



# **NOVEL APPROACHES TO CONTENT MODERATION OF END-TO-END ENCRYPTED IMAGES USING PERCEPTUAL HASHES**

Members:

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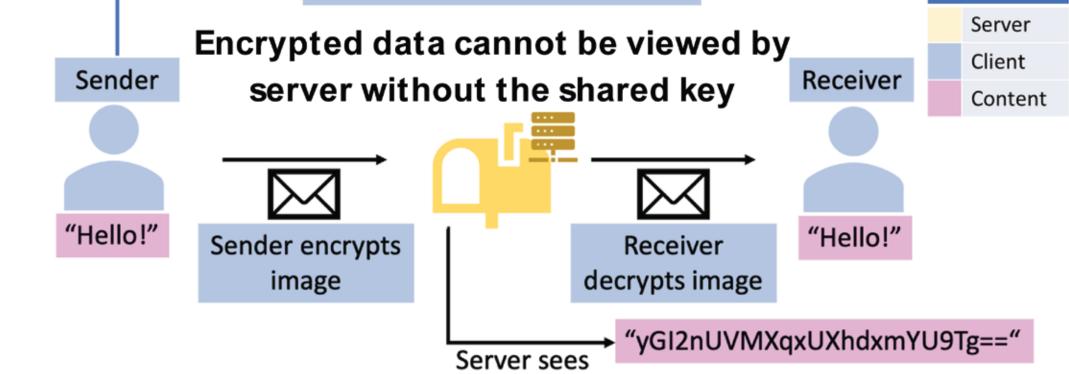
1. Background: Content Moderation of E2EE Images

I <b>OT</b> known to server
: ChickenPieYum@55
. Chicken rerundess



## 2. Perceptual Hashes of Images

98dc67d9c7394e37



## A) Setting: E2EE Image Communication

Two users (Sender, Receiver) send images via an untrusted server. The server should never get access to the original content being sent, **preserving user privacy**.

## **B) Challenge: Content Moderation with E2EE**

Shared

Server wishes to block undesirable ("R21") images without affecting neutral ("PG") images. But how does the server efficiently do this without decrypting the images? <u>C) Our Solution: Improved Content Moderation in E2EE</u>

Prior work proposed various "perceptual hashes" for comparing encrypted images with known databases of R21 content. We consolidate and improve upon this work by combining them using a novel **decision tree**.

#### Input : Image 18c6b23163639967f **Output** : Fixed length hash Hash Algorithm 30ccce6998cb0b00d 33d997e6c9c0cc Output Fixed-length hash string

• Hashes can be **compared** to determine whether two images are <u>visually similar</u>.

We utilised Difference Hash (dHash), Perceptual Hash (pHash), Wavelet Hash (wHash) [1] and Non-negative Matrix Factorisation Hash (NMFHash) [2] in our work.

# 3. Our Work

?: Can the <u>accuracy</u> of perceptual hashes in detecting <u>visually similar</u> images be improved via a <u>combination</u> of perceptual hash algorithms?

# **Our Contributions**

3) **Testing** on real-world

1) **Survey** of Perceptual Hashes datasets

2) **Combined hashes into novel**, 4) **E Python library** and

sim ≤ 0.277

Similar

**Decision Tree** approach

proof-of-concept application

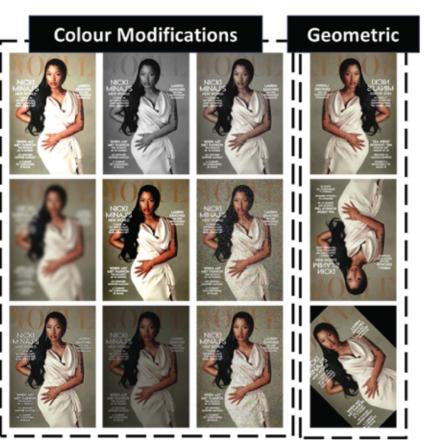
# 4. Novel Decision Tree Approach to Content Moderation using combination of Perceptual Hashes

4.1 Server - Client Protocol for E2EE images

**1. Setup:** Server hashes all images in database using all hash algorithms and stores resultant hashes dhash phash nmfhash whash

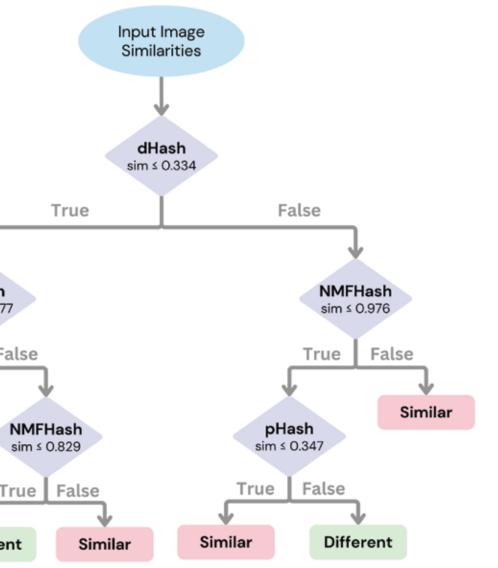
## 4.2 Visually similar?

