ScreenAvoider: Protecting Computer Screens from Ubiquitous Cameras*

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Abstract

We live and work in environments that are inundated with cameras embedded in devices such as phones, tablets, laptops, and monitors. Newer wearable devices like Google Glass, Narrative Clip, and Autographer offer the ability to quietly log our lives with cameras from a 'first person' perspective. While capturing several meaningful and interesting moments, a significant number of images captured by these wearable cameras can contain computer screens. Given the potentially sensitive information that is visible on our displays, there is a need to guard computer screens from undesired photography. People need protection against photography of their screens, whether by other people's cameras or their own cameras.

We present ScreenAvoider, a framework that controls the collection and disclosure of images with computer screens and their sensitive content. ScreenAvoider can detect images with computer screens with high accuracy and can even go so far as to discriminate amongst screen content. We also introduce a ScreenTag system that aids in the identification of screen content, flagging images with highly sensitive content such as messaging applications or email webpages. We evaluate our concept on realistic lifelogging datasets, showing that ScreenAvoider provides a practical and useful solution that can help users manage their privacy.

1 Introduction

Cameras are pervasive and their numbers continue to grow. In addition to surveillance cameras installed on streets and in businesses, most people now own and carry around multiple cameras, since modern laptops, smartphones, tablets, monitors, gaming systems, televisions, and home automation systems are now equipped with cameras by default. Meanwhile, wearable cameras like Google Glass [16], the Narrative Clip [29], and Autographer [3] have recently come on the market, allowing people to record their whole lives from a 'first-person' perspective (Figure 1). These wearable devices enable useful applications like allowing users to take visual diaries of their lives (a concept known as 'lifelogging'), for instance to help improve their personal security, to treat memory loss and forms of dementia [18], or just for fun.

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Figure 1: Wearable cameras: From left, Narrative Clip, Google Glass, and Autographer.

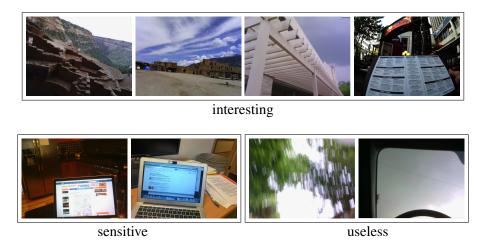


Figure 2: Some sample lifelogging images, showing that first-person cameras capture a mix of photos including interesting images (top), sensitive images of monitors (bottom-left panel), and useless images (bottom-right panel).

These wearable cameras can collect *thousands* images every day, many of which may capture private activities (like using the restroom) or information (like catching private documents) [19]. Many of these devices communicate with cloud-based applications, so that images are automatically shared with the cloud provider, and software features make it as easy to share images as it is to collect them. These features raise obvious privacy concerns, as research shows that users themselves often mistakenly disclose information electronically (through 'misclosures') [5]. This problem is exacerbated with large, unwieldy collections of lifelogging images, any of which may contain risks to privacy. Moreover one must trust the security of the cloud where many images are stored and used, with the recent case of celebrity photos stolen from hacked iCloud accounts showing that cloud photo storage is not always secure [32]. Ideally, sensitive images should be kept off the cloud and possibly deleted completely.

We thus need techniques for helping users control how images from wearable cameras are collected and shared. Some very recent research has considered this problem. For example, Klemperer et al. [24] suggest an access control system based on image tags that are assigned manually by users. A major difficulty with

this approach is that manually reviewing images from lifelogging cameras is prohibitively time-consuming, given that these devices capture images several times per minute, easily collecting thousands of images per day. Raval et al. propose MarkIt [34], where users can make annotations in private areas of a scene (like drawing a box around sensitive information on a whiteboard) which are recognized by the lifelogging camera and blurred or obscured. Roesner et al. propose a 'World-Driven Access Control' (WDAC) framework that relies on recognizing policy 'passports' [37] that are embedded in the physical world, like barcodes affixed to private objects. But the performance of both of these systems is limited by how well the physical world is annotated, and only certain types of private information can be annotated this way.

Templeman et al. [41] propose addressing this limitation through an attribute-based access control (ABAC) framework that would use computer vision techniques to detect visual attributes of a scene, allowing users to create policies based on the presence of these attributes. They present one implementation called PlaceAvoider [42] that recognizes room scenes with the goal of identifying photos taken in sensitive spaces, e.g., allowing users to block images taken in bathrooms and bedrooms. However, they consider only this single location attribute. Hoyle et al. [19] conducted a study of lifelogging users and confirmed that location is sometimes an important indicator of image privacy, but found that *other attributes like the presence of specific objects, especially computer monitors, are of much more concern to lifeloggers*. The finding that computer displays are a common concern is perhaps not surprising, given that the average American adult spends more than five hours a day in front of a digital device [10].

In this paper we address this specific problem of detecting and classifying images with computer displays, to help people protect sensitive information that is routinely displayed on their screens (like e-mails, instant messages, financial information, personnel records, etc.). We call this framework "ScreenAvoider." To help understand the features of ScreenAvoider, we first provide a motivating example:

Mary wears an Autographer lifelogging device to record her life. She uses a cloud-based lifelog archival service to curate her images. This service allows her to define policies based on where images were taken. She has a (PlaceAvoider) policy that marks photos from her office as private and photos taken in public places as public. Additionally she likes to keep her office images off the cloud. Today Mary decides to take her laptop to a local café for a working lunch.

Mary's policy reflects that she views private information (e.g. student grades) and conducts other private business in her office.

As Mary begins working at the café, she remembers that her lifelog service supports detecting images of monitors through a 'ScreenAvoider' policy. These policies allow her to define sharing preferences based on the presence of computer monitors in her images. She quickly enables a policy that prevents sharing images containing a computer screen. When she gets home in the evening and reviews her lifelogs, she realizes that there are many images of her playing Minecraft that she wants to share with her friends. She revises her ScreenAvoider policy to prevent images with her email or instant messenger applications from being uploaded to the cloud or shared with her friends by a cloud service.

As this example illustrates, simply detecting the presence of monitors may be useful to some users, but many will want to define policies based on finer-grained attributes like *what* is displayed on the monitor. Indeed, Hoyle et al. also found that many people wanted to share at least some images having monitors with some social contacts. Blocking all monitors in one's lifelogs would mean effectively erasing the five or more hours of their day that they spend interacting with the virtual world.



Figure 3: Examples of particularly difficult images for ScreenAvoider to classify. Each row shows two nearly-identical images, one of the real world and another displayed by a screen.

