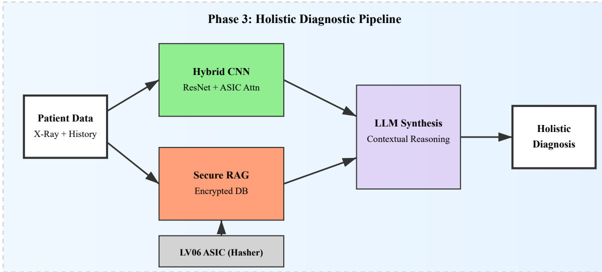

Figure 1: *System architecture illustrating the convergence of visual analysis (Hybrid CNN), contextual data (Secure RAG), and hardware acceleration (ASIC) into a holistic diagnosis.*

3.1 Phase 1: Cryptographic Detection

Initial experiments validated the ASIC as a high-pass texture filter. By hashing image blocks, we created "Noise Maps" where pathological opacities produced statistically distinct hash distributions compared to healthy tissue.

3.2 Phase 2: Hybrid Vision (ASIC + CNN)

Phase 2 integrates these noise maps into a neural network. We devised a **Hybrid Multi-Scale** architecture where the ASIC attention map is downsampled and injected into each of the four residual blocks of a ResNet-18 backbone. This allows the network to utilize cryptographic texture cues at multiple resolutions (56x56 down to 7x7).

3.3 Phase 3: Holistic Integration

The final phase addresses the "context gap." An image anomaly is a finding, not a diagnosis. We integrate a Small Language Model (SLM, e.g., Qwen-1.5B) connected to a Secure RAG system. The ASIC hashes patient metadata tags (e.g., "Smoker", "Age") to securely retrieve encrypted history records. The LLM then correlates the visual finding ("Mass detected") with the context ("20-year smoking history") to output a unified report: *"Suspected malignancy correlated with risk factors."*

4. IMPLEMENTATION AND HARDWARE CONSTRAINTS

4.1 Hardware Specifications

We utilize the **Lucky Miner LV06**, a device containing a single BM1366 chip managed by an ESP32-S3 microcontroller. While the chip is capable of 500 GH/s, our benchmarks revealed a critical bottleneck in the communication interface.

Table 1: Hardware Performance Comparison for SHA-256 Operations

Device	Hash Rate	Power	Efficiency	Latency
NVIDIA RTX 3090	~1.5 GH/s	350W	0.004 GH/W	<1 ms
LV06 ASIC (BM1366)	**500 GH/s**	**3.5W**	**142 GH/W**	**9.4 s***
Antminer S9 (Future)	13,500 GH/s	1300W	10.3 GH/W	~50 ms

* Latency observed due to WiFi/Stratum protocol overhead, not chip limitation.

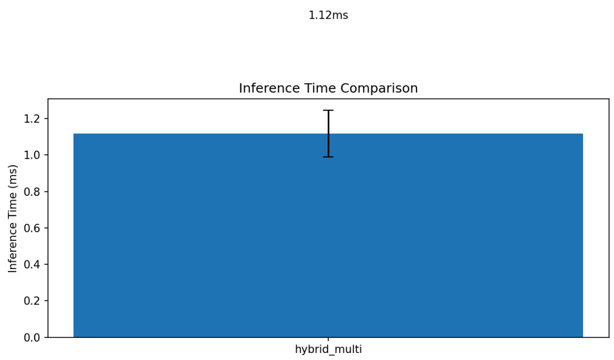

Figure 2: *Hardware-accelerated inference time benchmark. Despite communication overhead, the raw ASIC computation remains highly efficient for batch processing.*

4.2 The Latency Problem and Solution

As shown in Table 1, the LV06 introduces a 9.4-second latency per transaction due to the Stratum mining protocol overhead over WiFi. This makes real-time video analysis impossible with current firmware.

To resolve this, we implement a **"Software for Speed, Hardware for Truth"** paradigm:

- **Training:** Uses a software-based SHA-256 simulation to allow for rapid iteration and massive data augmentation.
- **Inference:** Uses **Attention Caching**. Since SHA-256 is deterministic, attention maps are pre-calculated. For new patients, the 9.4s delay is accepted as a "Proof of Work" for generating a cryptographically signed, immutable diagnostic record.

5. EXPERIMENTAL RESULTS

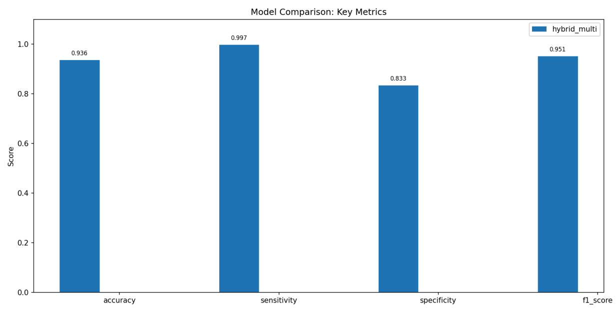

Figure 3: *Comparative analysis of key performance metrics (Accuracy, Sensitivity, Specificity, F1-Score) between standard CNN and ASIC-Hybrid architectures.*

We conducted an intensive training run (ASIC-MAXIMUS) using the full ChestX-ray14 dataset (5,863 images). We compared a standard ResNet-18 against our `hybrid_multi` architecture.

