Aragorn: A Privacy-Enhancing System for Mobile Cameras

ANONYMOUS AUTHOR(S)

Mobile app developers often rely on cameras to implement rich features. However, giving apps unfettered access to the mobile camera poses a privacy threat when camera frames capture sensitive information that is not needed for the app's functionality. To mitigate this threat, we present Aragorn, a novel privacy-enhancing mobile camera system that provides fine grained control over what information can be present in camera frames before apps can access them. Aragorn automatically sanitizes camera frames by detecting regions that are essential to an app's functionality and blocking out everything else to protect privacy while retaining app utility. Aragorn can cater to a wide range of camera apps and incorporates knowledge distillation and crowdsourcing to extend robust support to previously unsupported apps. In our evaluations, we see that, with no degradation in utility, Aragorn detects credit cards with 89% accuracy and faces with 100% accuracy in context of credit card scanning and face recognition respectively. We show that Aragorn's implementation in the Android camera subsystem achieves 20 frames per second that is adequate for real time operation.

CCS Concepts: • **Security and privacy** → **Privacy protections**; **Mobile platform security**; **Usability in security and privacy**; • **Computing methodologies** → *Computer vision.*

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1 INTRODUCTION

Billions of smartphone users use third-party camera apps to capture photos/videos [7, 19, 22, 57], experience AR/VR capabilities [45, 59], scan documents [3, 12], or employ assistive technologies [4, 10]. Cameras also enable app developers to design robust security challenges [8, 9, 15, 16, 24, 63]. For example, mobile cameras can be used to scan QR codes for two-factor authentication [1, 68], privately share contacts [44], or verify possession of credit cards [15, 16].

The rich information captured by mobile cameras exposes potentially sensitive information to camera apps. Currently, users only have coarse grained control to limit which apps can access camera frames, but not fine grained control over what apps can access within these frames. It is not uncommon for camera apps to inadvertently capture sensitive objects from user environments [43, 52]. Even in the absence of explicitly sensitive objects, apps have used background information captured by cameras to profile users [58]. A camera app can use this information to (re)identify users (§ 7.3.1) or collude with other camera apps for cross-app tracking [51]. While users can attempt to remove potentially identifying or sensitive objects from their environment, it is challenging – even for careful users – to ensure that their background cannot be exploited for tracking.

Prior research to protect privacy from the information contained in images either use (a) object block lists to conceal parts of images that are potentially sensitive or (b) object allow lists to reveal relevant parts of images and conceal everything else [17]. Solutions based on block lists are strongly tied to certain sensitive objects within images (e.g. faces [2, 26, 56].) Thus, extending their approach to other objects is difficult. While recent solutions based on allow lists are not confined to certain objects, they pose a manual and cognitive burden on users [33, 50]. For example, WaveOff [50] requires users to provide precisely marked references of objects to be preserved in camera frames. Thus, such systems only serve careful users who can bear this cognitive burden. To the best of our knowledge, prior research lacks an automated solution that operates with minimal user effort while also remaining extensible to cater to a diverse set of mobile camera apps.

In this paper, we present Aragorn—an *automated* and *extensible* privacy-enhancing system for mobile cameras that protects privacy from camera apps while preserving utility. To this end, Aragorn follows an allow list based appraoch, using an ML based *sanitizer* to automatically remove everything but objects that are relevant to an app's utility from camera frames. We integrate the sanitizer within the mobile operating system for seamless backward compatibility with existing apps. Aragorn employs a novel training strategy to retrain the sanitizer whenever apps seek support for previously unrecognized objects. For example, there are some apps that scan COVID vaccination cards – an object that did not exist prior to 2021. In such cases, Aragorn retrains the sanitizer by automatically inferring the training labels, without manual intervention, on images from different sources (including the users themselves while they interact with camera apps). Aragorn incorporates crowdsourced validation to ensure robustness of the sanitizer against data poisoning.

Aragorn has 89% accuracy in detecting credit cards and 100% accuracy in detecting faces in context of credit card scanning and face recognition respectively without degrading utility. Aragorn's crowdsourced approach to combat data poisoning detects 100% of all poisoned inputs while retaining over 94% of clean inputs. Our implementation of Aragorn in Android's camera subsystem produces frames at a rate of 20 frames per second (FPS), which is adequate for real time operation of most camera apps [50]. Our source code is available at this anonymous link.

Our key contributions include:

- An automated approach to sanitize camera frames for relevant objects while preserving app utility;
- An extensible approach to sanitize camera frames for previously unrecognized objects in a robust manner; and
- A backward compatible and real time implementation on Android.

2 MOTIVATING EXAMPLE

We use a contrived example of a credit card scanner to illustrate the interaction between the different entities involved in mobile camera apps.

Alice makes a purchase on an app, *MalApp* on her phone. MalApp asks her to scan her credit card to prove possession of her payment method [16]. Sitting in her living room, she positions her card in front of the camera as shown in Figure 1. On receiving frames from her camera feed, MalApp processes them to extract the card information and verify her payment method. We draw attention to the fact that while Alice expects MalApp to only extract credit card information from her camera frames, MalApp can also make other inferences from them. In the example shown in Figure 1, MalApp has access to information present on her driver's license, it can infer her political preference, her interest in gaming, her interest in soccer etc. MalApp could also collude with other apps to extract an identifier for Alice from this visual information (such as the position of her lamp, the soccer poster on her wall, her decorative plants, the color of her walls and other home decor) for cross-app tracking. Specifically, MalApp can exploit the visual information captured by her camera frames as a fingerprinting vector. It could adopt such fingerprints circumvent mobile operating system restrictions that limit an app's access to device identifiers [6, 21]. This is analogous to websites relying on fingerprinting-based stateless tracking in response to browsers phasing out third-party cookies [30, 64].

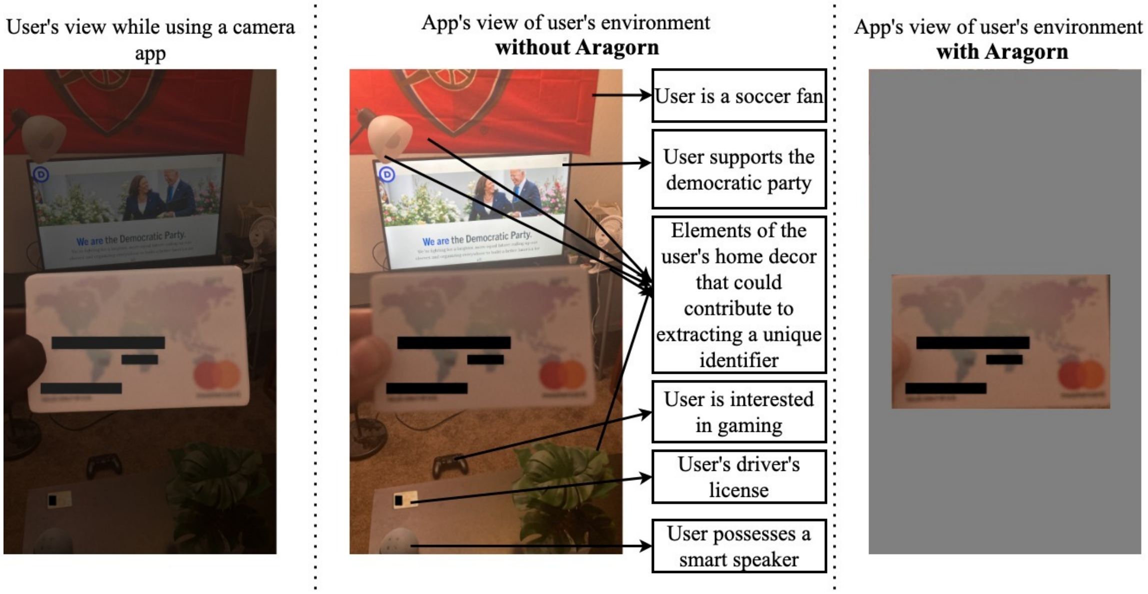

User's view while using a camera app
App's view of user's environment without Aragorn
App's view of user's environment with Aragorn
User is a soccer fan
User supports the democratic party
Elements of the user's home decor that could contribute to extracting a unique identifier
User is interested in gaming
User's driver's license
User possesses a smart speaker
We are the Democratic Party

Fig. 1. The figure on the left shows the user's perspective while using a camera app to scan her credit card. We have highlighted the credit card in this figure since the user expects the app to only process the card from the camera frame. The figure in the middle shows other inferences that the app can potentially make about the user's environment from regions of the camera frame that do not contain the card. The figure on the right depicts the frame shown to the app by Aragorn to ensure that the app cannot make inferences about the user's environment while preserving its utility.

Aragorn ensures that the camera frames sent to MalApp only contain credit cards so that Alice can use the app while ensuring that it cannot make any inferences about her environment as shown in the image on the right of Figure 1. More generally, Aragorn provides fine grained control over what can be present in camera frames before allowing apps to access them. To cater to diverse camera apps, Aragorn has to have the ability to recognize any object that a user may want to reveal to an app, including those that could emerge in the future. While Aragorn could use pretrained models or public datasets for common objects (such as pets, computers, faces etc), it is difficult to even procure training images of more nuanced objects like credit cards. Aragorn adopts a novel training strategy based on knowledge distillation and crowdsourcing to detect such objects.

3 BACKGROUND

We characterize the 4 different entities involved in the mobile camera app ecosystem based on the example: a *user* (Alice), an *app* (MalApp), an *object of interest* associated with the app (credit card) and the user's *environment* (Alice's living room where she scans her card). We describe each of these entities in detail:

User. The user runs an app on their mobile device that requires access to the camera. The user trusts the app to provide some utility (verify the payment method and complete the transaction in the example) by allowing it to access live camera frames but wants to ensure that the app does not capture sensitive information about their environment.