With ScreenAvoider, therefore, we aim to provide users with a way to specify privacy policies based on a) whether images contain computer monitors, and b) which applications are displayed on the captured screen.

Research Challenges. Our work addresses significant challenges to make the ScreenAvoider system work. Detecting monitors and recognizing their content is a challenging computer vision problem, especially given that lifelogging images are usually poorly composed (often capturing portions of monitors at unusual orientations with poor focus and motion blur). Moreover the content of monitors is so dynamic that it is difficult to define reliable and distinctive image features, besides very generic properties like rectangular shape. Detecting monitors is sometimes difficult even for a human, as illustrated in Figure 3, since modern monitors can render photo-realistic scenes that are hard to distinguish from reality.

However, computer vision techniques have improved dramatically very recently, due to the emergence of new machine learning techniques based on *deep learning*. While machine learning has been used in vision for over a decade, state-of-the-art approaches have typically used manually-created image features from which classifiers were learned. Deep learning is a new paradigm where the image features are learned with the image classifiers simultaneously, typically using a Convolutional Neural Network (CNN) [25] trained on large collections of images with huge amounts of computation made practical by high-end Graphics Processing Units (GPUs). These techniques have significantly surpassed a number of standard benchmarks in other recognition problems, causing excitement that deep learning may be a large step forward in vision technology.

In this paper we present a ScreenAvoider framework to control pictures that are taken of our monitors, using deep learning to build models of monitor images at the granularity of applications. To our knowledge, we are the first to attempt monitor detection and content recognition, as well as the first to apply deep learning to lifelogged images. Given the difficulty of this problem, we also study an easier variant of the problem where a custom computer application called ScreenTag displays machine-readable information on the monitor itself. This approach is in the spirit of the MarkIt [34] and WDAC [37], but is updated dynamically and automatically based on the current content and sensitivity properties of what is being displayed on the screen. As with WDAC and MarkIt, such policies can be used to control both screenowners' cameras as well as those carried by other people. However in the case where bystanders' monitors

are captured by other lifeloggers, one must rely on the camera owners for filtering out such images. Hoyle et al. found that camera owners have a sense of "propriety" where they are unwilling to share images that may violate bystanders' privacy. Their findings indicate that lifeloggers may be willing to use 'propriety policies' (e.g., "I am willing to discard 20% of my images if they violate other people's privacy").

Our Contributions. Our specific contributions are:

- 1. **Presenting ScreenAvoider**, a framework that can detect lifelogging images (which are often blurry and poorly composed) with computer screens with high accuracy, and even discriminate amongst running applications;
- 2. **Introducing ScreenTag**, a service that dynamically creates a recognizable visual element in order to aid ScreenAvoider:
- Implementing and evaluating ScreenAvoider using state-of-the-art deep learning techniques from
 computer vision, tested on lifelogging images collected from multiple sources to demonstrate the
 feasibility and limitations of such a system.

The remainder of this paper describes our contributions in detail. Section 2 describes our architecture, constraints, and concept of operation, while Section 3 reports our evaluation on several first-person datasets. We discuss the implications of our results in Section 4 before surveying related work in Section 5 and concluding in Section 6.

2 Our Approach

We now explain the ScreenAvoider framework for detecting images with monitors and specific types of on-screen content in detail. We begin by outlining our privacy goals and the adversary model.

2.1 Privacy goals and adversary model

Unlike with imagery taken from point-and-shoot cameras, where the photographer deliberately composes the scene, with wearable cameras the lifeloggers play the role of a 'curator' who must sift through and identify the interesting photos that are worth sharing and those that should be withheld or deleted. Our high-level objective for ScreenAvoider is to enhance a curatorial tool, e.g., one based on ABAC as proposed by Templeman et al., that reduces the workload for users in finding their private photos. We specifically target monitors because the lifelogging study by Hoyle et al. found that computer monitors were the single most frequent reason people chose not to share their photos: of the 10% of images that the users did not share, 30% contained monitors [19]. Computer monitors occurred in 30% of the images (based on a random sample), and of these 87% were actually shared. Our main objective of ScreenAvoider is to address this privacy concern by automatically identifying images with monitors, as well as to identify the content on the monitors, since some applications typically include private information while others show information that may be benign or even desirable to share. (As users of lifelogging devices ourselves, we informally confirmed that computer monitors represent the most frequent potential privacy leaks for us as well.)

Our problem reduces to an information retrieval task where images with monitors, or images with monitors that display *specific applications*, are identified and handled appropriately. The application of lifelogging also offers some leeway in terms of precision. Whereas it may be important to have high recall rates so that all sensitive monitors are identified, having moderate precision rates (i.e. relatively frequent false positives) may be acceptable (since with thousands of images being randomly captured per day, it may not matter much if some are censored unnecessarily). Of course, the exact best trade-off between precision and recall is likely to be application-specific, so we do not make any judgments on what this tradeoff may be and present complete Precision-Recall curves in Section 3. In practice, users could specify how conservative they want the detection to be, while being cognizant of the number of images that may be falsely blocked.

Of course, even at a relatively low precision, we cannot hope for perfect recall. Like Raval et al. [34], we do not believe this is a fatal problem: while it may be impossible to prevent the leakage of certain 'smoking gun' types of information, there are several other types of situations where privacy improves as more and more (e.g., embarrassing) content is removed. Thus while ScreenAvoider may leak private information through false negatives, we assume the overall impact of preventing the leakage of most sensitive images provides a clear, overall benefit to users.

In an application, ScreenAvoider could be used as an additional component to detect sensitive images either a) at the OS level to control what types of images are shared with untrusted applications or uploaded to an untrusted cloud service, b) in a cloud service that the user trusts for managing access (by other users) to his/her lifelogging photo albums, or c) as a mechanism that is used directly by a sensing device to control collection. In the first category, Jana et al's work with the Darkly system [22] and recognizers [21] address the access control problem with a general solution relying on a limited OpenCV API [4] (which does not support the detection of monitors) and can leverage our work.

In the following subsections we first describe our system architecture followed by overviews of the screen detection approach and the screen content classifier.