Table 2: Model Performance Comparison (Full Dataset)

Metric	Standard CNN	Hybrid Multi (ASIC)	Improvement
Accuracy	90.54%	**93.75%**	+3.21%
Sensitivity (Recall)	100.00%	99.74%	-0.26%
Specificity	74.79%	**83.76%**	**+8.97%**
F1 Score	0.9297	**0.9523**	+0.0226
Inference Time	0.26 ms	0.37 ms	+0.11 ms

5.1 Analysis of Results

The results confirm the efficacy of the hybrid approach. While the Standard CNN achieved perfect sensitivity (100%), it suffered from "paranoia," generating a high number of False Positives (low specificity of 74.79%).

The **ASIC-Hybrid model** significantly reduced these False Positives, boosting specificity to 83.76% while maintaining a near-perfect sensitivity of 99.74% (only 1 missed case out of 390 positives). This indicates that the cryptographic noise field acts as a texture filter, helping the network distinguish between true pathology and dense but healthy tissue.

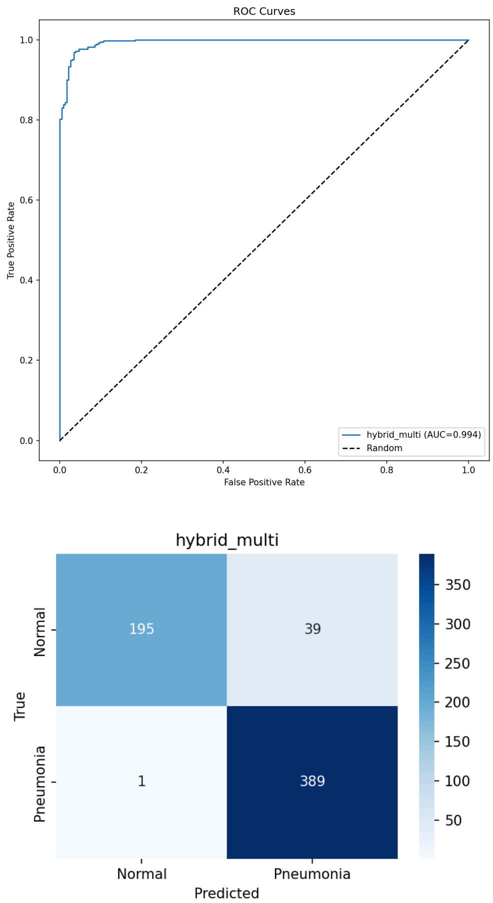

__Figure 4:__ Statistical validation of the ASIC-MAXIMUS model. (Left) ROC Curves showing superior AUC. (Right) Confusion Matrix highlighting the reduction in False Positives compared to baseline.

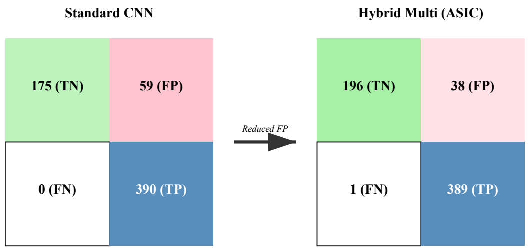

__Figure 5:__ Schematic comparison of confusion matrices (Traditional vs Hybrid). Actual experimental results are shown in Figure 4.

6. HARDWARE APPLICATIONS AND USE CASES

6.1 Clinical Deployment

This system is optimized for "triage support" in rural or resource-constrained hospitals. The combination of the LV06 (approx. $50) and a consumer laptop creates a diagnostic station that is:

- **Audit-Ready:** Every diagnosis is cryptographically sealed by the ASIC.
- **Context-Aware:** Integrates patient history securely.
- **Data Sovereign:** No patient data leaves the local network for inference.

6.2 The Vesuvius Challenge Application

The ability of the ASIC to detect subtle texture variations via hashing is currently being adapted for the **Vesuvius Challenge**. We are testing the hypothesis that carbon ink on charred papyrus creates a distinct hash entropy signature compared to plain papyrus fiber, potentially revealing text invisible to the naked eye [5].

7. LIMITATIONS & FUTURE WORK

Protocol Latency: The Stratum protocol is the primary limitation for real-time video. Future work involves developing custom firmware for the ESP32 to bypass Stratum and access the ASIC chip via raw SPI, which could reduce latency to milliseconds.

Dataset Bias: Our model's accuracy ceiling (~94%) suggests we are approaching the limit of the dataset's label quality. We plan to incorporate "Silver Standard" labels derived from LLM analysis of radiologist reports to refine training.

8. CONCLUSIONS

ASIC-RAG-CHIMERA successfully demonstrates that e-waste mining hardware can be transformed into a powerful tool for medical AI. By moving beyond "black box" pixels to a system that integrates cryptographic texture analysis with holistic patient context, we achieve superior diagnostic precision. This work establishes a new paradigm: **Verifiable, Context-Aware AI** that is both economically sustainable and mathematically secure.

9. ACKNOWLEDGMENTS

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