App. The app runs on the user's device and promises some utility to the user by accessing frames from the user's camera feed. Based on the expected utility, apps are typically associated with a particular object of interest (users

	I-Pic [2]	**Cardea** [56]	**Bystander privacy** [26]	**Recognizer abstraction** [32]	**PrivateEye** [50]	**WaveOff** [50]	**Aragorn** [This paper]
Compatible with diverse camera apps	x	x	x	x	✓	✓	✓
Requires minimal setup effort	x	x	✓	✓	x	x	✓
Requires minimal effort to use camera	✓	✓	✓	✓	x	✓	✓
Incurs minimal camera latency	x	x	?[1]	✓	x	x	✓
Compatible with live camera feed	x	x	x	✓	✓	✓	✓

The authors of the paper [26] did not report latency.

Table 1. Comparison of Aragorn with other research on protecting sensitive user information captured by camera frames. Compared to existing research, Aragorn caters to a wide range of apps without compromising user experience.

may also choose to associate an object of interest with an app that is not tied to any object, like a photo-sharing app). Malicious apps may attempt to leak information about the user's environment from the background captured in camera frames.

Environment. The user's environment contains information about the physical location where the user holds the camera. In addition to the object of interest, the environment could contain sensitive information about the user and/or other people who are in the background. Defining which objects in the environment are privacy sensitive is subjective, with the entire environment itself potentially being sensitive.

Object of interest. Objects of interest are objects present in the user's environment that are tied to the expected utility of the app. These are also the only objects that the user has consented to allow the app to access.

3.1 Related Work

Hasan et al. [26] proposed a block list based approach to protect the privacy of bystanders in images by automatically detecting and obscuring their faces. Their approach being strongly tied to by-standers means that they cannot detect other sensitive objects that could be present in the environment. This limits their extensibility and makes them unsuitable for protecting users from untrusted mobile camera apps in general. In addition to not being extensible, other block list based systems, such as Cardea [56] and I-Pic [2], also require significant user effort for operation. For example, I-Pic only protects the privacy of bystanders faces and also requires them to broadcast their presence, visual signatures, privacy policy etc. In order to adopt their approach to protect users from diverse camera apps, users would have to identify sensitive objects in their environment in different contexts and provide appropriate visual signatures and privacy policies for each context which would hamper their user experience.

Jana et al. proposed an allow list based recognizer abstraction [32] within the operating system to limit AR apps from directly accessing raw camera inputs. Their approach, however, is tied to certain objects related to most AR apps and they do not discuss extension to new objects. More recent allow list based systems like WaveOff and PrivateEye[50] let users define objects of interest using visual markers and treat everything else as sensitive. Subsequently when an app accesses the camera, they run computer vision algorithms to detect the object of interest in camera frames and block everything else. While extensible to different objects, PrivateEye and WaveOff still pose significant burden on the user.

PrivateEye can only be used with two dimensional objects and requires users to manually draw markers around their object(s) of interest prior to using the camera. Users would also have to carefully position the camera to ensure that the markers are visible. WaveOff, on the other hand, can also be used with 3-dimensional objects and requires lesser effort. It provides users with a graphical user interface to capture and mark their objects of interest prior to using a camera app. Once marked, users are protected from camera apps without any additional effort. The accuracy of WaveOff, however, is dependent on the user's skill in precisely marking these objects. Thus, only careful users who pay close attention while marking these regions can benefit from WaveOff. Additionally, WaveOff only detects object instances, which increases the effort required from users to mark each object instance. For example, a user with multiple credit cards would have to provide references for each credit card before using a card scanning app. We also note that WaveOff struggles to reliably detect certain objects such as human faces (which are commonly associated with camera apps) even with precisely marked references (§7.6).

Aragorn also follows an allow list based approach to associate apps with different objects of interest to ensure that apps can only see relevant objects from camera frames. However, Aragorn does *not* require marked references to accurately localize to the object of interest in camera frames. In contrast to prior work, Aragorn leverages deep learning to accurately localize the object of interest in camera frames while incurring minimal overhead. To extend support to objects that were previously not recognized by Aragorn, we employ a novel training strategy that uses training images from different sources and automatically infers their training labels. Aragorn only requires users to initially associate objects with camera apps and occasionally answer yes or no questions to ensure robustness against data poisoning. Thus, with Aragorn, users get privacy protection from a wide range of camera apps without incurring significant effort. We summarize the comparison of Aragorn with prior approaches in Table1.

3.2 Threat model

In our threat model, a user seeks to use a camera app on their phone. We assume that the user has explicitly provided permission to the app to access frames from the camera feed. Although the user has granted this permission, the app is not trusted with the information it could potentially infer from the camera frames beyond the intended object of interest. In the case of a credit card scanning app, we trust the app with information about the credit card, but not with the background that captures information about the user's scanning environment.

We assume that the app could make privacy-invasive inferences about the user's environment (e.g., by running machine learning models) from the camera frames or altogether transmit the frames to a third-party. While the app is unconstrained with what it can do with information about the user's environment, we assume that it cannot tamper with the phone's operating system. Accordingly, we envision OS vendors (such as Google or Apple) implementing Aragorn within the OS as part of their efforts to protect user privacy [5, 23]. Integrating Aragorn within the OS protects it from the app.

Aragorn relies on a trusted remote server (maintained by the OS vendor) referred to as Aragorn server when extending support to new objects. We assume that most users trust the OS vendors and thus, also trust Aragorn server. However, some users can consider Aragorn server to be honest-but-curious in which case they do not trust it with the confidentiality of their data. We consider both types of users in our threat model.

We also assume that most users are not malicious and would cooperate with Aragorn to improve privacy. However, a small fraction of users can collude with one or more malicious apps to compromise Aragorn.

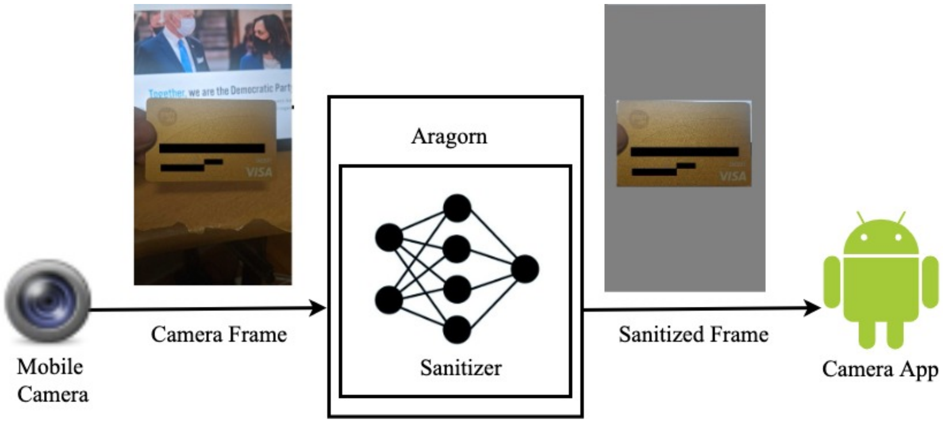


Fig. 2. In the steady-state workflow, Aragorn's sanitizer ensures that camera frames only contain the preestablished object of interest and obscures everything else before third-party camera apps can access them.

Under this threat model, our goal is to protect privacy without degrading app functionality over a wide range of camera apps. We specifically focus on apps that operate with a live camera feed, but Aragorn can also operate on previously captured camera images stored on the user's device.

4 OVERVIEW

4.1 Design Principles

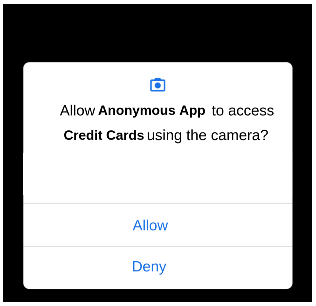
Devise a task-agnostic architecture: Camera apps accomplish a wide range of tasks. Devising independent privacy solutions for each task would not scale, be difficult to maintain and potentially increase Aragorn's attack surface. Accordingly, Aragorn introduces novel mechanisms to train, evaluate, and deploy a machine learning model (referred to as the sanitizer) that detects a given object of interest associated with an app and sanitizes the camera frames by obscuring everything else (§5.3).

Minimize load on users: Aragorn seeks to protect the privacy of all users, regardless of their intent to take up manual or cognitive load. In contrast to prior work that requires users to provide precisely marked samples of their object of interest [50], Aragorn only requires a fraction of its users to occasionally answer yes or no questions to secure the privacy of all users (§5.3.3).

Exercise the principle of least privilege: Since camera apps are untrusted in our threat model, Aragorn operates within the OS and limits the capabilities provided to them. For instance, Aragorn does not permit apps to directly access camera frames, instead, it lets apps access sanitized frames that only contain the intended object of interest (§6).

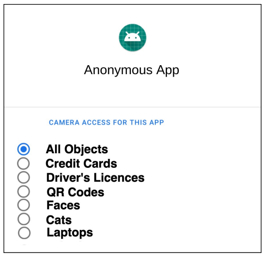
4.2 Aragorn architecture

Aragorn runs within the mobile operating system to intercept camera frames before they can be accessed by camera apps. Aragorn employs a machine learning based object detector, referred to as the sanitizer, to ensure that apps can only access a pre-established object of interest from camera frames. Aragorn also contains an auxiliary remote server referred to as the Aragorn server to help extend the sanitizer to detect previously unrecognized objects. Within the operating system, Aragorn operates in one of two workflows based on whether the sanitizer can reliably detect a given



Allow **Anonymous App** to access **Credit Cards** using the camera?

Fig. 3. One-time dialog box presented to users during an app's initial invocation. Users can use this interface to grant access to a specifc object requested by the app, via the camera.



