A Wild Manhunt for Stego Images Created by Mobile Apps

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Background

- As mobile Internet and telecommunication technology develops at high speed, the digital image forensics academic community is facing a growing challenge.
- Mobile applications (Apps) allow a user to easily edit/process an image for a variety of purposes.
- Thanks to the improved cameras and editing apps on smartphones, the volume of images presented to digital image forensic practitioners increases every day.
- Unfortunately, terrorists, spies and child pornography predators are also taking the advantage of the mobile app ecosystem to exchange illegal files and photos.

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Steganography Apps on Google Play

App Name	Installs	Open Source	Output Format	Image Resizing	Payload Pre-processing			Embedding Technique
					Encryption	Signature Strings	Length Data	
PixelKnot	100,000+	Yes	JPG	Downsampling	Yes	No	Yes	F5
Steganography Master	10,000+	No	PNG	No	No	Yes	No	1's digit replacement
Steganography_M	10,000+	No	PNG	No	No	Yes	No	LSB replacement
DaVinci Secret Image	5,000+	No	PNG	User specified	No	Yes	Yes	Alpha channel encoding
Steganography_T	5,000+	No	PNG	No	No	No	Yes	LSB replacement
Stegais	1,000+	No	JPG	Downsampling	No	No	Yes	Unknown
PocketStego	1,000+	No	PNG	Downsampling	No	Yes	No	LSB
MobiStego	1,000+	Yes	PNG	Downsampling	Yes	Yes	No	RGB channels LS2B
NiaStego	1,000+	No	PNG	Upsampling	Yes	Yes	No	RGB channels LSB
Passlok	1,000+	Yes	JPG	No	Yes	Yes	No	Non-shrinkage F5

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Steganography

- Steganography embeds data into an object, so that even the existence of the secret message cannot be discovered by visual observation.

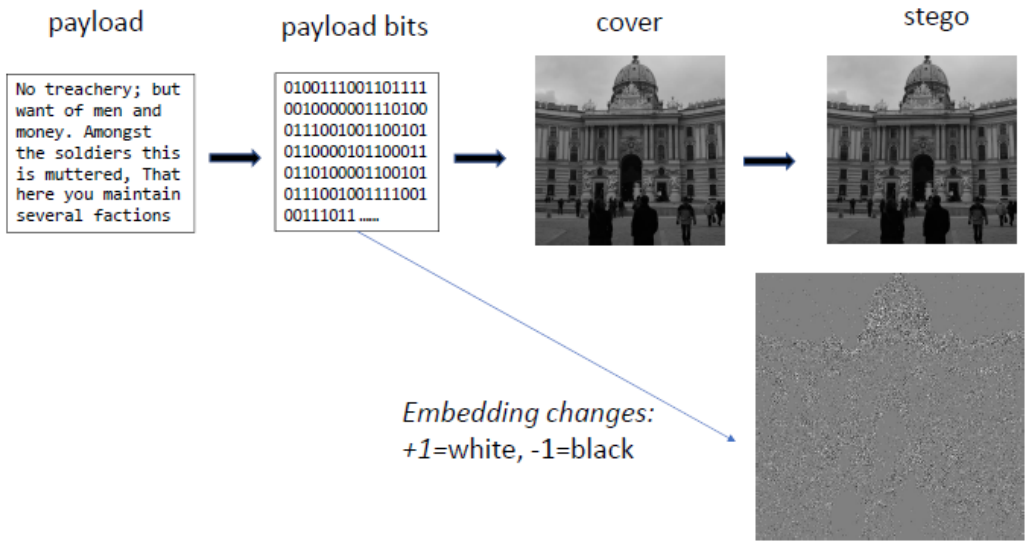

Figure: An example of steganography embedding in the spatial domain by embedding algorithm S-Uniward