2.2 System architecture

Current lifelogging platforms including Autographer and Narrative Clip, as well as more general-purpose devices like Google Glass that can run lifelogging applications, offer cloud-based services for storing and managing of images. Our ScreenAvoider system permits the organization of images by their content using a hierarchical classifier, as illustrated in Figure 4. When presented with an image, the system uses a classifier trained through machine learning to first determine whether a screen is visible. If a screen is detected, the image is passed to a multi-way classifier that attempts to infer whether any applications of interest are visible. Because this is a difficult classification problem to perform using visual features alone, especially when only a portion of the screen is visible, we have also explored a technique that eases the problem through a custom application running on the computer itself. This ScreenTag system, which is complementary to ScreenAvoider, dynamically creates and renders a machine-readable visual code overlaid on the computer's display, that contains information about which applications are running on the system. This way, lifelogging photos taken of the monitor include a "watermark" that is easier for the lifelogging system to detect and interpret.

2.3 Detecting computer screens and monitors in images

Detecting computer screens in images is a specific application of the general problem of *object category detection* in computer vision, where the goal is to recognize broad categories of objects whose visual appearance may vary dramatically from one object to the next (like cars, airplanes, pedestrians, etc.). Even the same instance of an object can appear very different from one image to the next, due to variations in lighting, camera angle, lens zoom, etc. The key challenge in object category recognition is how to build models that are invariant to this visual variation that does not relate to the object's identity, while being sensitive to features that differentiate monitors from other similar objects (e.g. picture frames, windows, hardcopy print-outs, etc.).

To separate these important visual characteristics from the ones that should not matter, most work in category recognition takes a machine learning approach. Low-level visual features are extracted from the raw pixels of an image, typically corresponding to properties of color, texture, and shape, and are represented as high-dimensional vectors in some feature space. Then a discriminative machine learning algorithm like Support Vector Machines (SVMs) or Random Forests is given these extracted feature vectors for a set of images with known ground-truth labels (e.g. monitor and non-monitors), and the algorithm attempts to learn a decision boundary between the two classes in the feature space. Given a new image at classification time, the same features are extracted and the learned classifier is used to estimate its unknown label. (We

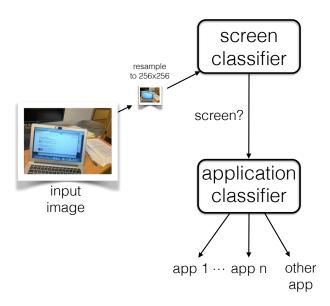


Figure 4: The ScreenAvoider hierarchical classifier. Native images are downsized for the Caffe CNN framework. While this depiction shows two classification levels, in Subsection 3.3 we also present a single classifier that includes applications and a class without screens.

summarize key related work in more detail in Section 5).

We applied this traditional category recognition approach to detecting monitors in lifelogging images, using a battery of state-of-the-art image features. These included simple image-level features like color histograms, more advanced scene layout features like GIST [30] and Local Binary Pattern histograms (which primarily capture global texture), and features that cue on local image regions including vector-quantized Histograms of Oriented Gradients (HOG) [9] and SIFT [28] features [42]. We then learned image classifiers with SVMs and thousands of annotated lifelogging images, and obtained promising preliminary results.

However, during just these few months of preliminary work, a new and potentially breakthrough technique emerged that has since far surpassed numerous long-standing benchmarks across a range of computer vision problems. Krizhevsky et al. [25] first reported results on the 2012 ImageNet challenge [38] dataset (which is perhaps the premier object category detection competition) that significantly cut the recognition error rate using a technique based on Convolutional Neural Networks. The key idea behind this approach is that instead of first designing low-level features by hand and then running a machine learning algorithm, a single unified algorithm should learn both the low-level features and the high-classifier simultaneously.

Krizhevsky et al. showed that this 'deep learning' could be accomplished efficiently using a neural network trained using backpropagation, very similar to classic techniques that have been known for many years [26]. However, they used more layers (typically seven or more, compared to more traditional values like three), and vastly more training data (tens to hundreds of millions of images). Training networks of this size requires massive amounts of computation, but modern Graphical Processing Units (GPUs) are well-suited for these calculations since they primarily involve simple linear algebra operations (e.g. dot products).

Here we apply Convolutional Neural Networks to our problem of screen detection in lifelogging images. To our knowledge, no other work has studied CNNs with this type of data. Unfortunately, because widespread use of CNNs is so new, not much is known about why these models work so well on some problems but not on others. One critical factor is that because the networks are so deep and thus have so

many parameters, they need a very large number of training images to work correctly (and otherwise they "overfit" to a specific training set instead of learning general properties about it).

A key challenge for applying this approach to lifelogging data is thus the lack of labeled large-scale training data; even though lifelogging devices capture several thousand photos per day, actually collecting and annotating millions of images would be prohibitively expensive. We tried several techniques to counter this problem, as described in more detail in Section 3, including downloading huge collections of images tagged "monitor" from Flickr. In the end, we followed Oquab [31] et al. and started with a model pretrained on the huge ImageNet dataset, even though that dataset has nothing to do with lifelogging or monitor detection. Using those network parameters as initialization, we then trained a network on monitor detection using our relatively small training dataset. The exact mechanism that allows this technique to work is not well understood, but may be that there is enough common visual structure in the world that a neural network trained for one problem still learns useful low-level features that also apply to other seemingly unrelated problems.

For our implementation, we use the open-source Caffe deep learning software [23]. Minimal preprocessing is necessary in order to use Caffe. Each image is downsampled such that the short axis is 256 pixels long. The center of the image is sampled along the long axis to offer a 256x256 pixel image to the network.

2.4 Classifying applications on computer screens

While detecting the presence of a computer screen alone may be useful in some applications, access control policies that apply restrictions to *all* images with a monitor may be overly aggressive. Thus, we seek a method that discriminates amongst screen content at the granularity of the application that is being used. While what constitutes 'sensitive' image content is subjective and likely differs from user to user, there are certain categories of applications that display information that most people would find sensitive. In this paper we consider three categories: email applications, social media websites, and instant messenger services. This is by no means an exhaustive list, but provides a starting point for evaluation.

The system must handle images of screens that contain sensitive applications but not necessarily when the quality of the image does not effectively resolve enough sensitive information. For instance, an image of a monitor displaying a very sensitive email is not actually sensitive if the camera is so far away that text cannot be resolved. Thus, during our evaluation in Section 3 we address how well the classifier performs with respect to screens that contain intelligible information. While further work is needed in determining what types of information are 'unresolvable' under which conditions in general (e.g., photos and video), we concentrate on the more specific problem of intelligible text.

As we did with the screen detection in the last subsection, we rely on deep learning methods using CNNs. Application detection is a strictly more difficult problem than monitor detection, because the system must choose the correct of several possible applications in addition to deciding if there is a monitor in the image at all. Also, appearance of some websites is highly variable; for instance, Gmail offers customized background "themes" that can dramatically alter its appearance, while different users' Facebook feeds appear differently due to differences in ads, friend activity, languages, browser settings, etc. We test the ability of the classifier to generalize across these differences, even if the training algorithm has never seen any images from a particular user's lifelog, in Section 3.