Anonymous App

CAMERA ACCESS FOR THIS APP

● **All Objects**
○ **Credit Cards**
○ **Driver's Licences**
○ **QR Codes**
○ **Faces**
○ **Cats**
○ **Laptops**

Fig. 4. Users can *optionally* use this interface to override previously assigned objects of interest to camera apps, or assign objects of interest to those that did not have one previously.

object of interest (we refer to this as the *steady-state* workflow), or requires additional training to do so (we refer to this as the *transient* workflow).

During its initial invocation in the steady-state workflow, an app specifies its object of interest from a list of supported objects (credit cards, driver's licenses, etc.), which can optionally be overridden by the user. Then, during the app's execution, the sanitizer blocks everything from camera frames retaining just the object of interest before sending them to the app. We summarize this workflow in Figure 2.

Aragorn predominantly operates in the steady-state workflow. However, in case apps require support for a new object (such as scanning a COVID vaccination card as discussed in §1), Aragorn switches them to the transient workflow. Prior to operating in this workflow, an app requests Aragorn to extend support to this new object. Upon approving the app's request, Aragorn allows it to process complete camera frames to ensure that users can use the app, while using these frames to train the sanitizer with assistance from Aragorn server. Eventually, once the sanitizer can recognize this object, Aragorn switches the app over to the steady-state workflow.

5 DESIGN

In this section, we first provide a detailed account of Aragorn's steady-state and transient workflows from the perspective of both apps and users. We then describe the design of the sanitizer which drives the overall design of Aragorn.

5.1 Steady-state workflow

Aragorn invokes the steady-state workflow in cases where Aragorn's sanitizer has already been trained to reliably detect and recognize the object of interest in context. Such an object could either correspond to a common user object that is well represented in public datasets [36, 40] (pets, computers, food items etc.), and hence supported by the sanitizer during Aragorn's initial deployment, or a more nuanced object for which the sanitizer was previously retrained via the transient workflow.

A camera app specifies a manifest file containing its intended object of interest from a list of objects supported by Aragorn. Subsequently, when the user invokes the app for the first time, Aragorn presents them with a one-time permission dialog asking to grant access to the specified object of interest as shown in Figure 3. Aragorn also allows users to optionally override a previously assigned object of interest to an app using the interface shown in Figure 4.

Users can also use this interface to assign an object of interest to an app whose utility is not tied to any particular object or an app that did not have one previously (e.g. assigning pet to a photo-sharing app when uploading the image of a pet on the app). Upon establishing the object of interest, the app requests camera frames as part of its execution. Aragorn then uses its sanitizer to only pick out the object of interest from camera frames and blocks out the rest to produce *sanitized frames*, which are then sent to the app. Aragorn also performs JPEG compression on these frames to purge high-frequency camera fingerprints (i.e., Photo-Response Non-Uniformity or PRNU [41]).

While the app only gets access to the sanitized frames, Aragorn renders camera frames completely onto the display to ensure that the user experience is not hampered. Accordingly, we do not allow apps to read the display to stop them from accessing the complete camera frames. However, we do allow apps to write to the display. While granting write access helps apps implement their own interfaces to better engage with users, malicious apps could abuse this to attempt to invade privacy by asking them to position objects other than the established object of interest. Aragorn thwarts such attempts in the steady-state workflow, since the sanitizer can accurately detect the object of interest. As a concrete example, consider a case where the established object of interest is a credit card. Even if an app attempts to trick users by asking them to position a different object, say a driver's license next to the card (or instead of the card), Aragorn would not detect this object as the object of interest, thereby protecting user privacy. However, even in the steady-state workflow, Aragorn needs to communicate with users to get their feedback on its predictions (§5.3.3), and apps can abuse their write access to interfere with this communication. To prevent this, Aragorn only communicates with users for their feedback after the app has completed its execution.

5.2 Transient workflow

Aragorn invokes the transient workflow whenever there is a need to extend the sanitizer to detect a previously unrecognized object. When an app wishes to access such an object from camera frames, it submits a request to Aragorn server, specifying the name of the intended object.[1] Once approved, Aragorn allows the app to initially operate in the transient workflow. In this workflow, Aragorn lets the app process camera frames completely (so that users can still use the app) while also using them to train the sanitizer for the new object. Since OS vendors (who are trusted in our threat model) maintain Aragorn server, one way to train the sanitizer would be to transmit these frames to Aragorn server for centralized training. However, some users may consider Aragorn server to be honest-but-curious in which case they would not trust it with the confidentiality of their camera frames. Thus, an alternate way to train the sanitizer would be to adopt federated learning. Once the sanitizer is trained to recognize the object, Aragorn adds it to its list of supported objects and moves the app into the steady-state workflow. During the app's initial invocation, Aragorn informs users that they are in the transient workflow and requests permission to use their frames for training. Since Aragorn does not need training images from all users (§7.4), it allows users to opt out of contributing their data to train the sanitizer. There is no feedback phase in this workflow since the sanitizer is not invoked.

5.3 Sanitizer

The sanitizer is an object detector (YOLOv3 [54]) that can classify and localize a given object from its input. Given a camera frame as input, the sanitizer predicts the classes and locations of objects contained in it. The classes map to one or more of the objects the sanitizer has been trained to recognize and the locations are bounding boxes of the predicted classes within the frame. In the steady-state, Aragorn preserves all objects from the sanitizer's predictions

[1] We discuss supporting requests from users in Appendix 11.7.

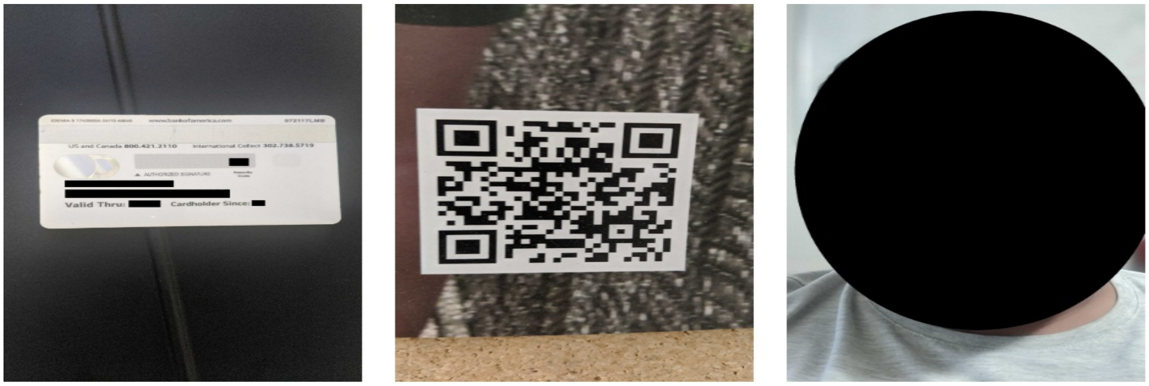


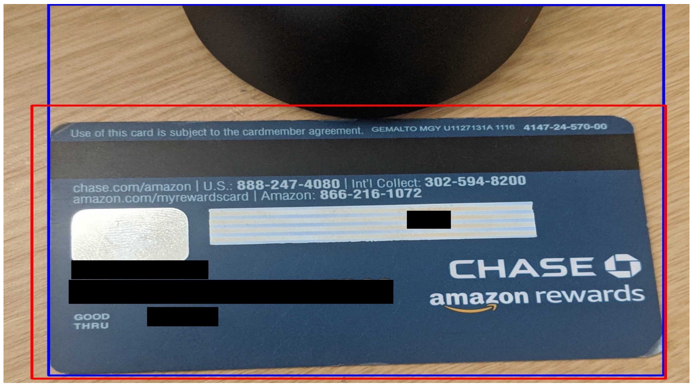
Fig. 5. Examples of frames sent to a credit card scanner, a QR scanner and a face verification system. In all 3 examples, we see that the respective objects of interest (credit card, QR code or face) are also the salient objects present in the frame.

that correspond to the established object of interest and blocks everything else to produce a sanitized frame which is then made accessible to the app. In case none of the detected objects in a camera frame map to the specified object of interest, Aragorn blocks the entire frame.

5.3.1 Sanitizer training. To train the sanitizer (a supervised object detector), we need labeled frames containing the intended object. To localize and classify this object, the labels should contain a class label as well as a localization (bounding box) label. This data needs to be obtained from a reliable source. While in some cases, we may be able to source this data from public datasets [36, 40], there could be more nuanced objects (such as credit cards) that are not well represented in any public dataset. We cannot simply source this training data from the app since we don't trust it in our threat model. Thus, we source this training data (unlabeled frames) from the users (most of whom are trusted in our threat model), while they use the app. We adopt a novel knowledge-distillation based strategy to automatically label this data. In this section, we describe our strategy to train the sanitizer with a centralized approach. We discuss how our strategy can be adopted with a federated approach in Appendix 11.1.

We first describe the flow when the training data is provided by good users and then discuss potential attacks from malicious users and their mitigations. To gather training data from users, we allow the app to initially run in the transient workflow where it can access complete camera frames. In the intended execution of the app, we expect these frames to contain the object of interest and thus, we forward them to the Aragorn server (from the users who consented to share their frames). Note that users undertake no additional effort and merely interact with the app as usual, and we use frames from their interaction as training images. Once we have gathered this data, we have training images containing the object of interest. The name of the object for which the app requested support, serves as a common class label for these images. However, we do not yet have the location (bounding box) of the object within these images.

To compute the bounding box labels for our training data, we rely on the fact that in most frames the object of interest is also expected to be the salient object. Figure 5 shows camera frames passed to a credit card scanner, a QR scanner and a face verification system, and we note that for each frame the object of interest is also the salient object in the frame. Accordingly, we use an off-the-shelf salient object detector (U^2-Net [48]) to localize the object of interest in these frames. The localization label coupled with the common object label corresponding to these frames is used to


Use of this card is subject to the cardmember agreement. GEMALTO MGY U1127131A 1116 4147-24-570-00
chase.com/amazon | U.S.: 888-247-4080 | Int'l Collect: 302-594-8200
amazon.com/myrewardscard | Amazon: 866-216-1072
[redacted]
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CHASE
amazon rewards
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[redacted]

Fig. 6. In this figure, the red box shows the prediction of our supervised YOLOv3 [54] based sanitizer, while the blue box shows the prediction of a U^2-Net [48] salient object detector.

train a supervised object detector, which serves as our updated sanitizer. This entire training procedure is executed at the Aragorn server, and once trained, the new sanitizer is shipped to user devices (as an update to the OS).