Legend



## 4.3 Our Decision Tree

- Each decision node makes use of one of the hashing algorithms with their specific threshold conditions.
- Threshold values are obtained by making use of machine learning to find patterns in similarity data



#### c9b4063a(ed55f2ce6fc00ff0ee7W!!\_!!w!!' aa16a9d6;c174b480]000074fe5P!!K!!Q!!e

**2. Send:** Image to be sent is hashed client-side to produce a list of four hashes. Hashes are appended to encrypted image data and sent to server.

vT...AM|c9b4...25b2|ed54...17e8|fc00...dd00|W!!\_...!;!! Encrypted Image DataldHashlpHashlwHashlNMFHash

3. **Similarity:** Server calculates a similarity score for each pair of hashes 0.939 | 0.848 | 0.799 | 0.977 \*arbitrary values

4. **Verdict:** Server passes similarity scores into decision tree to check if image is visually similar to any images in the database.

Malicious users may apply colour or geometric filters to their images, creating **modified** images to circumvent detection. Hence, we test the decision tree's ability to detect that these **modified** images are <u>visually similar</u> to the original image.

- from all four hash algorithms as a whole.
- Machine learning model **does NOT analyse** the <u>original images directly -- privacy-preserving</u> True
- **Decision Tree** remains <u>static</u> after its initial construction

#### 4.4 Evaluation Methodology A) Baseline Approaches

We compared our decision tree approach to two baseline approaches:

- Individual Hashes, where images are classified as similar or different considering only one hash algorithm.
- Majority Decision, where verdicts of all four hash algorithms are considered separately, and the majority verdict is taken as the final.

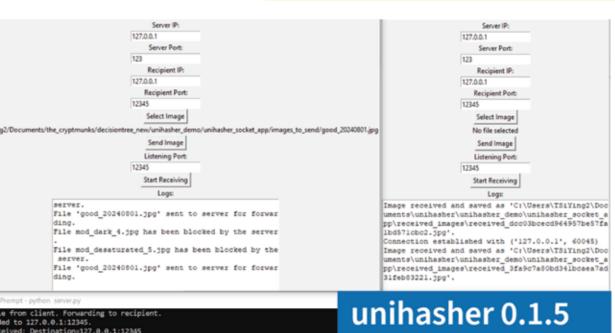
#### **B)** Performance Metrics

- Accuracy overall effectiveness considering both positive and negative predictions
- **Precision** how many <u>predicted</u> positives are actually positive
- **Recall** how many <u>actual</u> positives were correctly identified
- F1 Score provides a <u>balanced</u> view of precision and recall

-						
		Efficacy				
	<u>5.1 Summa</u>	5.2 Observati				
	Approach	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	<u>Using the best</u> hash (dhash) as • Majority De
	dHash	89.18	100.00	78.22	87.78	
	pHash	88.81	100.00	77.48	87.31	limited abilit
	wHash	88.76	99.18	78.04	87.34	performanc
	NMFHash	75.45	97.73	51.81	67.72	single hash a • The <b>Decisior</b>

## <u>oservations</u>

- <u>the best performing individual</u> hash) as benchmark,
- jority Decision approach has ited ability to improve formance beyond that of any gle hash algorithm.
- **Decision Tree**, using a



# 6. Software Contributions

- GitHub library, "unihasher", for developers to incorporate our decision tree solution into their applications.
- Proof-of-concept chat **application** demonstrating our library in action.

5.3 Discussion									
	Decision Tree	95.12	99.80	90.36	94.84				
	Majority Decision	89.18	100.00	78.22	87.78				

combination of all four hash algorithms, shows a **significantly improved** accuracy and F1 Score.

In particular, the **Decision Tree** produced **significantly fewer** false negatives, such that fewer visually similar images go undetected. For content moderation of images, this is desirable as it **prevents potential cascading effects** resulting from the spread of **harmful but unblocked** content.

We also tested our Decision Tree on a <u>completely separate</u> dataset of 10,000 images, with the **exact same** decision nodes as obtained in 4.3 above. Our Decision Tree approach achieved a high accuracy of 91.94% and F1 Score of 91.42%, showing its high generalisability - the same thresholds can be easily applied to different types of images, thus having high potential for application amongst wider contexts and more general use cases without requiring retraining of the tree.

pip install unihasher 🕻

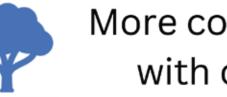
## 7. Future Work



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Extending to videos or animated images

Exploring more different hash algorithms



More complex decision tree with confidence score

# 8. References

[1] Buchner, J.. Image hash Python library. Available at:

https://github.com/JohannesBuchner/imag ehash?tab=BSD-2-Clause-1-ov-file#readme [2] Z. Tang, X. Zhang and S. Zhang, "Robust Perceptual Image Hashing Based on Ring Partition and NMF," in IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 3, pp. 711-724, March 2014, doi: 10.1109/TKDE.2013.45.