2.5 ScreenTag: conveying the sensitivity of screens

In Section 1 we described several methods for assigning labels to images during or after photo collection [34, 37, 24]. Here we propose to do both: in addition to the post hoc processing of raw lifelogging images that we discussed in the last two sections, we also consider marking screens themselves with labels that could help ease the burden of screen content classification.

For example, a regular lifelogger could then install the ScreenTag application on their home and office computers. ScreenTag displays a machine-readable barcode in a corner of the screen, encoding informa-



Figure 5: A screen capture with the ScreenTag visible in the upper left corner. This display is 1440x900 pixels and the QR code is set to 120x120 pixels. For this screen configuration, ScreenTag requires just 1.11% of the viewing area.

tion about which applications are currently running on the system. When processing lifelogging images, ScreenAvoider uses the monitor detection and application classification techniques presented above but also scans for this special barcode. If the barcode is missing, because the user captures another person's monitor, ScreenAvoider may still take the correct action as long as the system classifies the image correctly. If the barcode is present, the visual recognition task is eased significantly, and we hypothesize that there is a greater chance that ScreenAvoider will correctly handle the image. In an era of pervasive cameras, people may be sufficiently motivated to include such privacy signals on their screens.

While it would be possible to use out-of-band channels to communicate this information while leaving the screen content unaltered, these channels lack precision, e.g., by blocking images even when the screen is not within the field of view of the camera. Consider a policy to prevent the photography of emails. The system could use Bluetooth to inform nearby lifelogging cameras that the email application is running, but photos of an area nowhere near the computer would be assigned an incorrect label. Thus, we pursue an in-band method of a visual marker that is rendered on the screen, which we call ScreenTag. This approach is unique when compared to the MarkIt and WDAC systems in that the annotation changes dynamically with screen content and the images are algorithmically labeled.

We prototyped the ScreenTag system for Mac OS X 10.9. We constructed a blacklist of sensitive applications and websites, including Gmail, Facebook, and Apple Messenger for our evaluation. Our program polls system processes and the Safari web browser every second via bash and AppleScript, and constructs a bit vector encoding the state of these applications and if blacklisted websites are on the front tab of the browser. This vector is encoded in a QR code that is configured for maximum readability and the highest level of error correction using QRencode [14]. We use the Geektools software package to display the gadget persistently while providing the user the ability to resize or move the gadget at their will [15]. Figure 5 shows a screenshot of ScreenTag running while a browser window is open.

3 Evaluation

We evaluated ScreenAvoider through numerous experiments using a variety of image data to assess classifier accuracy and performance. We first describe the datasets that we used.

3.1 Evaluation datasets

In our search for suitable evaluation datasets, we came across none that were within the public domain. We sampled the lifelogs of the authors as our primary source of data for our machine learning approaches. The

Table 1: An overview of the datasets that were used to evaluate machine learning approaches. The *irb study* dataset is an aggregation of images from 36 users. The dataset from *author* was collected by the authors from their own lifelogging devices. The *flickr* images were manually scraped from Flickr and randomly sampled.

	Facebook	Gmail	Messenger	other	no monitor	total
irb study data	35	12	2	736	1957	2742
author	2750	2659	3046	3749	6594	18798
flickr	0	0	0	784	0	784
total	2785	2671	2799	5269	8551	22319

lifelogging devices used were a combination of Google Glass, Narrative Clip, Autographer, and lanyard worn smartphones with continuous photography applications. In all, the authors provided more than 18,000 images that were manually labeled. The authors' IRB office was consulted and this effort was deemed to not be human subjects research.

To augment our data, Roberto Hoyle at Indiana University made a subset of their 2014 UBICOMP [19] dataset available to us and we secured the necessary IRB permissions. This dataset is very valuable in that it was collected in situ by 36 participants in a human subject study.

Lastly, we scraped more than 784 manually labeled images from Flickr to bolster our dataset. These images are screenshots that contain monitor content that are largely devoid of the physical monitor structure (e.g., bezels, logos, buttons, etc). Details of our datasets can be found in Table 1.

The *irb* and *author* datasets are actual lifelog image sets that were opportunistically collected under uncontrolled conditions. As such, photographic quality is generally poor with a significant fraction displaying poor composition, exposure, or focus. All sources of data were given an opportunity to delete very sensitive images that should not be part of the study.

3.2 Detecting computer screens and monitors

Our initial task is to evaluate the efficacy of a classifier to retrieve images with computer screens in them. To do this, we conducted three experiments:

- *Experiment Screen1* Train on 9,986 images from the *author* training partition. Test the model on 1,842 *author* images from the test partition that are randomly sampled such that there is an equal class distribution, so that a random classifier will achieve a baseline classification accuracy of 50%.
- Experiment Screen2 Train on 9,986 images from the *author* training partition. Test the model on all 2,742 *irb study data* images. 28.6% of these images have screens in them, which is the observed behavior from aggregating images from 36 users (so that a majority-class classifier will achieve a baseline accuracy of 71.4%).
- *Experiment Screen3* Train on 9,986 images from the *author* training partition. Test the model on a mix of the 1,958 *irb* images without screens and 784 *flickr* images with screens. This experimental test set replaces the *irb* screen images with those scraped from Flickr (baseline remains 71.4%).

As described in Section 2, we trained the Convolutional Neural Network by starting with a model pretrained on the large ImageNet collection of Internet images. These network weights are then used as initialization for a second round of training on our 9,986 *author* life-logging training images. We use the BVLC Reference CaffeNet pre-trained model that is supplied with Caffe [23]. The network configurations for screen and application classification are shown in Table 2. The model has 2.3M neurons with over

Table 2: BVLC Reference CaffeNet pre-trained model configuration with modification for ScreenAvoider. There are five sparsely connected convolutional layers and three fully connected layers that serve as a traditional neural network. Observe that only the last layer, fc3, changes with respect to the number of classes that are used. The parameter n is equal to the number of classes.

layer	# of filters	depth	width	height
data		3	227	227
conv1	96	3	11	11
conv2	256	48	5	5
conv3	384	256	3	3
conv4	384	192	3	3
conv5	256	192	3	3
fc1	1	4096	1	1
fc2	1	4096	1	1
fc3	1	n	1	1

Table 3: Experiment Screen1 confusion matrix. Baseline is 0.501. Accuracy is 0.998.

predicted		
	no screen	screen
no screen	919	3
screen	1	919
		no screen no screen 919

60M parameters. This reflects the memory limits of the NVIDIA Tesla K20 processor that we used in our implementation (described in Section 3.5).