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Steganography

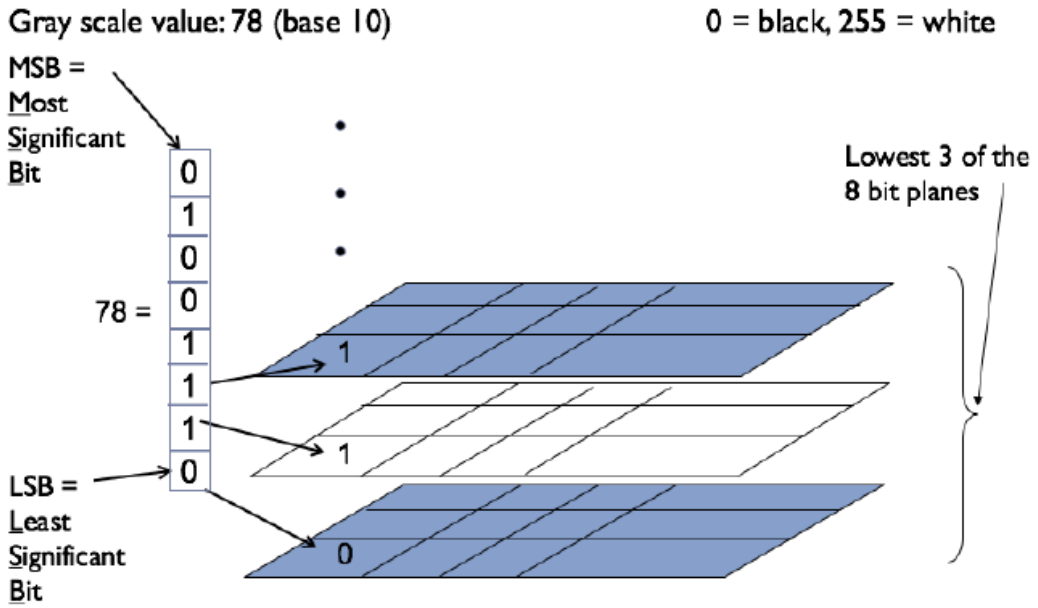

Figure: An example of the Least Significant Bit in the spatial domain

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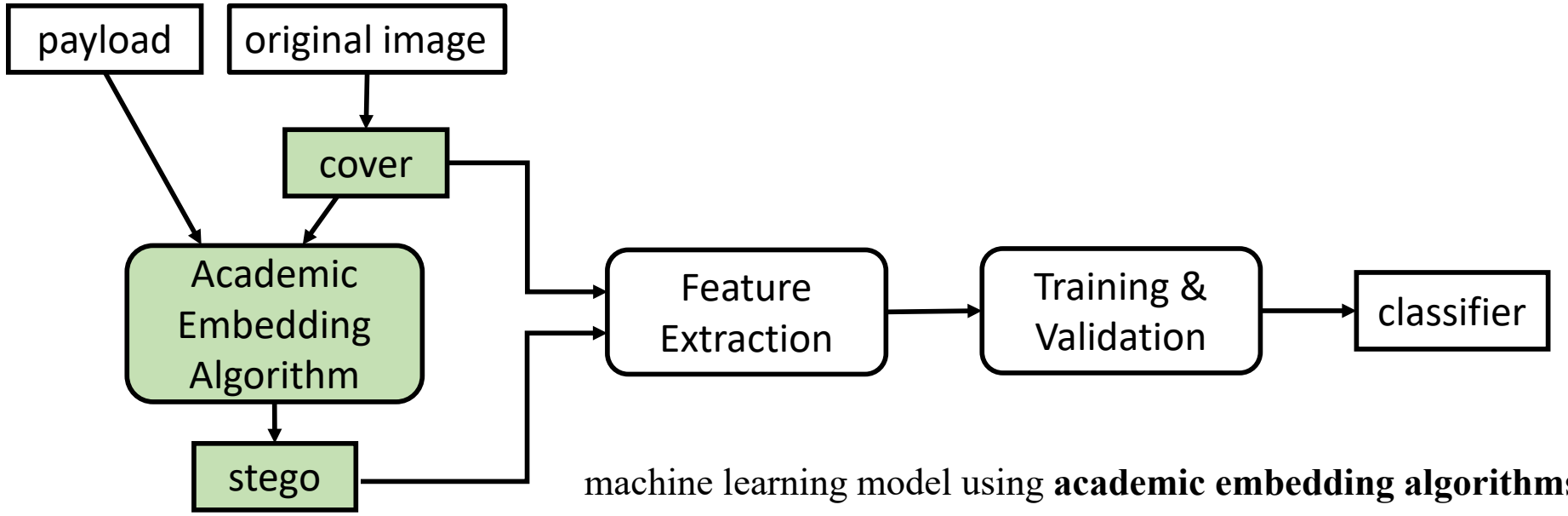
Academic Steganalysis