Once trained to recognize the new object, Aragorn switches the app back to the steady-state workflow. We note that during the initial phase, when an app operates in Aragorn's transient workflow, privacy is unprotected from the app. We refer to the state when Aragorn is able to protect privacy in context of a new object as the state of attaining “herd protection" for that object. We quantify the duration of the unprotected phase in terms of the number of images required until herd protection is attained in §7.4.

Can a salient object detector function as the sanitizer? A salient object detector alone could potentially be used as the sanitizer since the object of interest is expected to be the salient object in most cases. However, due to its inability to classify the object of interest, it can pick any salient object as the object of interest. While we can address these concerns by augmenting the salient object detector with a classifier, we instead choose to use an integrated supervised object detector for the following reasons. First, an integrated supervised object detector combines classification and localization into a single model [54]. The two tasks inform each other leading to more accurate localization and classification as opposed to training two separate models, one for each task.

Second, at run time, we get both classification and localization results from a single model inference with a supervised object detector, as compared to two separate inferences, one with a salient object detector and the other with a classifier. Thus, a supervised object detector gives Aragorn higher efficiency.

Anecdotally, we see in Figure 6 that even in the presence of multiple objects in a frame, Aragorn's sanitizer (a supervised object detector) more accurately localizes to the correct object (credit card in the figure) as compared to U^2-Net (a salient object detector). During training, the sanitizer learns to distil common object information from multiple salient labels to only pick out the relevant object. We present a quantitative comparison of a salient object detector against our supervised sanitizer in Appendix 11.2.

5.3.2 Threat of data poisoning. Attaining herd protection relies on users operating as intended by only positioning the expected object of interest in front of the camera. However, since not all users are trusted in our threat model (or users can be tricked into scanning incorrect objects by malicious apps), herd protection is subject to data poisoning attacks from users hired by malicious apps.

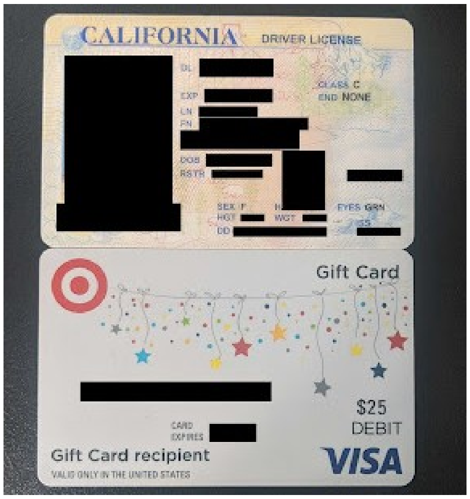

Fig. 7. This figure shows a user positioning a credit card next to a driver's license to provide poisoned data to Aragorn. If unchecked, Aragorn's sanitizer could learn the driver's license as being part of a credit card, and detect them from users' backgrounds whenever they use a credit card scanning app.

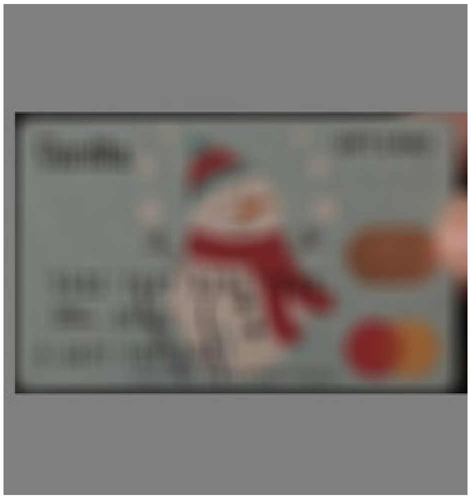

Fig. 8. Example of an image shown to users as part of our preemptive defense to combat data poisoning. We ask users if the blurred regions in this image only contain a credit card.

As a concrete example, consider a scenario where we seek to attain herd protection for credit cards. A malicious app, intending to evade Aragorn to invade user privacy could initially hire users who intentionally scan other objects, such as driver's licenses, in addition to credit cards. As a result, once trained, Aragorn's sanitizer would also recognize driver's licenses as credit cards. At this stage, once other users start using the app, any licenses present in the background would also be exposed to the app. We show a poisoned image sample in Figure 7. More generally, users colluding with an app can poison the training data with any generic objects that are expected to be in user backgrounds to help the app interfere with Aragorn's intended operation. While deep learning models are naturally robust to poisoning at low injection rates (i.e. fraction of poisoned images in the training set) [66], a malicious app can easily ensure an injection rate of 100% by only allowing users under its control to use the app while operating in the transient workflow.

5.3.3 Crowdsourced validation to defend against data poisoning attacks. Aragorn relies on two different crowdsourced strategies to defend against data poisoning attacks. The first strategy, which we refer to as the *preemptive defense*, operates during the transient workflow and discards poisoned samples. The second strategy, which we refer to as the *reactive defense*, operates in the steady-state workflow and detects if a previously trained sanitizer has been poisoned. We rollback and retrain the sanitizer with fresh data on detecting that it had been poisoned.

Preemptive defense: This defense relies on our assumption that the majority of Aragorn's users (i.e. all mobile users in general) can be trusted, even if all the users of a particular app at a given point in time are potentially malicious. We thus, take help from users to detect and discard poisoned images in the data obtained from other users. Concretely, we first detect the salient objects in the images and block out the other portions. Then, we blur the regions containing the salient objects and randomly ask other users if these images only contain the expected object of interest. We only include the corresponding images in our training set for which users provided a positive response. Figure 8 shows an example of an image displayed to users when extending to detect credit cards. In this case, we randomly ask other users if the blurred portion of the image only contains credit cards.

Drawing from existing research [2, 26, 56] we blur images to retain overall information about the object present in the image, while obscuring object specific information. We use a sufficiently high blur radius to ensure that users cannot recover this information [27]. However, despite blurring, some information can still leak about the object of interest. For example, in our evaluation in §7.5.1, we see that some users were able to guess the gender and hair color of users from their driver's licenses. We argue that targeted attempts by malicious users to gather such information are not possible since Aragorn server randomly picks users to validate user data. When OS vendors deploy Aragorn at a large scale (i.e., with billions of Android and iOS users) the probability of a particular user's images being validated by the same user would be negligible [2]. Nevertheless, Aragorn server can also choose to not employ the preemptive defense for an object that it deems to be sensitive and rely exclusively on the reactive defense to thwart data poisoning attacks against that object. As we discuss in the next section, doing so would require more frequent user involvement, which could lead to poor user experience. This defense would be ineffective when detecting certain objects that look similar to other objects, since users only get to see blurred images. For example, when asking users if an image only contains a particular document, it would be difficult for users to respond since the contents of the document would not be visible to them. In such cases, users can respond with a “Not Sure" option and we cover them using the reactive defense.

Reactive defense: This defense relies on the fact that all apps, including malicious ones that hire users to provide poisoned data, would eventually engage with users who are not controlled by the app. Thus, once a camera app completes its execution in the steady-state workflow, we annotate the frames produced during the execution with the sanitizer's predictions and show them to users for their feedback. Here, we do not blur or obscure the images in any way, since users only validate predictions on their own camera frames. Like the preemptive defense, users only respond with a “yes" or a “no" to indicate whether they were confident in the sanitizer's predictions (unlike the preemptive defense, the images are unblurred, making it easier for users to respond). If the number of negative responses from users crosses a particular threshold, we infer that our trained sanitizer has been subject to poisoning and roll it back to a previous version known to be robust to poisoning. We transition apps associated with the suspected poisoned object back to the transient workflow to train on fresh images. We trigger manual inspection in case the sanitizer needs to be rolled back repeatedly to detect and stop apps that attempt to force Aragorn back to the transient workflow. We keep running this defense periodically instead of running it for a fixed period to ensure that apps cannot evade this defense by initially hiring users to provide false feedback. The reactive defense also serves as a way to assess the generalizability of the sanitizer and detect potential changes to the design of the object of interest. We run the reactive defense across an optional channel for all users, where they can choose to not respond and a forced channel where random users are necessarily asked to respond. The optional channel allows us to evaluate against diverse use cases and backgrounds. However, relying solely on the optional channel could lead to not only insufficient, but also potentially false feedback from users colluding with the app. We detect such cases by correlating with responses in the forced channel.

There could be some cases where the sanitizer makes mistakes in presence of specific triggers which would be hard to detect despite having both channels. For example, the sanitizer could be poisoned with a backdoor such that it correctly detects credit cards in most cases, but detects the background too, if a specific trigger object, such as a pair of glasses is present in the background [66]. However, such cases can be mitigated with the preemptive defense. Thus,

[2] When deployed at a large scale, the frequency at which we request a response from the same user would also be low, thereby having minimal impact on user experience.

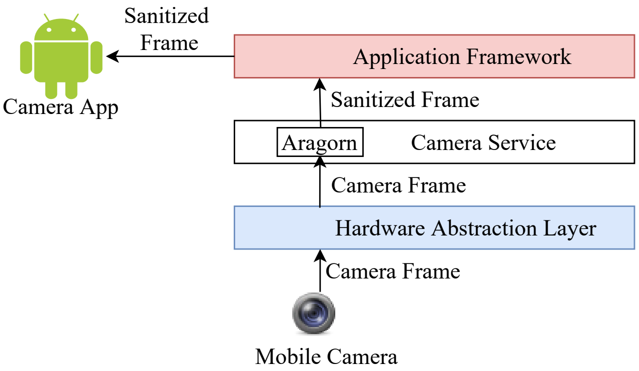

Fig. 9. The camera service is ideally suited to incorporate Aragorn, since it is both, hardware independent (unlike the hardware abstraction layer) and isolated from the app in a separate process (unlike the application framework).