Experiment Screen1 results - This experiment is conducted to serve as a sort of upper-bound on the accuracy for retrieving images that have computer screens in them, because it is designed to be the easiest of the experiments we consider. The algorithm must classify unseen test image based on an independent set of training images, but the training and test images are sampled from the same photo streams, which means that there are likely to be very similar images in the two sets. The test partition was randomly subsampled to obtain an equal class distribution — that is, a given image is just as likely to contain a computer screen as it does not.

The network demonstrated 99.8% accuracy for this experiment. Table 3 contains the confusion matrix that shows only three false positives and one false negative. The incorrectly classified images are displayed in Figure 7. Observe that the sole false negative image is of such poor quality that the no information can be retrieved from the photographed screen (i.e., there would arguably be no consequence if this image were classified incorrectly and shared). The three depicted images that do not contain monitors are labeled incorrectly and unnecessary restrictions would be applied in our proposed use case.

Figure 6 shows this experiment cast as a retrieval problem for recalling images with screens in them. Performance is excellent with the ability to recall 99% of screen images with 100% precision.

Experiment Screen2 results - This experiment tests the screen classifier under more difficult conditions. The test and training datasets in this experiment are completely independent, because the training images are from the *author* dataset while the test dataset is from the Hoyle et al. study, collected by 36 individuals in unconstrained settings. The class distribution in this case is not balanced but instead reflects the true distribution of monitors encountered in the real-world study, resulting in a high majority-class baseline. Finally, the camera used to collect the test data is a Samsung Y smartphone with software that is optimized to work under constrained battery power and network bandwidth resources [19]. This camera is not up to

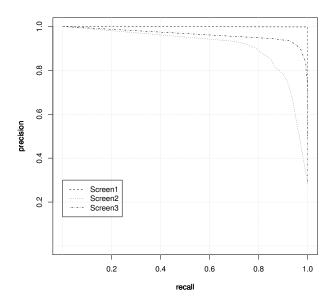


Figure 6: Precision and recall curves for retrieving images with computer screens.

modern standards and as such, the images display much higher degrees of motion blur, noise, and poor exposure (highlights).

The network demonstrated 91.5% accuracy for this experiment. Table 4 contains the confusion matrix that shows a near equal mix of false negative and false positive instances. These test images are IRB-controlled human subject study data so we are unable to include them in this paper. However, we did manually review all incorrectly classified images and report our observations. Table 5 provides an analysis of the 117 false negative images. In Section 1 we speak to the challenge of classifying computer screens that render content that looks unlike computer applications. This table shows that 49.6% of the false negative images had computer screens present that were displaying video games in full screen mode. Interestingly, the game Minecraft represented a large fraction of these. About 12.8% of the images capture media in full screen mode (movies, sports, and television shows). It is important to note that the training data had no examples of these types of images.

To assess the privacy impact stemming from classifier performance, we seek to identify false negative images that do in fact have sensitive content that would be potentially leaked. We found a total of 8 images that contained sensitive content by a conservative definition (1 Skype screenshot, 2 Microsoft Word screenshots, 3 Facebook shots, and 2 Adobe Illustrator shots). This represents a small fraction of the false negatives (6.8%) and only 0.3% of the overall test images.

We also manually reviewed the false positive images, and the results are presented in Table 6. A significant source of false positive instances came from images where windows or other framed objects were prominent. A key feature of computer screens is the boundary or frame that borders the display — this shows the reliance of the classifier on invariant screen frames versus the contents within. Additionally, about 16.4% of the false positive images were screens of televisions, projectors, or smartphones instead of computers. This is not necessarily an ill-effect because these displays also often display private information, and demonstrates the semantic power and the generalizability of deep learning techniques.





Figure 7: All four of the incorrectly classified Experiment *Screen1* photos (there were 1842 images in this test set). The top panel contains the only false negative case which is mostly occluded with the screen over-exposed. The bottom panel contains the three false positive cases.

Table 4: Experiment *Screen2* confusion matrix. Baseline is 0.714. Accuracy is 0.915.

	predicted		
		no screen	screen
actual	no screen	1842	117
	screen	116	667

The results are plotted in a PR curve in Figure 6. As expected, the results are significantly worse than the *screen1* experiment, but even in this difficult test case we are able to retrieve 88% of screen images with 80% precision and observe adequate performance.

Experiment Screen3 results - In this experiment, we test the ability of a classifier trained on one type of images to classify images of another type. This experiment is related to experiment *Screen2* in that they share the same negative class images (those without monitors), but the positive class contains monitor images that are randomly collected from Flickr and largely consists of screenshots of applications, not lifelogging photographs of screens. The difference is that here we are presenting the classifier with screen content sans computer monitor features (e.g., bezels, computer screen logos, etc).

The classifier had an improved accuracy of 95.3%, which was achieved by reducing the false negative rate when compared to experiment *Screen2*. The confusion matrix can be found in Table 7. For this experiment, the PR curve in Figure 6 shows that we recall 98% of screen images with 80% precision. This experiment further demonstrates the ability to detect monitors in general.

3.3 Classifying applications

While coarse policies that act solely on the presence of screens in images offer utility, these may be overly restrictive. That is, there may be nonsensitive images that users desire to share. Thus, we seek to classify images further based on screen content. We do this on the basis of applications that render content on the display. To evaluate ScreenAvoider in this manner, we conducted the following three experiments:

• Experiment App1 - Binary classification between sensitive applications versus other applications. Train on 9,986 images from the author training partition. Test the model on 5,050 author images from

Table 5: Experiment *Screen2* false negative (FN) analysis. The FN images were manually reviewed and the following observations were made about the listed fraction of images. We speculate that these observed properties frustrated classification attempts. Note that these observation categories are not mutually exclusive.

	fraction of FN images
full screen video games	0.496
less than 50% of screen visible	0.489
significantly out of focus	0.350
movie or TV show being played	0.128
screen with sensitive information	0.003

Table 6: Experiment *Screen2* false positive (FP) analysis. The FP images were manually reviewed and the following observations were made about the listed fraction of images. We speculate that these observed properties frustrated classification attempts. Note that these observation categories are not mutually exclusive.

	fraction of FP images
prominent window visible	0.336
other framed element	0.328
non-computer device with screen	0.164

the test partition that are randomly sampled such that there is an equal class distribution (baseline is 50%).