- The forensic process to detect steganography
- Machine learning models are used extensively in academics



machine learning model using **academic embedding algorithms**

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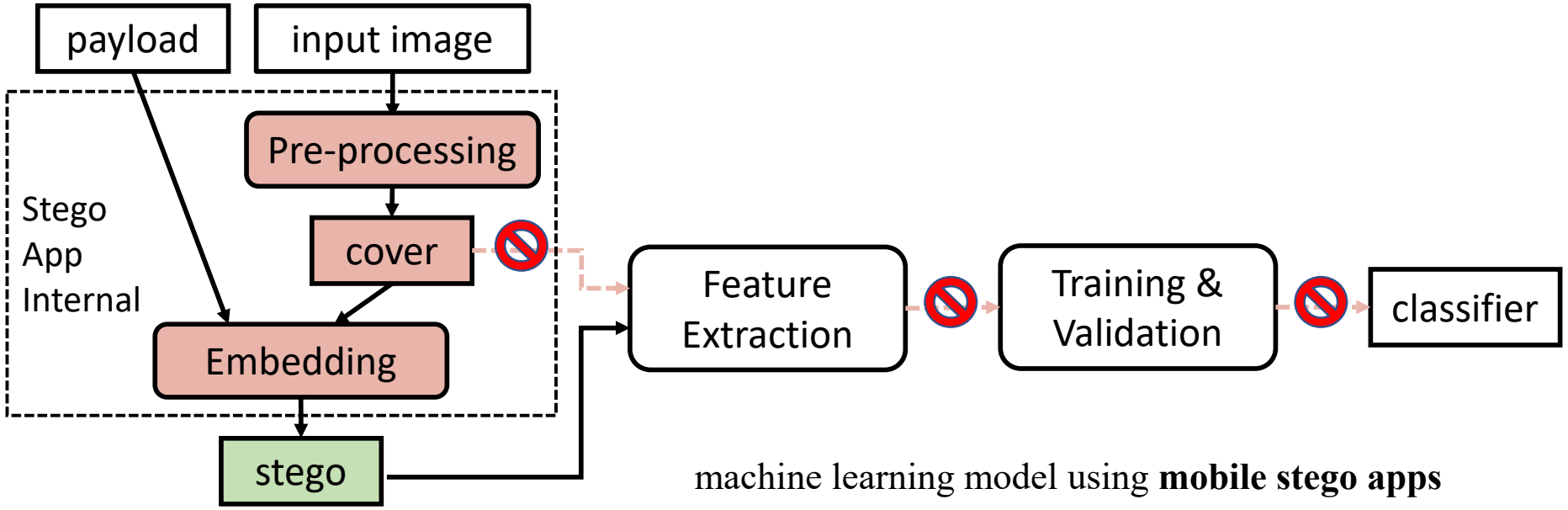
Challenges of Steganalysis for stego apps

- Unknown components when applied to mobile stego apps
  - No access to cover image
  - No control over the embedding rate (% of image data used for embedding)



machine learning model using **mobile stego apps**

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Our Contributions

- Construction of a heavily-provenanced digital image reference database, StegoAppDB, that simulates digital evidence and provides data for
  - Testing current steg detection tools – Stego Hunt, DC3 StegDetect
  - Developing tools that detect steg images created from mobile apps

- **StegoAppDB**: A mobile stego image dataset for steganalysis
  - https://forensicstats.org/stegoappdb/

- Detection of stego images from Android apps
  - Detection using machine-learning detection
  - Detection using signature-based methods

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StegoAppDB

Device Model	# Devices	ISO Range	Exposure Time Range	# Scenes	# Original Images	# Cropped Images	# Covers	# Stegos
Google Pixel 1	4	107 ~3735	1/120 ~1/10	404	8080	8080	36360	181800
Google Pixel 2	4	67 ~3155	1/252 ~1/12	404	8080	8080	36360	181800
Samsung Galaxy S8	2	57 ~6846	1/120 ~1/12	200	4000	4000	18000	90000
OnePlus 5	2	100 ~3000	1/10830 ~1/15	200	4000	4000	18000	90000
iPhone 6s	4	40 ~1600	1/60 ~1/3	404	8080	8080	8080	40400
iPhone 6s Plus	2	25 ~1250	1/66 ~1/3	213	4260	4260	4260	21300
iPhone 7	4	25 ~1000	1/60 ~1/3	404	8080	8080	8080	40400
iPhone 7 Plus	2	25 ~1000	1/80 ~1/3	202	4040	4040	4040	20200
iPhone 8	2	32 ~1600	1/60 ~1/3	202	4040	4040	4040	20200
iPhone X	2	20 ~1600	1/62 ~1/3	203	4060	4060	4060	20300
total	28	20 ~6846	1/10830 ~1/3	2836	56720	56720	141280	706400
total images								961120

