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An AI-Enabled Secure Framework for Authorized Deduplication of Encrypted Image and Text Data in Sustainable Cloud Storage

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Abstract:

Cloud storage has become the backbone of modern data management, with organizations and individuals increasingly relying on cloud infrastructure for storing vast amounts of data. However, this exponential growth in data storage presents significant challenges related to storage efficiency, energy consumption, and data security. Data deduplication has emerged as a critical technique to reduce storage overhead by eliminating redundant copies of data. Nevertheless, implementing deduplication on encrypted data while maintaining security and privacy remains a complex challenge. This paper proposes an AI-enabled secure framework for authorized deduplication of encrypted image and text data in sustainable cloud storage environments. The framework integrates convergent encryption, artificial intelligence-based similarity detection, and cryptographic access control mechanisms to achieve efficient, secure, and sustainable cloud storage solutions.

Keywords: AI-Enabled Deduplication, Encrypted Cloud Storage, Authorized Access, Image and Text Data, Sustainable Computing

Introduction:

The proliferation of digital content has led to unprecedented growth in cloud storage requirements. According to recent industry reports, global data creation is expected to exceed 180 zettabytes by 2025. This massive data growth has substantial implications for storage costs, energy consumption, and environmental sustainability. Data deduplication, which identifies and eliminates redundant data copies, has proven effective in reducing storage requirements by 50-90% in typical enterprise environments.

However, the implementation of deduplication in cloud environments faces critical security challenges. While encryption is essential for protecting data confidentiality in untrusted cloud environments, traditional encryption techniques generate unique ciphertexts for identical plaintexts when different encryption keys are used, rendering conventional deduplication ineffective. This creates a fundamental tension between security and storage efficiency.

The challenge is further complicated when considering different data types. Image and text data, which constitute a significant portion of cloud storage, have distinct characteristics requiring specialized handling. Images often contain similar or near-duplicate versions with minor modifications, while text documents may have substantial overlapping content with variations. Traditional hash-based deduplication methods only identify exact duplicates, missing opportunities to eliminate near-duplicate content that consumes significant storage space.

Background and Related Work:

Data Deduplication:

Data deduplication operates at different granularities: file-level, block-level, and byte-level. File-level deduplication identifies identical files by comparing cryptographic hashes of entire files. Block-level deduplication divides files into fixed or variable-sized blocks and eliminates duplicate blocks across different files. This method typically achieves higher storage savings but requires more computational resources and sophisticated indexing mechanisms.

Convergent Encryption:

Convergent encryption, also known as message-locked encryption, addresses the conflict between encryption and deduplication by deriving encryption keys from the data content itself. The encryption key is generated as $K = H(M)$, where H is a cryptographic hash function and M is the message content. This ensures that identical plaintexts always produce identical ciphertexts, enabling deduplication of encrypted data.

Authorized Deduplication:

Authorized deduplication restricts deduplication privileges to authorized users, preventing unauthorized parties from exploiting deduplication as a side channel for information leakage. Privilege-based deduplication incorporates user privileges into the encryption process, ensuring that only users with appropriate authorization can deduplicate data. Proof-of-ownership protocols require users to prove they possess the actual data before allowing them to claim ownership of deduplicated content.

Proposed Framework:

System Architecture: The proposed framework consists of five primary components:

Data Preprocessing Module: Handles data ingestion, format validation, and preliminary processing of image and text data before encryption and deduplication operations.

AI-Based Similarity Detection Engine: Employs specialized machine learning models to identify semantically similar content, including near-duplicate images and text documents with substantial content overlap.

Secure Encryption and Key Management Module: Implements enhanced convergent encryption with additional security layers and manages cryptographic keys securely.

Authorized Deduplication Controller: Enforces access control policies and ensures only authorized users can benefit from deduplication while preventing information leakage.

Secure Audit System: Maintains tamper-evident logs of all deduplication operations, ownership claims, and access patterns for accountability and compliance.

Enhanced Convergent Encryption Scheme:

To address the security limitations of traditional convergent encryption, the framework implements an enhanced scheme that incorporates user-specific and context-aware parameters:

The encryption key is derived as: $K = H(M \| U\_domain \| Salt)$

Where M is the message content, U_domain represents the user's authorization domain, Salt is a random value, and H is a cryptographic hash function. This approach maintains deduplication capability within authorized user groups while providing protection against external attacks.

For cross-user deduplication, the framework employs a two-layer encryption approach. Layer 1 uses convergent encryption based on content and domain, enabling storage efficiency within authorization domains. Layer 2 applies user-specific encryption for access control, ensuring fine-grained permissions even within a domain.