- Experiment App2 Four-way classification between Facebook, Gmail, Apple Messenger, and an "other" category. Train on 9,986 images from the *author* training partition. Test the model on 6,868 *author* test images sampled for an equal class distribution (baseline is 25%).
- Experiment App3 Five-way classification between no-screen, Facebook, Gmail, Apple Messenger, and an "other" application category. Train on 9,986 images from the *author* training partition. Test the model on all 2,742 *irb study data* images. 28.6% of these images have screens in them, which is the observed behavior from aggregating images from 36 users (baseline is 71.4%). The distribution of other applications is extremely unbalanced as shown in Table 10.

For these experiments with increased numbers of classes, we modify only the last layer of the convolutional neural network as shown in Table 2.

Experiment App1 results - This experiment expresses application classification as a binary task — a 'sensitive application' class includes images from Facebook, Gmail and Apple Messenger while an 'other application' class applies to screens displaying anything else.

The classifier demonstrates an accuracy of 75.1% which is 50% better than randomly guessing whether an image is sensitive or not. Table 8 shows the confusion matrix which interestingly shows that the classifier has a greater bias for false positives than false negatives. That is, the classifier is more likely to be overly restrictive by labeling 'other applications' as sensitive than vice versa. The PR curve in Figure 8 shows that this classifier can recall 80% of sensitive applications with 71% precision.

Experiment App2 results - We now seek to determine the performance of a classifier that attempts to discriminate amongst individual applications. Such fine-grained discrimination enables more expressive poli-

Table 7: Experiment *Screen3* confusion matrix. Baseline is 0.714. Accuracy is 0.953.

		predicted	
		no screen	screen
actual	no screen	1842	117
	screen	12	771

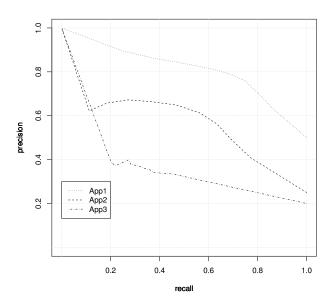


Figure 8: Precision and recall curves for the application classification experiments.

cies that could for example allow a user to wholly restrict images taken of their email application while allowing them to share images of their social media applications with friends.

The network was able to classify the test images with an accuracy of 54.2%. While this is degraded from the previous binary classification case, the baseline is similarly decreased to 0.25. Table 9 contains the confusion matrix for this experiment. This shows that the classifier is much more likely to label 'other applications' as Apple Messenger than it is to label Messenger images as an 'other application' on our dataset. But, this also shows that the classifier undesirably labels both Facebook and Gmail images as 'other applications' more often than vice versa.

The same table also shows the inter-app confusion. While the performance is not good, we can look to some example images to see how the classifier performs. Figure 9 contains an example image from each of the four categories that was classified correctly. Observe that the classifier was able to distinguish between Google search and Gmail even when they contain similar visual features. The correctly classified Facebook image that is shown displays a picture in a mode where the expected blue Facebook banner is absent — it would be a challenge for the typical user to accurately label the application in this case.

Table 8: Experiment *App1* confusion matrix. Baseline is 0.500. Accuracy is 0.751.

		other app	sensitive app
actual	other app	1717	808
	sensitive app	449	2076

Table 9: Experiment *App2* confusion matrix. Baseline is 0.250. Accuracy is 0.542.

		other app	messenger	facebook	gmail
actual	other app	1165	378	24	150
	messenger	148	1403	0	166
	facebook	379	635	524	179
	gmail	460	602	23	632

We carefully chose the representative applications that we did in order to rigorously evaluate ScreenAvoider:

- Facebook displays a large degree of variation in visual content. Signature visual features (e.g., the blue banner) come and go depending on context. Much of the screen contains content personalized to the user.
- Gmail is an example of an email service that is browser-based and difficult to visually distinguish from other web content (especially other Google web services).
- Apple Messenger has a minimalist visual theme that was deliberately chosen as an example of a messenging application that is not easily recognizable.

It is intuitive that ScreenAvoider's ability to discriminate amongst a given pair of applications is largely dependent on the choice of applications. Our evaluated applications and lifelogging datasets present challenging cases and would expect improved performance in the general case.

The *screen2* PR curve shown in Figure 8 demonstrates a degradation of retrieval performance as compared to the *screen1* curve, since we seek to make an already difficult problem even more challenging. The classifier in this case can recall 80% of the desired images with a precision of less than 40%.

Experiment App3 results - Lastly, we consider an experiment that reflects more difficult conditions, by introducing data with five classes, including four application classes and the case that there is no screen in the image. While our *author* training data has reasonably balanced classes, the *irb study* test data for this experiment has a high degree of imbalance.

The resulting accuracy for this experiment is 77.7% which is marginally above the 0.714 baseline. Thus, in this case the classifier cannot do much better than random guessing. The confusion matrix is displayed in Table 10. We can see that the classifier performs well at the coarse level of inferring whether or not a screen is present, but classification amongst sensitive applications is very poor. We conclude this subsection with the PR curve shown in Figure 8. This classifier is able to retrieve 80% of desired images with a precision of about 25%.

Other application classification approaches - Given the demonstrated difficulty of application classification, we explored other experiments outside of the three that we detail above.

An advantage of using CNNs is in the manner by which they extract useful features in the convolutional layers — thus, we consider using CNN-generated features with a different choice of classifier. We extracted

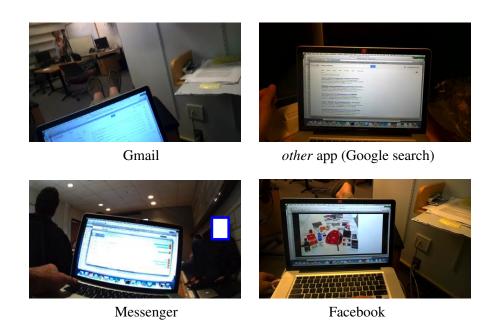


Figure 9: Examples of images that were correctly classified in experiment *App2*. Note the ability of the classifier to discriminate amongst Google search and GMail which have similar visual features. The blue box is added for anonymity.

Table 10: Experiment *App3* confusion matrix. Baseline is 0.714. Accuracy is 0.777. predicted

		no screen	other app	messenger	facebook	gmail
actual	no screen	1882	59	6	0	12
	other app	157	243	143	35	158
	messenger	0	2	0	0	0
	facebook	4	12	11	5	3
	gmail	0	7	3	0	2

the features from the network and applied them to SVM classifiers [13]. We applied two models to extract the features: the standard BVLC Reference CaffeNet pre-trained model and the fined-tuned model based on our data set (the latter case coincidentally represents the features used internally to the CNN in *App1*, *App2*, and *App3*). However, these attempts end up being inferior to the neural network classifier that is provided by Caffe.