Aragorn relies on both, the preemptive and reactive defenses to cover for each other's shortcomings to defend against diverse data poisoning attacks.

6 IMPLEMENTATION

We implement Aragorn within Android 11 by modifying the camera subsystem of the Android Open Source Project (AOSP). Since we envision Aragorn being implemented by mobile OS vendors, we integrate it within the Android OS in our prototype instead of implementing it as a standalone library. This also provides protection from apps that attempt to tamper with or bypass Aragorn to directly access the camera. Android's camera subsystem is broadly split into 3 distinct processes that communicate using binder interfaces: the hardware abstraction layer (HAL), the camera application framework, and the camera service. On one end, the HAL directly interacts with the camera driver and at the other, apps use camera application frameworks (such as Camera2 or CameraX) to access the camera. The camera service connects the application framework to the HAL by exposing standard interfaces to both. Concretely, the application framework uses these interfaces to submit a request to the HAL to capture camera frames, and the HAL invokes callbacks present in the camera service to deliver frames in response.

We integrate Aragorn's sanitizer with the camera service to reap dual benefits of preventing apps from bypassing the sanitizer as well as not having to maintain multiple hardware dependent implementations. Since the camera service runs in its own process and is the only process that can access the HAL, apps would necessarily have to compromise the OS to bypass the sanitizer. Further, since the camera service is hardware independent, the same implementation can be used on all devices. Alternatively, integrating the sanitizer within the HAL would also protect it from apps, since it is the only process that can access the camera driver, but doing so would require maintaining different implementations based on the hardware. In contrast, integrating the sanitizer with application frameworks would not require different implementations, but apps would be able to evade Aragorn by directly accessing the camera service. Figure 9 summarizes this discussion.

Aragorn's sanitizer that supports 3 objects (credit cards, QR codes and faces) occupies 5.6 MB on disk. We implement the sanitizer using TensorFlow Lite C++ API [62]. In the steady-state workflow, an app that uses Aragorn would specify a manifest file containing its intended object of interest from the global list of objects recognized by Aragorn. As discussed in §5.1, users can choose to grant or deny permission to the app to access the specified object, or assign a different object of interest to the app (again from the global list of objects). However, Aragorn can also work with apps that do not produce such a requirements file, since users can assign objects of interest to them (from the global list of objects recognized by Aragorn). Thus, Aragorn is also backwards compatible with existing camera apps.

On a Google Pixel 2 phone, without using hardware acceleration, the sanitizer uses the equivalent of 2 CPU cores and consumes 42 MB of memory. Performance evaluation of this implementation shows that the sanitizer takes 38ms on average for execution, correspondingly producing frames at roughly 20 frames per second. The sanitizer's latency does not increase when multiple objects are to be detected in a frame [53]. The performance of the sanitizer is largely unaffected as it scales to support more objects. See Appendix 11.5 for details.

We describe Aragorn's federated implementation and discuss associated performance metrics in Appendix 11.1.

7 EVALUATION

7.1 Privacy

We evaluate the effectiveness of Aragorn's sanitizer in removing background information.[3] This evaluation measures the sanitizer's ability to accurately detect and localize to the object of interest. In context of privacy, we are interested in measuring the sanitizer's classification false positive rate, i.e., mistakenly detecting a background object as the object of interest, and the localization false positive rate, i.e., regions that were predicted to contain the object of interest but contain the background. We first, perform this evaluation when having credit cards as the object of interest and then having faces as the object of interest.

Object of interest	Classification FPR	Localization FPR
Credit cards	10.99%	7.96%
Faces	0.00%	8.81%

Table 2. Low false positive rates in detecting credit cards and faces indicate that Aragorn's sanitizer captured minimal background information, leading to better privacy.

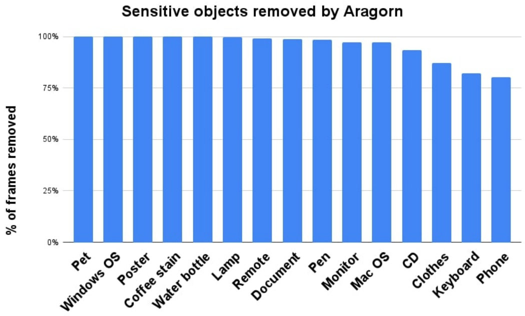

Fig. 10. Chart showing the proportion of frames in the card scanning dataset where Aragorn removed sensitive objects from the background.

For credit cards, we run our evaluation on a dataset of credit card scan videos from prior research [15]. This dataset contains videos from the live camera feed of 19 different users while scanning 30 credit cards each using the Daredevil card scanning app. On a subset of 2, 206 frames from 20 random scan videos from this dataset, the sanitizer has a classification false positive rate of 10.99% and a localization false positive rate of 7.96%. For faces as the object of interest, we evaluate the sanitizer on images from the public CASIA-Webface dataset [13]. We pick 200 random face images from this dataset and combine them with 200 random indoor background images (to evaluate images that do not contain a face) from the indoor scene recognition dataset [49]. On this dataset, the sanitizer has a classification false positive

[3] We present results in context of centralized learning and anticipate similar results with federated learning [18].

	Credit cards		**Faces**	
	Precision	Recall	Acc. on same identity	Acc. on diff. identities
No sanitizer	96.15%	83.33%	91.09%	92.55%
With sanitizer	100.00%	86.66%	92.01%	92.02%

Table 3. Results showing that Aragorn does not affect the utility of Daredevil card scanner [15] and MobileFaceNet [60] face verification system.

rate of 0% and localization false positive rate of 8.81%. These low values for the false positive metrics indicate lesser information about user background being captured in the sanitized frames, leading to improved privacy. We report these results in Table 2.

We also qualitatively evaluate Aragorn's ability to remove potentially sensitive information from camera frames. On 2, 206 frames from 20 random videos from the card scanning dataset, we manually identified 15 potentially sensitive objects (such as a document containing the user's address, a pet, etc.). We then measure the ratio of frames where these objects were blocked by the sanitizer to the frames that originally contained them. Figure 10 shows that the sanitizer removes 11 out of the 15 identified objects from 97% of frames and removes the other 4 objects on over 80% of frames that contained them. Overall, these results show that Aragorn's sanitizer significantly reduces the number of frames containing potentially sensitive objects.

7.2 Utility

Aragorn should not prevent apps from providing their intended utility to users. We evaluate the impact of Aragorn on the utility of a public credit card scanner, Daredevil [15] and a public face verification system, MobileFaceNet [60].

7.2.1 Credit card scanner. We measure Daredevil credit card scanner's precision and recall on a subset of 30 random scan videos from the card scanning dataset. We then sanitize frames from these videos and measure the card scanner's precision and recall for comparison. Here, precision refers to the ratio of the number of scan videos on which the card scanner predicts the right number to the number of scan videos on which it predicted a credit card number (including incorrect credit card numbers). Recall is the ratio of the number of scan videos on which the card scanner is able to predict the right number to the total number of scan videos. The metrics in Table 3 show a slight increase in both precision and recall when using Aragorn. We attribute this increase to the removal of extraneous information, helping the card scanner localize the card number better. Running Daredevil card scanner on our prototype of Aragorn yields an average scanning duration of 6.72 seconds. Equivalent runs without incorporating Aragorn into the camera subsystem yield an average scanning duration of 6.52 seconds. Thus, Aragorn only increases the latency of Daredevil card scanner by 3.07%.

7.2.2 Face verification. We first measure the verification accuracy of the MobileFaceNet face verification system [60] on a subset of 2, 104 images from 220 distinct identities from the standard Labeled Faces in the Wild [29] dataset. We then measure its verification accuracy on the same set of identities after sanitization. We evaluate 10, 000 random pairs of images of the same identities and 10, 000 random pairs of images of different identities selected from the dataset. Before sanitization, MobileFaceNet has an accuracy of 91.82% in detecting if image pairs belong to the same or different identities. Repeating the experiment on sanitized images yields an accuracy of 92.01%. We report detailed results in Table 3. MobileFaceNet crops to a tight bounding box around the user's face as an initial preprocessing step before extracting an embedding for verification. We suspect that this step extracts the same crop in both cases, leading to

	Multi-Class Classifier (Closed-world)	**Background Fingerprint Model (Open-world)**
No sanitizer	97.32%	83.41%
With sanitizer	5.25%	50.09%

Table 4. Aragorn vs user identification attacks. The first row shows the accuracy of two different models that identify users from the background information of their camera frames. The second row shows the degradation in the accuracy of the same models on Aragorn's sanitized frames.

similar accuracies. We do not measure the latency introduced by Aragorn to MobileFaceNet since their system does not work with a live camera feed.

7.3 User Identification

We first show an example of how malicious apps can identify users using background information captured in their camera frames as a fingerprint. We then evaluate Aragorn's effectiveness in thwarting such an attack. We conduct this evaluation on the previously described card scanning dataset from 19 users. While we present results with credit cards as the object of interest, our goal with these experiments is to explore the extent to which users can be identified from the background information in the camera frames irrespective of the presence of identifying information in the object of interest itself.

7.3.1 User identification attacks.

Closed-world We first consider a multi-class attack setting, where the malicious app has representative images from each of its users. Given a new camera frame, the app's goal is to use the background information in the camera frame to identify a returning user. Concretely, we train a 19-class classifier, with each class representing a distinct user from the dataset. While this closed-world scenario is not practical in the real world, it simulates a harder use case for Aragorn. We subsequently evaluate Aragorn with a more practical attack. To ensure that the model only uses background information to identify users, we block out the credit cards in the frames and also purge high-frequency fingerprints tied to the device, i.e. PRNU [14, 41] via JPEG compression [65] (See Appendix 11.8). We train the classifier using a convolutional neural network (CNN) on frames from videos in the card scanning dataset. The model attains an accuracy of 97.32% on a 10% held-out test set.