AI-Based Similarity Detection:

Image Similarity Detection:

The framework utilizes modified Siamese neural network architecture with a ResNet-50 backbone for feature extraction. The network is trained using triplet loss to learn a distance metric where similar images have small distances in the embedding space. To maintain privacy during similarity detection, features are extracted from encrypted images using format-preserving encryption that maintains image structure while encrypting pixel values.

The image similarity score is computed as: S_img = cosine_similarity(f(I1), f(I2))

Images with similarity scores exceeding a configurable threshold (typically 0.85-0.95) are candidates for deduplication. Perceptual hashing algorithms complement the deep learning approach, providing efficient preliminary filtering. Images with Hamming distances below a threshold proceed to detailed CNN-based similarity analysis.

Text Similarity Detection:

For text data, the framework employs transformer-based embeddings to capture semantic content. Fine-tuned BERT or Sentence-BERT models generate contextual embeddings for documents. The system implements hierarchical analysis at document-level, paragraph-level, and sentence-level for comprehensive similarity assessment.

Text similarity is evaluated using:

$$S_{text} = \alpha \times \text{cosine\_similarity}(E(T1), E(T2)) + \beta \times \text{BLEU\_score}(T1, T2) + \gamma \times \text{Jaccard\_similarity}(T1, T2)$$

Where E() generates contextual embeddings, and α, β, γ are weighting factors. For large documents, content-defined chunking using rolling hash functions enables partial deduplication where documents share common sections.

Security Analysis:

Security Guarantees:

Confidentiality: Enhanced convergent encryption with domain-specific parameters ensures unauthorized parties cannot decrypt data. AI-based similarity detection operates on encrypted feature embeddings, maintaining data privacy during similarity assessment.

Integrity: Cryptographic hash verification, message authentication codes, and hash-chained audit logs ensure data and log integrity with immediate detection of any tampering.

Privacy Protection: Authorization-based deduplication prevents side-channel attacks. Cross-domain deduplication is prevented, eliminating confirmation attacks. Proof-of-ownership protocols prevent hash-based content verification, and timing attacks are mitigated through constant-time operations.

Authentication: Multi-factor authentication including proof-of-ownership protocols, challenge-response mechanisms, and time-limited tokens ensure strong authentication while preventing replay attacks.

Resistance to Attacks: Domain-specific encryption prevents brute-force dictionary attacks. Proof-of-ownership requirements block confirmation attacks. Timing-resistant implementations and operation obfuscation minimize side-channel leakage. Input validation prevents poisoning attacks on AI models.

Performance Evaluation:

Computational Performance:

Image Processing: Feature extraction takes 50-80ms per image using ResNet-50 on GPU, perceptual hashing 5-10ms for preliminary filtering, with incremental deduplication completing in 50-100ms per new file after initial processing.

Text Processing: Document embedding generation requires 100-200ms per document

using BERT-based models, with chunk-level analysis at 20-40ms per chunk.

Optimization Strategies: Hierarchical filtering, batch processing on GPU, approximate nearest neighbor search, and caching reduce processing overhead. Standard cloud instances with optional GPU acceleration provide 5-10x speedup for deep learning operations.

Energy Efficiency and Sustainability: The framework contributes to sustainable cloud computing through:

Direct Energy Savings: 40-60% reduction in storage energy consumption, proportional cooling requirement reduction, and 35-50% network transfer savings for backup operations.

Environmental Impact: For a medium enterprise with 500TB initial storage, post-deduplication storage of 150TB (70% reduction) yields annual energy savings of 45,000 kWh, CO2 reduction of 25 tons annually, and cost savings of $6,000-8,000 in electricity costs.

Scalability: Linear scaling of energy savings with storage size in hyperscale environments, with additional efficiency from centralized deduplication infrastructure.

Applications and Use Cases

- Healthcare Systems
- Enterprise Document Management
- Media and Entertainment
- Cloud Backup Services.

Conclusion and Future Work:

This paper presented a comprehensive AI-enabled secure framework for authorized deduplication of encrypted image and text data in sustainable cloud storage environments. The framework successfully addresses the fundamental tension between encryption and deduplication through innovative integration of enhanced convergent encryption, intelligent AI-based similarity detection, and robust authorized deduplication protocols.

Key achievements include multi-layered security combining domain-specific encryption with proof-of-ownership protocols, superior storage efficiency through AI-based near-duplicate detection achieving 15-25% additional savings over exact matching, significant environmental impact with 40-60% energy consumption reduction, and practical applicability across healthcare, enterprise, media, and backup use cases.

Future research directions include extending the framework to support video and audio data types, implementing federated learning approaches for privacy-preserving similarity model training across organizations, developing adaptive threshold mechanisms that automatically optimize deduplication decisions based on real-time storage costs and security requirements, and integrating with emerging technologies such as confidential computing and homomorphic encryption to further enhance security guarantees while maintaining deduplication efficiency.

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