3.4 ScreenTag performance

We evaluated our ScreenTag system by running it as described in Section 2. We defined a set of monitored applications and websites (Facebook, Gmail, and Apple Messenger) and ran our ScreenTag service to persistently display the QR code marker in the upper-left corner of the 1440x900 screen at a size of 120x120 pixels as shown in Figure 5. In this configuration on the test machine, ScreenTag covers 1.11% of the viewable screen area. The system is configured to update the marker at a rate of 1Hz. We invoke the highest level of error correction, H, to improve the readability of the QR code [20]. In theory, this allows the code to be read with nearly 30% of the visual information missing.

Table 11: ScreenTag results.

fraction of ScreenTag visible	# of images (%)	% of ScreenTags read
full	511	89.6
partial	11	0.0
none	13	0.0
TOTAL	535	85.6

We collected 535 images while using a laptop computer with ScreenTag rendered. To assess performance, we ran each of these images through the open source ZBar program to scan the QR code [48]. The results are shown in Table 11. We first seek to understand the readability of photographed codes in cases where the QR code is fully visible (no cropping or occlusion). We find that of these 511 images, we were able to successfully scan 85.6%.

There were 24 (4.5%) images where monitor was content was visible, but the marker was cropped by some degree, including cases where it was missing altogether. None of the codes in this subset were scannable, even those codes that were cropped by less than the 30% that the error correction should have recovered. While the error correction in QR codes adds a layer of robustness, our codes are scanned from images that are taken from some distance away with noise, illumination, and rotation transforms applied.

In all, there were 64 images where the ScreenTag was present, but was not able to be scanned. Manual review of these images shows 13% of these had such a high degree of poor exposure and focus that nothing on the screen was intelligible. Figure 10 shows examples of challenging images where ScreenTag was read correctly and examples of those images that could not be scanned.

Because of the built-in robustness of the QR code standard, codes that were readable were scanned with 100% accuracy. Thus, we can perfectly classify applications to the extent that we can detect and read the ScreenTag marker. The effective classification rate of 89.9% means it performs significantly better than the five-way application classification results of experiment *App3* in Subsection 3.3. When considering screen images, our experimental baseline is 0.25 with only 2 bits of information encoded in the QR code. A version 1 QR code allows the encoding of 72 data bits, so ScreenTag has the ability to discriminate amongst a *much* larger number of applications while retaining the same accuracy.

When evaluating ScreenTag as a classifier, we see that there are no false positive instances (i.e., codes are only scanned if they are exist) and that our error stems from false negative examples (i.e., where a code exists, but is not scanned).

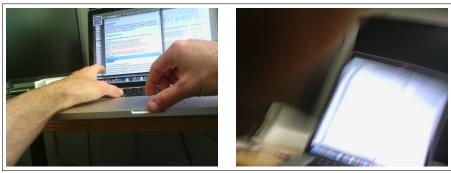
This insight permits a very useful application. Suppose there are applications or websites that a given user wants to share with their friends and family. They could set policies such that only positively identified images of these screens can be shared. Otherwise, they would have a default restrict policy. Such a mode of use could act in a privacy preserving way so long as we trust the system to not render a ScreenTag that marks private information as something to be shared. Consider our running example:

Mary decides that she only wants to share her screen images while playing Minecraft and while using her illustration application. She configures ScreenTag to mark her screen when she is using these applications and creates a ScreenAvoider policy that allows these pictures to be shared.

We limited our evaluation to the single marker size and location, but other options are possible. Adding additional markers and increasing its size should increase the likelihood of successful scans at the expense of a further reduction in usable screen space. Furthermore, even a version 1 QR code allows more capacity



ScreenTag was successfully scanned



ScreenTag was not scanned

Figure 10: Examples of images where ScreenTag is rendered on displays. Observe that bottom left image has sufficient resolution and sharpness to reveal the text on the screen. The example on the bottom right has a large degree of motion blur so neither the QR code nor anything else can be interpreted.

than may be necessary for our application. A bespoke code configuration could decrease data density in order to improve readability. We reserve this additional evaluation for future work.

3.5 Computational performance

For the machine learning approaches that we presented in Subsections 3.2 and 3.3, we used a workstation with an AMD Opteron 16-core Interlagos x86_64 CPU processor and one NVIDIA Tesla K20 GPU accelerator with a single Kepler GK110 GPU. The Caffe implementation ran on the single GPU. We began with the BLVC Reference CaffeNet model so we only had to fine-tune the network with our labeled training images. For the experiments described in Subsections 3.2 and 3.3, the training period ranged from 3 to 5 hours. However, classification computation time for individual images was just 0.12 seconds on average to include preprocessing and oversampling steps. The same classification task on the CPU averaged 1.5 seconds per image, which validates that it is feasible that computation can be performed on the users' machines in order to avoid relying on an untrusted cloud.

The ScreenTag system involves a much less computationally-intensive task. On average, it took just 0.44 seconds for the ZBar program to scan the image using an Ivy Bridge i7 laptop. This means that it is feasible that images can be curated in real time by the collection device when screens are annotated.

4 Discussion

Thwarting the photography of screens. As discussed in Section 1 we spend a large fraction of our time in front of computer screens engaging in private communications, conducting business among other sensitive functions. The confluence of our uses of portable computing and wearable cameras creates an environment where we can conduct these functions almost anywhere while within the view of others.

While we focus on photography of screens, a related vulnerability exists if the person sitting nearby at the coffee shop can read a private email directly from your screen. Systems have been proposed that seek to identify people [2] looking at your screen, but a motivated attacker with inexpensive magnification devices could still leave a victim vulnerable in public settings. The problem is worse when attackers employ camera devices. One system seeks to identify and disable nearby cameras [44], but prior work has shown powerful attacks on our screens where the attacker is up to 50 meters away and only views a reflection of your monitor [33, 46].

A different approach is to design the screen and content in such away that undesired viewing and photography is made difficult. This can be done by using a physical filter that is placed over the screen to restrict the possible viewing angle [1] or by creatively engineering the screen content. For instance, the Yovo messaging application renders screen content in a highly dynamic way, such to make static photography more difficult [47].