Open-world We now consider a more practical scenario, where a malicious app does not need to know the total number of users to identify them. The app employs a model, which we refer to as a *background fingerprint model*, to determine if the background information contained in a pair of images map to the same user. The app needs at least one reference frame for a user, and all subsequent frames obtained are compared against the reference to identify the user.

Drawing from existing research [14, 37, 55], we use the triplet loss to train the background fingerprint model. We train the model to produce embeddings such that the Euclidean distance between those extracted from frames captured by the same user are below an empirically determined threshold, while the distance between those from two different users is above the threshold. We train this model on frames from 15 users in the card scanning dataset and evaluate it on the remaining 4 users. On 1, 000 random pairs of frames captured by the same users, the model makes correct predictions on 804 pairs. On another set of 1, 000 random pairs of frames from different users, the model makes correct predictions on 863 pairs. The overall test accuracy of the attack is 83.41%. These results demonstrate that malicious apps can use background information in credit card scans to identify users.

Num. Images		Credit Card		Driver's License	
Credit Cards	**Driver's Licenses**	**Class. Accuracy**	**Loc. Accuracy (IOU)**	**Class. Accuracy**	**Loc. Accuracy (IOU)**
449	85,669	100.00%	84.85%	100.00%	93.30%
85,649	461	100.00%	89.71%	100.00%	90.40%
1697	1719	100.00%	83.52%	100.00%	92.24%
0	882	N/A	N/A	100.00%	82.43%
869	0	100.00%	80.12%	N/A	N/A

Table 5. Results showing the number of images needed to attain herd-protection with credit cards and driver's licenses. We measure the number of images needed for each object to attain acceptable localization and classification accuracies on a held-out test set. The results show that the sanitizer needs less than 500 images of the new object, when there is a large number of images of the other object. Additionally, to support both objects, the sanitizer needs close to 1700 images of each object. The sanitizer needs less than 900 images to support each object in isolation.

7.3.2 Aragorn vs. user identification attacks. We test both attack models on sanitized frames produced by Aragorn. We use the sanitizer to sanitize images from the same test sets described above while not changing the training images. Table 4 shows that the multi-class classifier's attack accuracy drops from 97.32% on complete camera frames to 5.25% on sanitized frames. Similarly, the background fingerprint model's attack accuracy drops from 83.41% on complete camera frames to 50.09% on sanitized frames.

For both attacks, the attack accuracy drops to near random chance after sanitization. Specifically, 5.25% accuracy for 19-class classification is equivalent to randomly guessing between 19 classes. 50.09% accuracy for the background fingerprint model is also equivalent to random guessing (binary decision of whether two frames were captured by the same user). We were unable to train similar fingerprint models when training on sanitized frames. See Appendix 11.3 for details. In conclusion, these results show that Aragorn's sanitizer removes the background information in camera frames that can be used by apps to identify users.

7.4 Herd protection

In this section, we quantify the number of training images needed to attain herd protection for certain objects. It is important to estimate when herd protection can be attained since privacy is unprotected until then. Accordingly, in this section, we evaluate training the sanitizer in two potentially difficult scenarios, one where we assume that we had previously gathered driver's license images and need to gather images of credit cards and vice versa. We consider these to be difficult scenarios since these objects look similar and have the same form factor, thereby making it difficult for the sanitizer to discern differences between them.

We report the number of training images we need for each object given that we had previously gathered data for the other object. Concretely, we report the number of credit card images we need to train the sanitizer in three different use cases: (1) where we had previously gathered a large number of driver's licenses (85, 669 images), (2) previously gathered fewer driver's licenses (1, 719 images) and (3) not gathered any driver's licenses. We then report the equivalent metrics for the number of driver's license images needed given that we had previously gathered credit card images. We computed these metrics by iteratively increasing the number of images of the new object until we attain acceptable classification and localization accuracies.

We use two datasets corresponding to scanning credit cards and scanning driver's licenses, both obtained from the authors of Daredevil. To label them, we use the U^2–Net salient object detector [48] to generate the bounding boxes and assign class labels based on the objects in the dataset (i.e., credit card or driver's license).

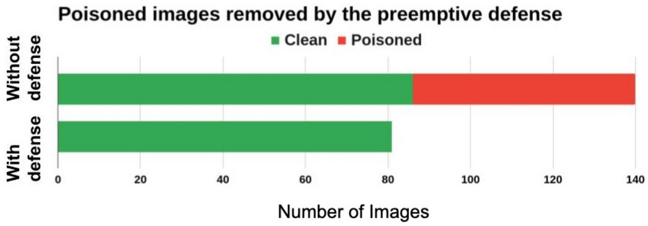

Fig. 11. Chart showing the effectiveness of Aragorn's preemptive defense in detecting poisoned images. Based on the majority of responses, we were able to remove 100% of poisoned images in our dataset while losing less than 6% of clean images.

Table 5 reports our results on held-out test sets containing 270 samples for each object. From these results, we see that in all use-cases fewer than 1, 800 images of the new object are sufficient to attain herd protection. Concretely, we see that we attain 100% classification accuracy and over 84% localization accuracy (IOU) with fewer than 500 images of the new object when we had previously trained on close to 86, 000 images of the other object. Similarly, we see that 1, 697 images of the new object are sufficient to attain 100% classification and 83.52% localization accuracy when we had previously trained the sanitizer on 1, 719 samples of the other object. Lastly, training on the new object with no previous history of the other object also requires fewer than 900 images of the object to attain 100% classification and over 80% localization accuracy.

Thus, even if we use one frame per user for training, as long as the app seeking Aragorn to recognize a new object can engage with at least 1, 719 users, we would attain herd protection relatively quickly, even in case the sanitizer needs to detect similar objects like credit cards and driver's licenses. These numbers validate the flexibility in our design where users can choose to opt out of sharing their camera frames with Aragorn server.

7.5 Crowdsourced validation

We simulate Aragorn's preemptive defense with a user study,[4] where we show blurred and sanitized images (using the salient object detector as described in §5.3.3) of clean and poisoned credit cards (we define clean and poisoned credit card images in context of our evaluation in the next paragraph) and ask participants if the images *only* contain credit cards. We also ask them to describe any other potentially sensitive information they are able to glean from these images. We then quantify the proportion of poisoned images that remain after removing images based on responses from the study. We capture clean and poisoned images of credit cards for the user study. The clean images simulate users scanning credit cards, where objects could be present in the background but are not intentionally placed around the card. For poisoned images, we either capture images of driver's licenses in place of cards, or position driver's licenses close to credit cards, similar to the image shown in Figure 7. Overall, our dataset contains 140 images, of which 38.75% (54 images) are poisoned.

7.5.1 Preemptive defense. We obscure images in our dataset to only retain blurred out salient objects as described previously (§5.3.3). We randomly show these images to participants of our user study (using Google forms) and ask them if each image only contains a credit card. Participants can respond with a "Yes", "No" or "Not Sure". Each image also has a text box where participants are asked to describe any potentially sensitive information they can infer from the image. We ran the user study for 2 weeks and obtained results from 35 different participants. Based on the majority

[4] Our university's IRB reviewed our user study and exempted it from IRB.

	WaveOff		Aragorn	
Object of interest	**Class. Accuracy**	**Loc. Accuracy (IOU)**	**Class. Accuracy**	**Loc. Accuracy (IOU)**
Credit cards	80.24%	31.50%	91.32%	79.82%
Faces	50.04%	2.78%	98.16%	75.17%

Table 6. Results showing that Aragorn more reliably detects and localizes to both credit cards and faces when compared to WaveOff.

of responses, we remove all 54 poisoned images from our dataset. Of the 86 clean images, participants were unsure of 4 images, and incorrectly marked one clean image as poisoned. Thus, with a conservative approach of treating unsure responses as poisoned, we are able to retain 94.16% of clean images from the dataset, while completely removing all poisoned images (see Figure 11). We manually peruse the descriptive responses from participants and observe that none of them were able to infer any sensitive or personally identifiable information from the images shown to them. At best, they were able to identify certain cards as belonging to Visa or MasterCard, and in some cases guess the users' hair color or gender based on their image in driver's licenses. We were also unable to sharpen these images to recover any sensitive information with simple traditional vision filters as well as complex deep learning algorithms. See Appendix 11.4 for details.

Current research [66] shows that adversaries who poison as little as 10% of a dataset can exploit models trained on that data. However, our experiment shows that we are able to completely remove poisoned images, making Aragorn resilient to data poisoning attacks using the preemptive defense.

7.5.2 Reactive defense. With the reactive defense, we expect most users to clearly respond to whether the sanitizer had made the right prediction, since they are shown predictions from the sanitizer on unobscured frames from their own camera. To verify this expectation, we ran an experiment where 3 authors of this paper independently observed the sanitizer's predictions on 10 random frames each from 10 different scans from the card scanning dataset. As expected, all three authors ended up picking the exact frames as frames on which the sanitizer had made mistakes.

7.6 Comparison with WaveOff

Similar to Aragorn, WaveOff also employs an extensible allow list based approach to protect privacy. Aragorn primarily differs from WaveOff in terms of automation. WaveOff provides users with a graphical user interface that they can use to capture and mark their objects of interest prior to using a camera app. Once marked, users are protected from camera apps without any additional effort. The accuracy of WaveOff, however, is dependent on the user's skill in precisely marking these locations. Thus, only careful users who pay close attention to accurately mark these regions can benefit from WaveOff.