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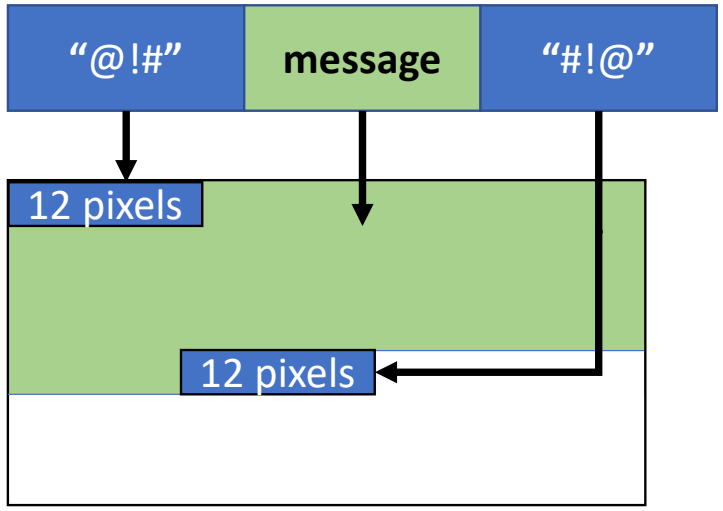
Signature-based Steg Detection

- Signature definition:
  - A fixed bit string pattern extractable from the stego image
  - Constant strings embedded into fixed locations, to demarcate the message
- Example for the app “MobiStego”

Payload composition:

Stego Image:



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Signature-based Steg Detection

- Four stego apps contain embedding signatures

Stego App	Payload Composition (constant strings + user input)
Steganography Master	constant (102 bits) | password | constant (24 bits) | message | constant (88 bits)
Da Vinci Secret Image	constant (32 bits) | length (32 bits) | password | length (32 bits) | message
MobiStego	constant (24 bits) | encrypted message | constant (24 bits)
PocketStego	message | constant (8 bits)

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Signature-based Steg Detection Results

- Results of signature-based detection on 202,080 images

Stego App	Test Images	Image Count	Accuracy
Steganography Master	SM Stego Images	42,100	100%
	Other Images	159,980	100%
DaVinci Secret Image	DV Stego Images	42,100	100%
	Other Images	159,980	100%
MobiStego	MS Stego Images	42,100	100%
	Other Images	159,980	100%
PocketStego	PS Stego Images	42,100	100%
	Other Images	159,980	0.23%

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Machine Learning Detection Method

- **Dataset of two case study**
  - 6000+ original images from 3 selected Phone models: half JPEG, half DNG.
  - Cover/stego pairs created from two apps: **PixelKnot** and **Steganography_M**
- **Feature sets**
  - JPEG rich model for frequency domain[1] (for PixelKnot data)
  - Spatial rich model for spatial domain[2] (for Steganography_M data)
- **Classifier**: ensemble FLD[3] (Fisher Linear Discriminant)/Random Forest
- **Average error rate**: (Missed detection rate + False alarm rate)/2

[1] J. Kodovsk`y and J. Fridrich. Steganalysis of jpeg images using rich models. In Media Watermarking, Security, and Forensics 2012.
[2] J. Fridrich and J. Kodovsky. Rich models for steganalysis of digital images. IEEE Transactions on Information Forensics and Security, 2012.
[3] J. Kodovsky, J. Fridrich, and V. Holub. Ensemble classifiers for steganalysis of digital media. IEEE Transactions on Information Forensics and Security, 2012.

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Detecting **PixelKnot** stego images*

- No known software package that can test for steganography content in ***mobile phone photographs from stego apps on mobile phones***
- StegoHunt, DC3 cannot detect mobile stego images

Table 5: Error of detection on images generated by PixelKnot

Error Type	Stego Hunt	DC3–StegDetect	Provos–StegDetect
False Alarm	0%	0%	24.6%
Misdetection	100%	100%	75.4%
Avg. Error	50%	50%	50%

- However, **machine learning** trained with proper data – available currently only from StegoAppDB - gives similar performance as in academic setting