The lifelogging mode of use, made possible with modern wearable camera devices, begs for different solutions. The Hoyle study shows that continuous opportunistic photography represents a privacy threat to the users of the devices and those that are around them [19], but without malicious intentions. ScreenAvoider is a system that allows lifeloggers to more easily curate their vast collections of images in a privacy preserving way. Absent approaches to keep pictures of screens out of our lifelogs, we provide a manner in which to handle them with usable policies.

Avoiding the photography of bystanders' screens. Concern of other people's privacy out of a sense of propriety is a subset of our problem. The previous discussion focused on potential images of screens from the perspective of the bystander. Here, we consider lifeloggers collecting images in the presence of strangers using their electronic devices. The coarse screen detector component of ScreenAvoider remarkably labels images with screens in them agnostic of content.

While outside of the scope of this work, it is also possible that bystanders can communicate policies about their screens in the WDAC schema [37], which is similar to the work of Schiff et al. where bystanders wear visible markers to communicate policies to surveillance cameras [39]. However, our system does not easily differentiate between our own screens and devices that belong to bystanders. Thus, propriety policies for bystanders and default sharing policies of our own screens are contradictory if dependent on the same attribute. We reserve further exploration of these solutions for future work.

Screens signaling sensitive information. The ScreenTag system leverages the QR code which benefits from a well-embraced standard with demonstrated success in many applications. Our application of it permits the transmission of a significant amount of data about screen context. An alternative approach might use a bespoke method of communicating visual information to cameras. This can be done using some sort of rendered watermark [27] or with visible elements that provide informative features to machine learning approaches.

Our ScreenTag system is limited in that it only provides machine readable information. While it is effective in communicating contextual information to cameras, users may benefit from knowing when their screen has sensitive information that requires judicious behavior. An added feature could display a marker that is visible to users that dynamically changes based on screen content. A motivating example is the classification banner that is rendered on computer displays on DoD information systems [45]. We envision that visual elements can be added to our existing QR code to let users know they are using an application that is especially sensitive. We offer examples in Figure 11 and save further evaluation for future work.





Figure 11: A standard QR code may be modified to add visual elements to convey information to the user. Consider these two examples that might signal a sensitive context. Error correction permits the modification of the code itself to a degree as the code on the left is still readable.

Usability. Machine learning techniques require some degree of training data. For instance, the PlaceAvoider system required that the user 'enroll' their spaces to create labeled training data [42]. This approach is not feasible for ScreenAvoider — our deep learning-based system benefits from copious numbers of labeled images (on the order of thousands of images or more). Our results show that ScreenAvoider offers good general performance using a limited training set of less than 10,000 images sourced from just two users. The performance stands to increase with a richer source of training data. A usable ScreenAvoider application would leverage existing trained models that users could benefit from immediately only having to define policies.

While the screen detection algorithm performed extremely well, the application classification task suffered from a high degree of error to the extent that reliance on the classifier for policy enforcement is not prudent. More work remains to be done in this area. However, the ScreenTag system performed well at discriminating amongst different applications. The ScreenTag approach allows the user to balance performance and usability by defining the size and location of the marker.

As described in Section 3.5, the running time of our classifier benefits significantly from having a GPU. Advanced mobile devices like smartphones have GPUs that could be used for this purpose, although current-generation wearable devices do not. However, ScreenAvoider could easily be implemented alongside the cloud-based services that accompany our current lifelogging devices or though an OS-level cloud service akin to Apple Siri [40] or Google Voice [17]. In addition to our privacy objectives, the more general application of image tagging could serve to help users curate their images.

5 Related Work

Lifelogging and privacy. The recent availability of wearable devices for consumers has resulted in even greater interest by the research community. Work by Hoyle et al. explores privacy issues for lifeloggers [19] while Denning et al. consider the issues of bystanders that find themselves in the vicinity of users of wearable cameras [11]. Roesner et al. address the general security and privacy issues for augmented reality devices which apply also to wearable camera devices [35]. Caine explores mistakes that users make when they share information with an unintended group, a problem that ScreenAvoider addresses [5]. The PlaceRaider system is a smartphone based attack that shows how opportunistically-collected images can be exploited by an adversary to reconstruct 3D models of their personal spaces [43]. These works motivate the necessity of controls that can help users best collect and manage lifelogs.

Access control. Discretionary- and mandatory-access control frameworks underpin many traditional computer operating systems [12], but research on access control concepts for sensing platforms is bringing about new ideas. These sensor-enabled products include wearable and mobile devices that differ in how files (objects) are created and used. User-driven access control [36] seeks to add abstraction layers that confirm user

intent before the system grants access to user-owned resources like cameras. World-driven access control (WDAC) reads policies that are embedded in the environment (e.g, tags on physical objects) [37]. Attribute-based access control (ABAC) collects or infers attributes from the environment from which to apply policy rules to [41].

Moreover, other systems perform access control functions for image objects by filtering content such that applications can only access necessary information. The Darkly system [22] and the related OS recognizers [21] perform this function using computer vision approaches. ScreenAvoider combines elements from each of these systems to offer a solution to the problem of screens that are photographed by wearable cameras.

Object detection. Object detection is an active field in the computer vision community. Great strides have been made in the last 10 years with the identification of useful visual features including SIFT [28] and HOG [9] that are used with traditional classifiers like support vector machines. Greater advancement was seen when newer approaches were applied to existing features — this includes the 'bag of words' approach by Csurka et al. [8]. Chatfield et al. provide a comprehensive review of these techniques in their comparative paper [7]

Object detection competitions help to motivate new approaches and provide an objective measure by which to compare different algorithms. As described in Section 2, techniques based on deep learning with CNNs have surpassed existing techniques. Again, Chatfield et al. provide a useful survey of this new technology [6].

6 Conclusion

Research on the use of wearable cameras shows a need for solutions that allow users to freely collect images of their lives in a way that preserves privacy; both their own and the privacy of people around them. A specific and interesting problem arises when considering the amount of time that we spend sitting in front of computer screens. In this paper we presented a potential solution to help users manage images collected from wearable devices. We show that policies based on the presence of computer screens in images can accurately be enforced at a coarse level. While fine-grained policies that work on types of screen content are more challenging to enforce, we remain optimistic based on our initial results, especially when characterizing 'sensitive' vs. 'non-sensitive' applications.

Much work remains to be done in this area. We are the first that we know of to apply deep learning to lifelogs in order to gain semantic meaning and offer increased levels of management and organization. Our hope is to continue this work leading to deployable systems that increase our comfort with the wearable cameras that increasingly surround us.

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