In this section, we compare the accuracy of Aragorn and WaveOff to detect objects that are often associated with camera apps. Concretely, we measure the classification and localization accuracies of WaveOff on credit cards and faces and compare them to Aragorn. WaveOff matches BRISK features [38] extracted from a given test image against those from a marked reference to localize to the object of interest in the test image. In our evaluation, we threshold the number of matches to classify the presence of the object of interest within the test images[5] and draw the smallest bounding box that covers all matches to localize to the object of interest.

[5] We also attempted to threshold based on the area covered by the matched regions but observed higher accuracies for WaveOff when thresholding using the number of matches.

7.6.1 Comparison on credit cards. We use data from the card scanning dataset. We pick 1, 021 random frames corresponding to 10 random scan videos, each containing a different card. We then take one sample image of each card in this set and mark a tight bounding box around the card to use as a reference image for each scan (to evaluate WaveOff in context of a careful user). At the empirically determined optimal threshold, WaveOff has a classification accuracy of 80% on this test set while Aragorn has a classification accuracy of 91.32%. Correspondingly, WaveOff has a localization accuracy of 31.50%, while Aragorn has a localization accuracy of 79.82%. We summarize these results in Table 6.

7.6.2 Comparison on faces. We observe that WaveOff is unable to detect human faces, despite using tightly cropped reference images, even when user backgrounds do not alter significantly. We first quantitatively evaluate WaveOff on 200 random face images from the CASIA-Webface dataset [13] and 200 random indoor background images from the indoor scene recognition dataset [49]. Across 10 different thresholds for the number of matchings, WaveOff has a rough classification accuracy of 50%, with the highest recorded accuracy being 50.04%. WaveOff correspondingly has a localization accuracy of 2.78%. On the same dataset, Aragorn reports a classification accuracy of 98.16% and a localization accuracy of 75.17%. While the CASIA-Webface dataset allows us to evaluate with a large number of faces, the images are not representative of users looking into their mobile cameras. We thus run a qualitative evaluation of WaveOff, using 10 images each of 2 authors of this paper looking into the camera. On these images too, we observe that WaveOff was unable to localize to the face. We attribute the lower accuracy of WaveOff to the inability of BRISK features to sufficiently represent variations in human faces, with Aragorn overcoming this using learned features.

8 LIMITATIONS

Sensitive information within the object of interest: Aragorn is designed to protect privacy while retaining app utility by allowing apps to only process regions within camera frames that contain their object of interest. Apps can still attempt to invade privacy via sensitive information or inadvertent fingerprints within the object of interest. For example, an app that scans hand-written documents can attempt to fingerprint users based on the user's handwriting.

Supporting uncommon objects: Aragorn can support objects that are represented in public datasets as well as more nuanced objects that are requested by apps, since we train on data from the users of the app. Aragorn, however, cannot support uncommon objects. Assuming that the uncommon object is still the salient object in camera frames, Aragorn can employ a salient object detector to detect them.

9 ADDITIONAL RELATED WORK

Camera Privacy In addition to building systems that incorporate block lists [2, 26, 56] or allow lists [25, 32, 50], Animesh et al. propose Camforensics [58] to monitor an app's execution while processing inputs from the camera. Researchers have also conducted extensive surveys in context of AR apps to understand the awareness and attitudes of users and bystanders towards AR headsets [46].

Knowledge Distillation: Knowledge distillation [28] is a form of model compression and acceleration technique where a smaller student model learns from a large teacher model. Related to our work, weakly supervised object detectors [11] are trained with weaker forms of supervision like high-level category labels, alleviating the need for precise bounding boxes. Researchers in [39, 67] use an iterative training procedure to alternatively train weakly supervised and supervised object detectors from one another. Researchers have also used teacher and student models to improve the accuracy of human activity recognition [61].

Protecting user privacy from untrusted ML models Orthogonal to our approach, researchers have proposed cryptographic approaches to protect user privacy from untrusted ML models [34, 42]. These techniques run ML inference on inputs that have been encrypted by users to produce an encrypted result that can only be decrypted by them. These techniques work well for camera apps where users consume the result of ML inference (such as medical diagnosis from X-rays) but not when apps have to consume the result (like scanning a credit card).

10 CONCLUSION

While mobile cameras allow app developers to implement rich functionalities, their unfettered access also poses a serious threat to privacy. Thus, it is important to limit camera access of mobile apps. To address this problem, we presented Aragorn, a new privacy-enhancing system that uses deep learning, knowledge distillation, and crowdsourcing to automatically and extensibly implement fine grained object-level permissions for mobile camera apps. Aragorn protects privacy by limiting access of camera apps to sanitized camera frames that contain only user-designated objects. Our evaluation showed that Aragorn can accurately sanitize camera frames without degrading app functionality in a robust and efficient manner.

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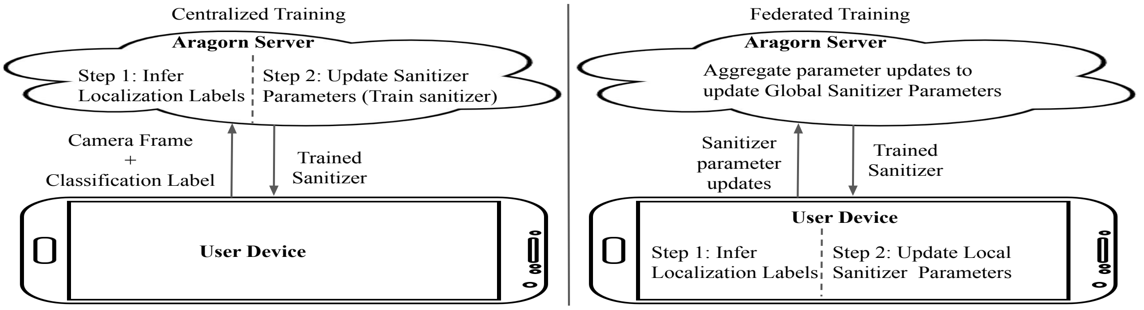
Centralized Training
Aragorn Server
Step 1: Infer Localization Labels
Step 2: Update Sanitizer Parameters (Train sanitizer)
Camera Frame + Classification Label
Trained Sanitizer
User Device
Federated Training
Aragorn Server
Aggregate parameter updates to update Global Sanitizer Parameters
Sanitizer parameter updates
Trained Sanitizer
User Device
Step 1: Infer Localization Labels
Step 2: Update Local Sanitizer Parameters

Fig. 12. A centralized implementation (left) of the transient workflow to train the sanitizer would involve transmitting camera frames to Aragorn server which would then infer localization labels and train the sanitizer. In contrast, a federated implementation (right) would locally infer the localization labels and compute updates to the parameters (trains) of a local sanitizer within the user's device. Aragorn server would then aggregate updates from multiple user devices to train a global sanitizer.

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11 APPENDIX

11.1 Aragorn with federated learning

Aragorn's federated implementation would make use of a local sanitizer present on each user's device and a global sanitizer in Aragorn server. Here, we would execute the training procedure described in § 5.3.1 within the user's device to compute parameter updates to the local sanitizer. Then, we would transmit these updates to Aragorn server which would aggregate updates from multiple devices to update the global sanitizer. With federated learning, we run a salient model to generate the localization labels within the user's device instead of running it on Aragorn server. We provide an overview of the variants in Figure 12. Upon training, user devices would be updated with the global sanitizer to operate in the steady-state workflow.

Training a multiclass sanitizer with federated learning In practice, using a multiclass object detector for the sanitizer that has been trained to recognize multiple objects would have higher accuracy than multiple single class object detectors as independent sanitizers, each of which have been trained to recognize a different object [47]. This is particularly true when dealing with similar looking objects. For example, a sanitizer that has only been trained on credit card images may mistakenly recognize a driver's license as a credit card, since it has not seen driver's licenses with a different class while training. With centralized learning, training a multiclass sanitizer while extending support to a new object would be trivial with access to training images (including those gathered previously for other objects) at Aragorn server. This would allow retraining the model from scratch with the appropriate number of objects. However, we cannot follow the same approach with federated learning since we would not have access to training images. Previously trained models cannot be reused as is, since their output layers would have fewer dimensions than the required number of dimensions for extension. We discuss the following methods to train the sanitizer in a federated manner.

First, we could require all users, including those running apps in the steady-state workflow to contribute to training by computing parameter updates on their respective objects of interest. This way, Aragorn server will obtain model parameter updates for all objects, which it can aggregate to update the global model. This approach would be the federated equivalent of retraining the sanitizer from scratch. However, this approach would impose additional load on all user devices (in terms of running additional computations), including those devices that are not running apps that seek extension to recognize a new object. One way to reduce the load would be to fine-tune a previously trained sanitizer, where we replace the last layer with random weights of appropriate dimensions. Fine-tuning (updating the parameters of only the last layer) this model would require fewer updates for previous objects, and can be obtained from a smaller set of users.

Alternatively, we could use multiple single class sanitizers in case of federated learning. This would not increase the load on all user devices, but could lead to less accurate predictions from the sanitizer, especially when objects similar to the intended object of interest are present in the background. Despite this limitation, this approach could still protect privacy in most cases since similar looking objects to the intended object of interest may not be present in the user's environment. Scans from the card scanning dataset did not have objects similar to credit cards in the background.

Implementation The biggest bottleneck with Aragorn's federated implementation is running ML inference on a salient object detector within the user's device. We run a public TensorFlow Lite version of U2-Net [20] as the on-device salient object detector on a Google Pixel 2 phone. The model occupies 43 MB on disk and on average takes 44s for inference on a single image on the CPU. The high latency contributed by this operation necessitates running the federated variant in the background (regardless of the latency of computing gradient updates to the local sanitizer) once the user has completed their interaction with the app to preserve user experience. Based on existing research [18], we expect the sanitizer trained with federated learning to attain similar accuracy to that attained with centralized learning.