Table 6: Classification accuracy of detecting cover-stego pairs by ML algorithms

Apps	Pixel 1	Pixel2	Samsung S8	One Plus 5	Mix of four devices
PixelKnot	97.5%	97.6%	97.6%	98.3%	99.0%
Steganography	98.0%	97.8%	99.4%	97.7%	98.6%
Pocket Stego	96.8%	97.3%	99.5%	98.3%	98.4%
Passlok Privacy	99.0%	97.1%	98.3%	98.3%	98.6%

J. Newman, L. Lin, W. Chen, S. Reinders, Y. Wang, M. Wu, Y. Guan. “StegoAppDB: A steganography apps forensics image database,” IS&T Int’l. Symp. on Electronic Imaging, Media Watermarking, Security, and Forensics 2019, Burlingame, CA, pp. 536-1-536-12, (12), 2019.

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Machine Learning Detection Results

- Detecting stego images created from **Steganography_M**
  - **Spatial domain** embedding with pseudo-random path
  - 850 cover/stego pairs created from 850 center-cropped **PNG** images from **JPEG** images as originals
  - 500 for training, 350 for testing
  - All stegos have 10% embedding rate

Input Image Source	Input Image Size	Stego Image Size	Average Error
Google Pixel	512*512	512*512	0.0%
Samsung Galaxy S7	512*512	512*512	1.0%
OnePlus 5	512*512	512*512	1.4%
Mixed	512*512	512*512	0.8%

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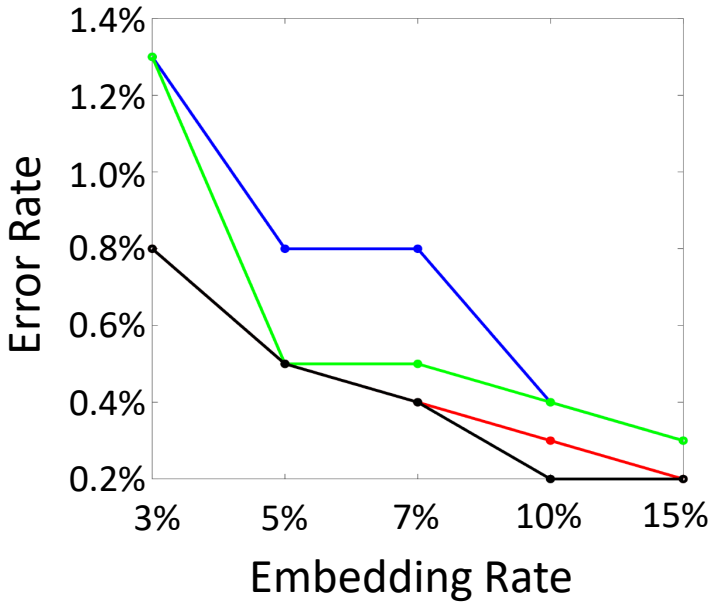
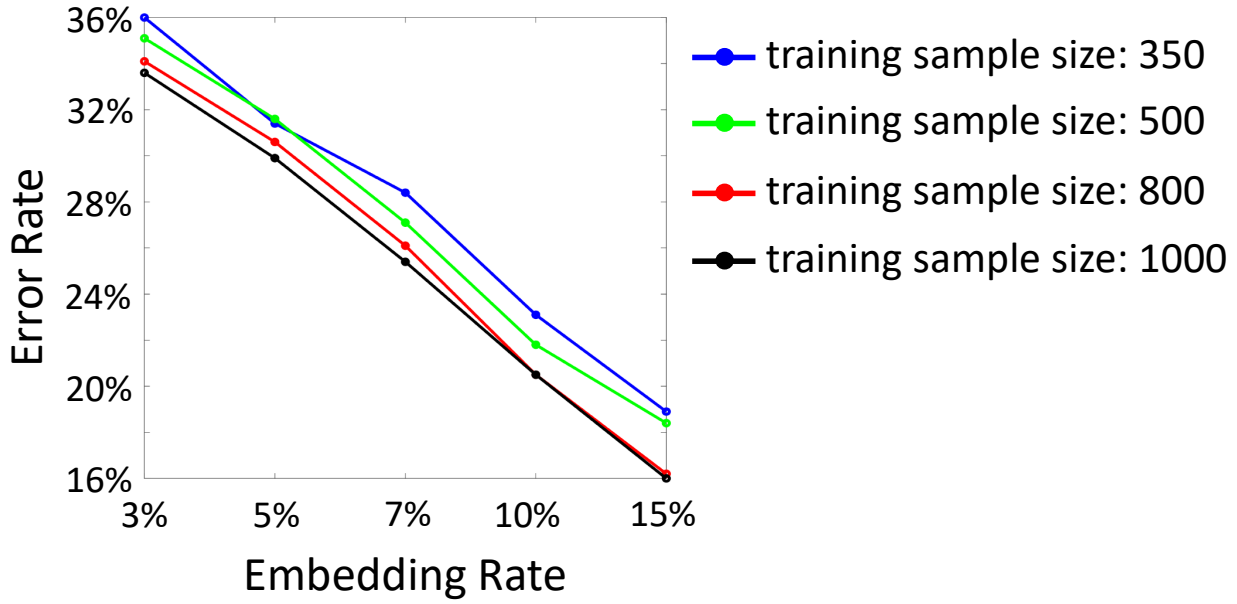
Machine Learning Detection Results