11.2 Using a salient object detector with Aragorn

The supervised sanitizer employed by Aragorn performs classification and localization with a single inference unlike a salient object detector which only provides localization. Thus, a salient object detector like U^2-Net has to be complemented with a classifier in order to be employed by Aragorn. Results in §6 and §11.1 also show that U^2-Net takes over 3 orders of magnitude more time for inference over the supervised sanitizer. The sanitizer also has a marginally higher localization accuracy (IOU) over U^2-Net. On a subset of frames from 20 random scan videos in the card scanning dataset, the sanitizer has a localization accuracy of 81% while U^2-Net has a localization accuracy of 77%.

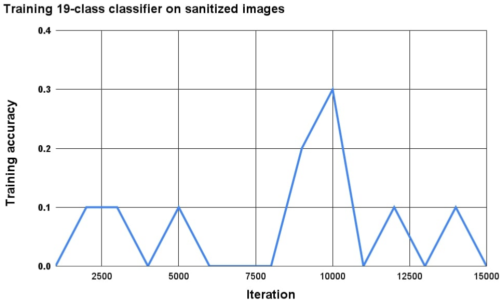

Fig. 13. Training the 19-class classifier on sanitized frames from the sanitizer does not even lead to any improvement in training accuracy. This provides empirical evidence of a lack of fingerprintable information in the sanitized frames.

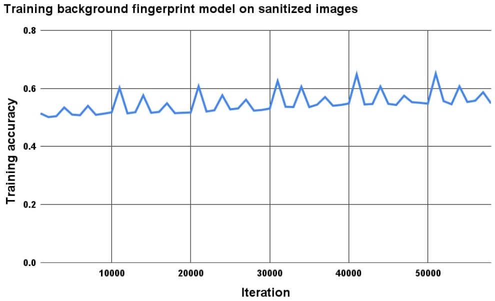

Fig. 14. Training the background fingerprint model on sanitized frames from the sanitizer does not even lead to any improvement in training accuracy. This provides empirical evidence of a lack of fingerprintable information in the sanitized frames.

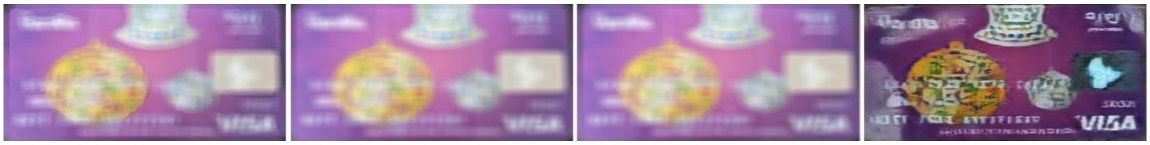

Fig. 15. Results of attempting to sharpen a blurred credit card image. The leftmost image is a blurred credit card image, followed by the result of sharpening the image using a sharpening filter, sharpening the image using DeblurGAN [35] and sharpening using Pix2pix GAN [31]. These results show the difficulty malicious users would face in attempting to recover sensitive information from blurred images shown to them as part of Aragorn's preemptive defense.

11.3 Are fingerprints present in the sanitized frames produced by Aragorn?

We seek to understand if there is information contained in the sanitized images produced by Aragorn that can be used to identify users. We answer this question by training a 19-class classifier and a background fingerprint model on the sanitized frames produced by Aragorn on frames from Daredevil's card scanning dataset. However, we were neither able to train a background fingerprint model nor a classifier to fingerprint the sanitized images. Both models are unable to even reliably make predictions on their respective training sets, with the background fingerprint model attaining no more than 65% accuracy on its training set, and the classifier attaining no more than 40% on its training set. This inability of the classifier (a simpler model to train than the background fingerprint model) to even learn the training data provides strong empirical evidence of lesser information being present in the sanitized images that can be used for fingerprinting. Figure 13 and Figure 14 show the variation in training accuracy of the 19-class classifier and the background fingerprint model respectively on the sanitized frames with training iterations.

11.4 Users attempting to sharpen blurred images to overcome the preemptive defense

As discussed in §5.3.3, the preemptive defense validates images gathered from users by showing them to other users. In order to protect the privacy of the gathered images, we blur these images before showing them to other users. Malicious users could attempt to sharpen the images shown to them in order to recover and leak any private information contained in them. We ran experiments to sharpen the blurred images using image sharpening filters as well as two different deep learning based conditional generative adversarial networks (GANs) [31, 35], but were unable to recover any sharpen the images to recover any sensitive information from them. We show an example of the sharpened images produced by these methods in Figure 15.

11.5 Scaling the sanitizer to support a large number of objects

We observe that the classification and localization accuracies of object detectors such as YOLOv3 (which we use for the sanitizer) decrease when they support more than 15 objects. While this could raise concerns over how Aragorn can scale to support a large number of objects, such concerns can be easily addressed by employing multiple sanitizers, each of which supports a different set of objects. Then, based on the established object of interest, we can load the appropriate sanitizer to interface with the camera. We also ran a performance evaluation of a sanitizer supporting 15 objects on a Google Pixel 2 phone. This sanitizer roughly consumed the same amount of CPU and memory as the sanitizer supporting 3 objects (mentioned in § 6), while adding less than 1ms to the execution time.

11.6 Security Analysis

In this section, we list ways in which apps could attempt to undermine Aragorn to invade privacy and how Aragorn is robust to such attacks.

Apps requesting support for redundant or nonsensical objects Apps could request Aragorn to extend support to an object that is already supported in an attempt to run in the unprotected transient workflow. For example, say Aragorn supports "Credit Card" as the object of interest. A malicious card scanning app that is aware of this, could purposely request support for "Payment Card". Firstly, this would lead to the app operating in the transient workflow where it can access complete camera frames from the app. Second, it would add a redundant object to the list of objects supported by Aragorn that could potentially affect its ability to accurately localize to the object. Similarly, a malicious app could also request support for some nonsensical object defined through some gibberish. Aragornis robust against such attacks since requests for to extend the sanitizer to new objects go through manual review for approval. Requests for redundant or nonsensical objects would thus be caught and discarded in the review. The manual review also thwarts cases where the same app repeatedly requests support for different objects to continually operate in the transient workflow.

Apps forcing users to grant access to complete camera frames Aragorn also supports cases where users there is no object of interest and users have to show complete camera frames (All Objects option in Figure 4). Similar to some websites forcing users to disable ad blockers to access them, malicious camera apps could force users to grant access to complete camera frames. However, users can instead choose honest variants of such apps that provide the same utility which do not forcing users to do so.

11.7 Supporting requests from users for extension to new objects

Before Aragorn's initial deployment (prior to any invocations to the transient workflow), we train the sanitizer to detect common objects from public datasets to cover most objects that users could seek to scan that are not associated with any particular app. In case multiple users request support for a previously unrecognized object, Aragorn can support them as long as the object can either be associated with at least one camera app, or is present in a public dataset. Currently, Aragorn cannot support user requests to support arbitrary objects that do not map to either of these two options.

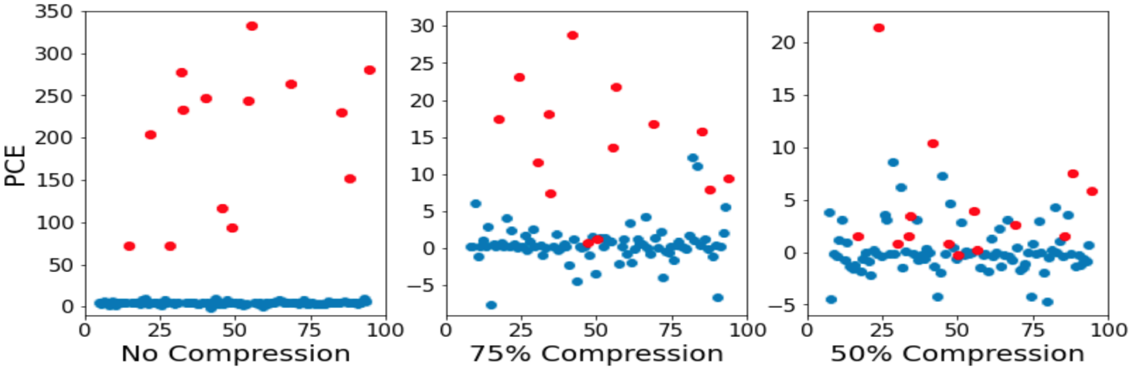

Fig. 16. PCE ratios for 100 candidate images at three different compression amounts; red values are ratios from the same device, blue values are different devices. With Aragorn, we use 50% compression to obscure PRNU fingerprints.

11.8 JPEG compression vs Photo-response nonuniformity (PRNU)

Aragorn uses JPEG compression to obscure inherent high-frequency camera fingerprints also known as photo-response nonuniformity (PRNU). In this section, we evaluate the effectiveness of JPEG compression in obscuring PRNU. We use a public implementation of the ABC protocol[9] that calculates the Peak-to-Correlation Energy ratio (PCE) between two images to determine if the same PRNU can be detected from both images. A higher PCE implies that the two images are likely to have the same PRNU, meaning that they were captured on the same device.

Concretely, we used 6 devices (Samsung Galaxy S7, Samsung Galaxy Tab S7, Google Pixel 2, Google Pixel 3A, Google Pixel 4 and Redmi Note 7) and picked 20 reference images from them. We then pick 100 candidate images randomly chosen from these devices for comparison. A fingerprint can be successfully extracted if it is feasible to draw a clear bound between the PCE values of the devices that are the same as the reference device, and those that are different. As seen in Figure 16, that there is a clear separation between the PCE values when both the reference images and the candidate images have not not gone through JPEG compression. However, for 75% and 50% JPEG compression, there is significantly more overlap between the PCE values for the candidate images, indicating that JPEG compression is an effective technique at obscuring PRNU. We repeated the experiment by considering JPEG compressed reference images and observed similar results.