- Detecting stego images created by **Steganography_M,** with different embedding rates, training sample sizes, and original image formats.



Original image format: **JPEG**



Original image format: **DNG**

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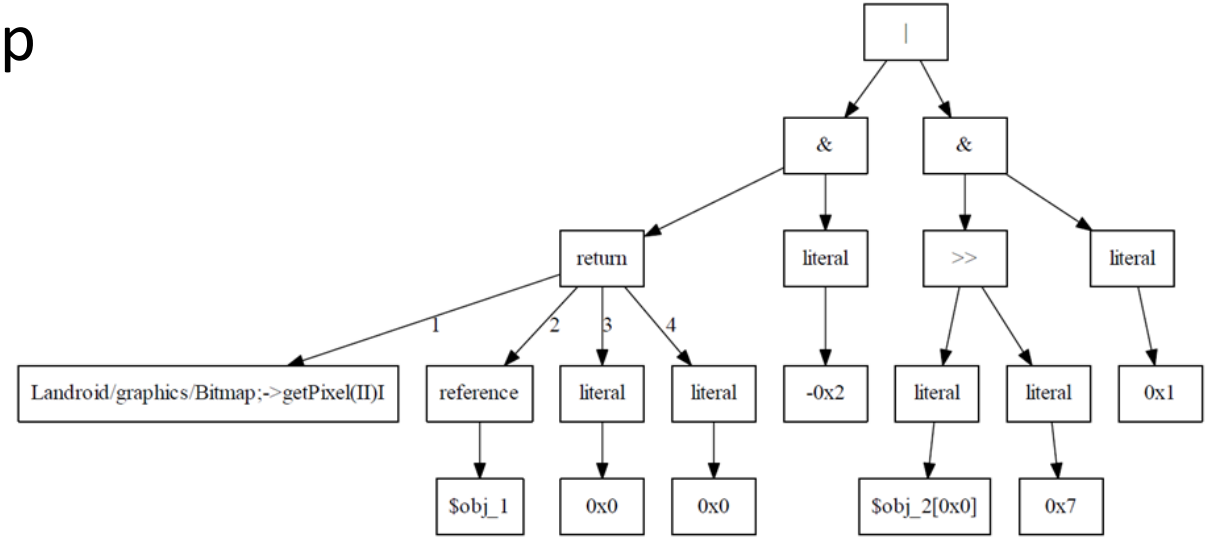
Wild Manhunt for Stego apps

- Goal: determine whether any given app (NOT images) contains function/code that performs image steganography.
- Approach:
  - Extract expression trees (ET) by symbolic execution on the app's binary code.
  - Match extracted ETs with a set of pre-defined ETs (domain knowledge) using k-nearest neighbor algorithm
  - The kNN algorithm is based on Tree Edit Distance – the minimum-cost sequence of node edits to transform one tree to another



An example of expression tree, representing how a stego pixel is generated from a cover pixel:

new_pixel = cover.getPixel(0,0) & 0xFFFFFFFE | (p[0]>>7 & 1)

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Conclusion

- We generated a mobile stego image dataset by reverse engineering and instrumenting Android stego apps
  - Available at: https://forensicstats.org/resources/datasets-tools/
  - Current analysis process is manual, but future work will focus on automating the procedure to efficiently add new data
- Analysis of stego apps showed embedding signatures existed and can be utilized for high accuracy detection.
- Machine learning can work well without relying on signatures, given access to the devices and cover images.
- A tool for hunting stego apps is still in development, and the progress is encouraging.

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